Financial Development and Domestic Conflict: Can Finance Combat Conflict?

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Abstract

A conflict is typically a complex phenomena with multiple dimensions; social (ethnic and religious differences), political (civil wars), economic (control of natural resources). In this paper, we investigate whether an economic intervention can mitigate conflicts, given its multi dimensional nature. In particular, we are interested in understanding whether a financial intervention within a market framework, either an increase in bank credit supply or an increase in the number of bank accounts, in conflict-affected areas can reduce the volume and intensity of conflicts. Using a model as well as extensive empirical tests with district-level data from India over a long sample period (1983 2010), we find strong evidence that supports our models prediction that financial development mitigates conflicts. Multiple identification checks establish causality of our findings. We also investigate the channel through which credit impacts conflict. Our tests indicate that employment growth due to financial development serves as a beneficial channel from financial development to conflict. However, in the case of mining credit two opposing chan-

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nels, employment growth and rising inequality in land distribution offset each other. It is the first paper to connect financial development with conflicts.

Keywords: conflict, credit supply, number of bank accounts, economic growth, channel tests

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1 Introduction

A conflict is usually a complex phenomenon. A conflict may have many roots and causes, ranging from social conditions, ethnic differences, religious differences, and economic shocks. Lack of educational and employment opportunities have been shown to be positively correlated with onset and intensity of conflicts (Collier and Hoeffler (1998, 2001, 2002)), so have ethnic and religious differences (Esteban and Ray (2008, 2011), Mitra and Ray (2013)). Income shocks, due to variation in rainfall (Migues, Sergenti, and Satyanath, 2004), variation in exported commodity prices (Bazzi and Blattman, 2013), droughts and floods (Bai and Kung, 2011), have been used to identify causal effects of economic shocks on conflicts. Similarly, a conflict is typically very costly and destabilizing to society. It may affect society in multiple dimensions, including social, political, and economic spheres. Among economic consequences, the effects of displacement due to conflicts (Kondylis, 2010; Di Maio and Nandi, 2013), the effects of conflict on human capital including educational attainments (Chamarbagwala and Moran, 2010) and health (Arkesh et al, 2012) of children exposed to violence, the effects of conflict 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 effects of conflicts on firm preference (Abadie and Gardeazabal, 2003; Guidolin and LeFerrara, 2007) have been documented. Just the direct costs of a conflict in terms of property damage and deaths and injuries can be overwhelming. Over the period 1983 2010 in India alone there have been 5,548 reported incidents of conflicts. 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.

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 conflicts? Can financial development, measured either as an increase in supply of bank credit or in number of bank accounts in a geographic area, be that strategy and mitigate conflicts in the area? Can financial development serve this role within the market framework and outside of the sphere of government sphere? There is recorded evidence of failure of government or community initiatives to use financing to contain insurgency in different parts of the world (India, Philippines). These are the issues we investigate in the present paper. None of them has been investigated so far in the existing literature. Using a model as well as extensive empirical tests, in this paper we investigate 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. We are primarily interested in understanding the impact of financial growth and development within a market framework.

Our paper represents the first work that attempts to investigate if financial development mitigates conflicts. Our investigations also make another contribution to the existing literature. A sizeable literature examines connections between conflicts and economic activity. The connections studied in the literature include economic effects of conflicts as well as effects of economic events over conflicts. We have referred to some of specimens of the literature above. There is also an extensive literature that investigates the impact of financial growth and development on economic outcomes. A growing body of empirical analyses, including firm-level studies, industry-level studies, individual country-studies, time-series studies, panel-investigations, and broad cross-country comparisons, demonstrate a strong positive link between the functioning of the financial system and long-run economic growth.[1] Subject to many qualifications and alternative interpretations, the preponderance of evidence suggests that both financial intermediaries and markets matter for growth even when controlling for potential simultaneity bias. Furthermore, microeconomic-based evidence is consistent with the view that better developed financial systems ease external financing constraints facing firms, which suggests one mechanism through which financial development causally impacts economic growth (Rajan and Zingales, 1998). However, there is very little existing research to indicate if and how financial development impacts conflicts. The connections may work in conflicting ways. Educational opportunities and employment generated by financial development may mitigate conflicts. There could be other beneficial channels from financial development to conflict as well. On the other hand, diversion of funds meant for productive uses to conflicts has been documented. Our paper fills in this gap.

Since there is little existing literature and limited accumulated knowledge to guide the researchers, we develop a model to understand the possible connections between finance and conflict, and the direction of causation, if any. The model is parsimonious by design but quite broad in its scope. It models both onset and continuation of conflicts, and has several innovative features including social costs of conflicts in addition to the individual costs that the combatants face. In a two-sector economy

[1] Levine (2005) presents a comprehensive survey of this literature

(industry and conflict), two parties invest in conflict for a reward. The reward can potentially have many forms: political (effective control of a district); economic (control of mineral resources in a contested area); ethnic (displacement of Muslims from a contested part of the country). To finance their conflict-related activities, the parties divert bank credit given to them for projects in industry. Engaging in conflict is tempting, because the expected value of the reward from the conflict exceeds the certain outcome from the industry for any given amount of investment. However, it is also costly. The costs are of two types. The parties face the opportunity costs of not investing in industry. The other type of costs is represented by a social cost function in the model. It arises from death of manpower and destruction of infrastructure that a conflict causes, and increases in the total amount of capital invested in conflict. At some point, for a given party the rate of increase in the total costs exceeds the rate of increase in the expected outcome of the conflict. At that point the party stops investing further in conflict and uses the rest of the funds in industry. If the social cost function is concave in conflict investment, the model predicts that at a high level of conflict further supply of bank credit will reduce conflict. On the other hand, if the social cost function is convex, credit infusion will reduce conflict at all levels of conflict. Whether the cost function is actually concave or convex in the data is an empirical issue at this stage. For our data our empirical tests determine that the social cost function is convex.

Our model is a two-period model with exogenous credit supply in the first period. In the second period, the supply is endogenous. The banks use their experience from the first period to determine the level of credit for both parties. However, in the second period too, infusion of new credit causes a decline in conflict. In other words, financial intervention always mitigates conflicts.
Using an extensive sample of conflicts in Indian districts over e long period (1983

-2010), we test the predictions of the model. The conflict data comes from Global Terrorism Database. Since we are interested in studying conflicts with primarily economic motivations, we exclude religious conflicts and terrorist attacks from our sample. For robustness of our test results, we use three alternative measures of conflict in our tests: Conflict (General); Conflict (Intensity); and Conflict (Frequency). The first measure assigns a value of 1 to a district-year if there is a report of a conflict in that district-year. The second measure is an index, created by assigning 1 if the reported deaths in a conflict is 1 5, 2 if the range is 8 10, 3 if the range is 11 25, and 4 if the number exceeds 25. The third measure is the total number of reported conflicts for a given district-year.

The source of district-level 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. BSR provides occupation-wise credit supply data, such as credit to industry, agriculture, professional services etc. Since bank finance constitutes a small part of total agricultural finance in a given year in India, and professional services do not have a significant presence in the poorer parts of the country which witness most conflicts, we use industrial credit supply and industrial credit accounts in our tests. We also use an array of control variables that have been shown in other studies to influence conflicts. The control variables include:

1) worker participation rate, literacy rate, urbanisation, population density, schedules tribes population in Indian districts (source: Indian population census 1991, 2001, and 2011)

2) monthly average consumption expenditure and unemployment in Indian districts (source: National Sample Survey five thick rounds)

3) area covered under forests and net state domestic product (source IndiaStat)

4) district roads, national and state highways (source: Pradhan Mantri Gram Sadhak Yojana website).
The sample size for all our tests is large, exceeding 8,000 district-year observations. The test results overwhelmingly support our models prediction of a negative association between financial development and conflict for the full sample. The observed effects are significant statistically as well as economically. Using Conflict (G) as the dependent variable, an increase of 1 million in credit supply appears to result in a fall in probability of conflict by 9 percent. The results for the other two measures of conflict, Conflict (I) and Conflict (F), are in fact stronger. Throughout this paper we present results for Conflict (G) in the interest of making our claims cautious and conservative. We also conduct a number of other robustness tests.

We carry out multiple checks for identification of our test models. All results confirm that they are well-identified. 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, average consumption expenditure in a district, for the likely omitted variable, level of economic activity or GDP of the district, and verify that the proxy variable has the intended effect. For more verification, we use instrumental variable (IV) technique to identify the causal impact of industrial credit supply on conflict. The Debt Recovery Tribunal (DRT) Act, 1993, allowed the central government to establish DRTs in different Indian states for speedy recovery of overdue debt by creditors. 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. We use the phased introduction of DRTs (Visaria, 2009; Lilienfeld-Toal et al, 2012) in

Indian states to find two alternative instruments for credit supply: establishment of DRTs in the first group of states and duration of DRTs. 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 effect for the period 2008 - 10. We suspect financial crisis confounds the results beyond 2008.

We also conduct tests to determine whether the conflict-mitigating effects of credit infusion are stronger for more conflict-prone districts than for districts that are less conflict-prone. Affirmation would suggest that the social cost function is concave, while rejection would indicate that it is convex. We compute average conflict level of each district over the sample period by assigning 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 28 years in the entire the sample period is between 0 (minimum) and 1 (maximum). The districts above a certain threshold are more conflict prone; below less conflict prone. Thirty percent of the districts register a value of 0. We vary the threshold and divide up the full sample of districts into two groups with the following proportions: 60/40, 50/50, 40/60, 30/70, 20/80, and 10/90. In each ratio, the numerator indicates the proportion of districts in the top group. The test results indicate that for each pair the negative association is stronger for the bottom group. In other words, the social cost function is convex. An implication of the result is that financial intervention is more effective in earlier stages of conflicts.

Further tests indicate that employment growth due to financial development serves as a beneficial channel from financial development to conflict in our data. However, credit supply to mining industries in mineral-rich districts in India provides an exception to our results. In this case two opposing channels, employment growth and rising inequality in land distribution, appear to offset each other. Barring this case, our results make a strong case for more financial development within a market framework as a means to combat conflicts in affected areas. Further, the intervention should take place in earlier stages of a conflict than in later stages. The paper proceeds in the following manner. Section 2 below presents a review of the relevant literature. Section 3 presents our model. Section 4 discusses the data and the variables used in our empirical investigations. Section 5 presents the main results of the investigations. Section 6 discusses the mechanism. Section 7 discusses the unique case of the mining industry in mineral-rich states in India. Section 8 presents our conclusions.

2 Relevant Literature

Under Progress

3 Theoretical Framework

In this section we describe a theoretical framework to model the impact of credit supply on conflict. There are two sectors in our model, Industry and Conflict. There are two groups i and j engaged in industrial activity. The two groups also fight for a prize worth X. Capital inputs invested in industry and conflict by the ith group is denoted by K_i^I and K_i^c respectively.

Group i's industrial output is produced using the production function, $f_i(K_i^I)$ where $f_i : [0, \infty) \to [0, \infty)$ is assumed to be strictly increasing, concave, twice differentiable and it satisfies Inada conditions. Let us suppose that the per unit price of the industrial output is 1, so f_i is the value of industrial output.

Conflict is an uncertain sector with a positive probability of losing the prize X[2]. The probability with which group i wins the prize X is $\frac{F_i(K_i^c)}{F_i(K_i^c)+F_j(K_j^c)}$ where F_i is group i's production function of conflict, whose output can be interpreted as number of deaths or destruction caused by group j. $F_i : [0, \infty] \to [0, \infty]$ is assumed to be strictly increasing, weakly concave, twice differentiable and satisfies Inada conditions.

Notice, probability with which group i wins the prize decreases in the level of capital investment in conflict by group j. In other words this probability implicitly captures the cost that one group can impose on the other group by increasing its level of investment in conflict. Given that we assume F_i to be concave, the probability of winning the conflict for i can also be easily shown to be concave in K_i^c

We assume that group i is more efficient in fighting than group j, that is $F_i(K_i^c) > F_j(K_i^c)$ for all K_i^c. However, groups are equally efficient in case of industrial sector, that is $f_i(K_i^c) = f_j(K_i^c)$ for all K_i^c, therefore from now on we drop subscript i from the industrial production function. In case of a 2 period setting, we also assume that the efficiency of the group increases in period 2 if it wins the conflict in period 1. Though conflict is an uncertain sector, both the groups are tempted to invest in conflict because we assume $X > f(K_i^c)$ for all K_i^c.

There is also a financial market in our model where groups i and j can borrow money at an interest rate of r for industrial activity. We assume that the lender is not willing to lend money for an uncertain and violent sector, conflict. Let $\overline{K}$ be the amount of industrial credit to both the groups. Both the groups get the same amount of funds because they are equally efficient in industrial sector. However,

[2]Note that only one of the group wins the prize X. We don't assume X to be divisible.

both the groups can divert a part of the total credit supplied to conflict but the lender is unaware of this. Let K_i^c be the amount transferred to conflict by group i. So the amount left to be invested in industry by group i is $\overline{K}$- K_i^c. The output from industrial sector is sufficient to repay the loan amount, $f(\overline{K}) \geq \overline{K}(1+r)$ but $f(\overline{K} - K^c) \leq \overline{K}(1+r)$ that is if a group loses the conflict, it cannot repay its loan amount. In the next two subsections we'll separately consider cases in which $\overline{K}$ is exogenous and endogenous.

3.1 Exogenous Credit Supply

The set up of the model is as described above, but in this sub section we consider one period economy in which $\overline{K}$ is assumed to be exogenous. Objective of group i is to maximize

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

Where U_i is assumed to be a concave function.

However, this utility function doesn't capture the idea that undertaking violent activity can be costly for both the groups (regardless of which group increases the level of capital in conflict). To do this, we introduce a cost function in our model. Groups i and j face cost $C(K_i^c + K_j^c)$ of taking up violent activity. This cost function is strictly increasing in the total amount of capital invested in conflict by both the groups. The cost function C can be thought of as the damage to property, industrial sector and/or loss of lives due to fighting.

Since, both the groups face cost C of taking up violent activity, we now model utility to be a decreasing function of the cost function C. That is, group i will instead maximise the augmented utility function, $\overline{U_i}$

$$\overline{U_i}(K_i^c) = f(\overline{K_i} - K_i^c) + \frac{F_i(K_i^c)}{F_i(K_i^c) + F_j(K_j^c)} X - r(\overline{K_i}) - C(K_i^c + K_j^c) \qquad (2)$$

If we assume the cost function to be convex, that is, if the cost due to conflict increases at an increasing rate then, this $\overline{U_i}$ is also concave as U_i. This is because the cost function enters with a negative sign in equation 2.

However, if the cost due to violent activity increases at a decreasing rate, i.e. cost function is concave then $\overline{U_i}$ would not always be concave. Let us consider the two cases separately.

3.1.1 Convex cost function

In case of a convex cost function, as argued above, the new utility function $\overline{U_i}$ is also concave[3] because the convex cost function enters $\overline{U_i}$ with a negative sign.

Equilibrium outcome K_i^{c*} is given by the first order condition

$$\frac{\partial \overline{U_i}}{\partial K_i^c} <= 0 \qquad (4)$$

or

$$-f^{'}(\overline{K} - K_i^{c*}) - C_{K_i^{c*}}(K_i^{c*} + K_j^c) + \frac{F_i^{'}(K_i^{c*}) F_j(K_j^c)}{[F_i(K_i^{c*}) + F_j(K_j^c)]^2} X <= 0 \qquad (5)$$

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

$f^{''}(\overline{K} - K_i^c) - C^{''}_{K_i^c}(K_i^c + K_j^c) +$

$$\frac{X F_j(K_j^c)[F_i(K_i^c) + F_j(K_j^c) F_i^{''}(K_i^c) - 2F_i^{'}[(K_i^c)^2]]}{[F_i(K_i^c) + F_j(K_j^c)]^3} < 0 \qquad (3)$$

or

$$f^{'}(\overline{K} - K_i^{c*}) + C_{K_i^{c*}}(K_i^{c*} + K_j^{c*}) = \frac{F_i^{'}(K_i^{c*})F_j(K_j^c)}{[F_i(K_i^{c*}) + F_j(K_j^c)]^2}X \tag{6}$$

Notice, left hand side of (7) is increasing in K_i^c whereas right hand side is decreasing in K_i^c, hence unique equilibrium exists.

The first order condition for group j, computed in exactly the same way is

$$f^{'}(\overline{K} - K_j^{c*}) + C_{K_j^{c*}}(K_i^c + K_j^{c*}) = \frac{F_j^{'}(K_j^{c*})F_i(K_i^c)}{[F_i(K_i^c) + F_j(K_j^{c*})]^2}X \tag{7}$$

We claim that equilibrium investment in conflict by group i is greater than investment by group j, i.e. $K_i^{c*} > K_j^{c*}$. Let us suppose otherwise, $K_j^{c*} > K_i^{c*}$. From 6 and 7 and given our assumption that $K_j^{c*} > K_i^{c*}$, we have $f^{'}(\overline{K} - K_{j*}^c) > f^{'}(\overline{K} - K_i^{c*}), C_{K_j^{c*}}(K_i^c + K_j^{c*}) > C_{K_i^{c*}}(K_i^{c*} + K_j^c), F_i^{'}(K_i^{c*}) > F_j^{'}(K_j^{c*})$. So, in order to maintain the equality in equation 7, we need $F_i(K_i^c) > F_j(K_j^c)$, but this is not necessarily true given our supposition.

Hence, we have a contradiction using which we claim that equlibrium investment in conflict by group i is higher than group j. The result is intuitive given that i is more efficient in conflict sector, it has a comparitive advantage in this sector and hence its equilibrium investment in conflict is higher than group j. The figure below graphically depicts what we just formally proved. The equilibrium investment in conflict by group i is higher since it has a higher marginal product from conflict (at ecah level of investment) as compared to group j.

The main aim of our paper is to see the impact of an increase in credit supply on the level of conflict. In our model we can compute the impact of an increase in credit supply by looking at the sign and the magnitude of $\frac{dk_i^{c*}}{d\overline{K}}$ or equivalently the sign of

$$\frac{f''(\overline{K} - k_i^c)}{f''(\overline{K} - K_i^c) - C''_{K_i^c} + \frac{XF(K_j^c)[(F(K_i^c)+F(K_j^c))F''(K_i^c)-2[F'(K_i^c)]^2]}{([F(K_i^c)+F(K_j^c)]^3)}} \tag{8}$$

In case of a convex cost function the sign of denominator is negative[4] whereas the numerator is positive given our assumption of strictly concave industrial production function. Hence, the sign of $\frac{dk^c}{d\overline{K}}$ is negative. The intuition for this result is that as credit supply goes up, with convex cost it becomes increasingly costly to increase investement in conflict as compared to industry. That is, as credit supply increases, the rate with which cost due to conflict increases is greater than the rate of increase in conflict outcome. Hence, we get the result that credit supply reduces conflict in case of a convex cost function. Here, cost due to conflict includes cost as a result of investment in conflict, i.e. $C(.)$ as well as loss of industrial output. First result of our model is the following:

Result 1: If the cost due to coflict is convex, increase in credit supply reduces conflict for the full sample. That is, supply of credit in a given economy encourages non violent productive sector as opposed to conflict.

[4]since the new utility function, U' is concave, hence second order condition guarantees the sign of denominator to be negative

3.1.2 Concave cost function

In case of a concave cost function, the new utility function $\overline{U_i}$ is not necessarily concave because the concave cost function enters with a negative sign in $\overline{U_i}$. The double derivative of the utility function is given by the following expression

$$f_i^{''}(.) - C_{K_i^c}^{''}(.) + \frac{XF_j(.)[F_i(.) + F_j(.)F_i^{''}(.) - 2F_i^{'}[(K_i^c)]^2]}{[F_i(.) + F_j(.)]^3} \tag{9}$$

Concavity of the new utility function, $\overline{U}$ depends on the relative concavity of the cost function and the industry and conflict production function. Thus, $\overline{U_i}$ will be concave if $f_i^{''}(.) + \frac{XF_j(.)[F_i(.)+F_j(.)F_i^{''}(.)-2F_i^{'}[(K_i^c)]^2]}{[F_i(.)+F_j(.)]^3} < C_{K_i^c}^{''}(.)$ or when expression 9 is negative.

Given that expression 9 is negative, outcome K_i^{c*} is given by equation 6 as in the case of a convex cost function and by the same argument as before, $K_i^{c*} > K_j^{c*}$. However now unique equlibrium will exist only if $f^{''} > C^{''}$, we need this condition because although the right hand side of equation 6 decreases in K_i^c, the left hand side increases in K_i^c only if $f^{''} > C^{''}$

The magnitude of the impact of credit supply on the level of conflict is given by equation 8 as in the case of convex cost function. However, now the sign of $\frac{dk_i^c}{d\overline{K}}$ is different. The sign of the numerator of $\frac{dk_i^c}{d\overline{K}}$ is positive like the convex cost case but the sign of denominator is ambigous. Denominator will be negative if expression 8 is negative. That is, if the rate of increase in conflict output is less than the rate of increase in the cost due to investment in conflict, then the sign of $\frac{dk^c}{d\overline{K}}$ will be negative. In order to satisfy the above condition, we'll have to compute the range of K_i^c for which the condition gets staisfied.

To get the value of critical investment level for which the expression 8 becomes negative, let us assume the following functional forms:

$$f(K_i^a) = K_i^\alpha \tag{10}$$

where $\alpha < 1$

$$F(K_i^c) = \beta + K_i^c \tag{11}$$

$$C(K_i^c + K_j^c) = log(K_i^c + K_j^c) \tag{12}$$

$$\frac{dk^c}{d\overline{K}} = \frac{\alpha(\alpha-1)[(\overline{K} - K^c)]^{\alpha-2}}{\alpha(\alpha-1)[(\overline{K} - K^c)]^{\alpha-2} + [K^c]^{-2} - X\frac{\beta^2}{[\beta+K^c]^2}} \tag{13}$$

Assuming X=100 ,$\alpha = 0.5$,$\beta = 1$ and $\overline{K} = 80$. 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 $\frac{dk^c}{d\overline{K}}$ is negative turns out to be 23.82. Thus the range of capital investment in conflict for which the impact of credit supply on conflict is negative is [23.82,80]. Result 2 states another prediction from our model.

Result 2: In case of a concave cost function, supply of credit encourages industrial sector and has a negative impact on the violent sector only when the capital investment in conflict crosses a threshold.

The intuition for this result is that for K_i^c above the threshold level, the rate of increase in conflict outcome is less than the rate of increase in cost and hence investment in conflict falls. Whereas for capital investment below the threshold level, both conflict outcome and cost increase in response to increased credit supply and hence the net effect is unknown.

Result 1 and 2 provide the predictions for the impact of credit supply on conflict in case of convex and concave cost functions respectively. But we don't know whether the cost due to conflict is actually concave or convex. We intuitively think that convex cost due to conflict seems more plausible given the argument that after a point conflict becomes increasingly costly for the society. However, we can only empirically confirm the nature of the cost function. The data on conflict that we employ in the next section will guide us on the nature of cost function and thereby impact of credit flow on conflict.
Using our data, we find out that the actual cost function is convex and therefore in the next subsection we work with convex cost function.

3.2 Endogenous credit supply

Till now, we have considered a one period economy where the two groups fight over a prize X and undertake industrial activity using an exogenous supply of credit, $\overline{K}$. Now, we introduce a dynamic set up with two periods in which we no longer assume the credit supply to be exogenous. As in the previous static case we assume that groups i and j are equally efficient in the indutrial sector but group i is more efficient in fighting than group j. After they have participated in conflict in period 1, one of the group wins and the efficiency of the winner group increases in period 2. Banks do not have any idea about the illegal transfer of funds to conflict by the two groups in period 1 and hence supply $\overline{K}$ to both the groups. So, at time t=1, the set up is the same as that in the static case hence nothing changes from the previous case in the first period.

From the static case we know that groups i and j invest in both the sectors and since i is more efficient in conflict sector than j, $K_i^{c*} > K_j^{c*}$. That is, in equilibrium in period 1, i has a higher probability of winning the conflict than group j. Ater t=1, one of the group wins, say i wins and it therefore repays the loan whereas group j which loses cannot repay.

When t=2 begins, efficiency of the group i increases as compared to period 1. Groups i and j also realise that group i is more efficient in this period and hence they update their probability of winning after observing group i's victory, i.e. for both group i and j now, $\tilde{F}_i(K_i^c) > F_i(K_i^c)$, where $\tilde{F}_i(K_i^c)$ is the production function for group i in period 2. That is the posterior probability of j winning becomes less whereas the posterior goes up for group i as compared to period 1.

Since group i won in period 1, it is able to repay its debt in period 2, therefore banks continue to give loan amount of $\overline{K}$ to group i in period 2 too. With a total of $\overline{K} + f(\overline{K} - K_i^c)$ amount of funds group i maximises, $U_i(K_i^c) = f(f(\overline{K_i} - K_i^c) + \overline{K_i} - K_{i2}^c) + \frac{\tilde{F}_i(K_{i2}^c)}{\tilde{F}_i(K_{i2}^c)+F_j(K_{j2}^c)} X - r(\overline{K}) - C(K_{i2}^c + K_{j2}^c)$. Since the efficiency of group i increases (along with increase in investible funds) in period 2 , it further increases its investment in conflict as compared to period 1, i.e. $K_{i2}^{c*} > K_i^{c*}$, where K_{i2}^{c*} is the equilibrium investment in conflict by group i in period 2.

Note that, this results shows that the overall impact of increase in funds and efficiency is positive on capital investment in conflict. However, if we only consider the increase in funds without changing efficiency, the negative relationship between credit supply and conflict that we derived in the previous subsection would hold here too. We prove it again by contradiction. Suppose, $K_i^{c*} = K_{i2}^{c*}$, where there is no change in the efficiency of i in this case. Because of our assumption, $-f(f(\overline{K} - K_i^{c*}) + \overline{K} - K_i^{c*}) > -f(\overline{K} - K_i^{c*})$ and hence, K_{i2}^{c*} should be lower than K_i^{c*}. So, the effect of increase in credit supply, ceteris paribus has a negative impact on the investment in conflict.

Group j on the other hand has lost the conflict and therefore has defaulted. In such a situation bank can either bail out j or stop giving the loan. In case j gets bailed out, that is it receives $\overline{K}$ in addition to industrial output from the last period, $f(\overline{K} - K_i^c)$, then it maximises its utility after taking into account the higher efficiency level of group i, that is

$$\overline{U_j}(K_{j2}^c) = f(f(\overline{K} - K_j^c) + \overline{K} - K_{j2}^c) + \frac{F_j(K_{j2}^c)}{\tilde{F}_i(K_{i2}^c) + F_j(K_{j2}^c)} X - r(\overline{K}) - C(.) \quad (14)$$

The first order condition for j is

$$-f^{'}(f(\overline{K} - K_j^{c*}) + \overline{K} - K_{j2}^{c*}) - C_{K_{j2}^{c*}}(.) + \frac{F_j^{'}(K_{j2}^{c*})\tilde{F}_i(K_{i2}^c)}{[\tilde{F}_i(K_{i2}^c) + F_j(K_{j2}^{c*})]^2} X = 0 \quad (15)$$

In this case of bail out to group j, now since posterior probability is less from period 1, $K_{j2}^{c*} < K_j^{c*} < K_i^{c*} < K_{i2}^{c*}$. Group 2 after realising the efficiency of group 1 invests considerably less as compared to period 1.

Now, we consider the case when bank does not decide to bail out group j. Since group j does not get any loan in period 2, the only source of funding is the industrial output produced in period 1, $f(\overline{K}-K_j^c)$. With this funding, let us suppose that group j diverts $\hat{K_{j2}^c}$ to conflict and the remaining amount is invested in the industry. So, the utility in case of no bail out is

$$f(f(\overline{K}-K_j^c)-\hat{K_{j2}^c})+\frac{F_j(\hat{K_{j2}^c})}{\tilde{F_i}(.)+F_j(.)}X-r(\overline{K})-C(.) \tag{16}$$

The first order condition for group j now with no bail out is

$$-f^{'}(f(\overline{K}-K_j^c)-\hat{K_{j2}^{c*}})-C_{\hat{K_{j2}^{c*}}}+\frac{F_j^{'}(\hat{K_{j2}^{c*}})F_i(\tilde{K_i^c})}{[F_i(\tilde{K_i^c})+F_j(\hat{K_{j2}^{c*}})]^2}X=0 \tag{17}$$

Now we claim that $\hat{K_{j2}^{c*}}>K_{j2}^{c*}$, that is investment in conflict would be higher if j does not get bailed out. To prove this, let us suppose that $\hat{K_{j2}^{c*}}<K_{j2}^c$. Given this supposition, comparing equation 15 and 17, we see that the last two terms on the left hand side of equation 17 is greater than the corresponding terms in equation 15 (because F is assumed to be concave and cost is assumed to be convex). Also since $-f^{'}(f(\overline{K}-K_j^{c*})-\hat{K_{j2}^{c*}})>-f^{'}(f(\overline{K}-K_j^c)+\overline{K}-K_{j2}^{c*})$, equation 18 is positive when $\hat{K_{j2}^{c*}}<K_j^{c*}$ which contradicts that K_{j2}^{c*} is the equilibrium investment level. Hence, in equilbrium, group j invests more in conflict with no bail out as opposed to the bail out situation.

Intuitively, the result follows from the fact that industrial output is so low in case of no bail out (because of scarcity of funds) that group j prefers to invest more in conflict rather than industry. This happens because low industrial output, due to absence of credit from the bank, creates perverse incentives for group j to invest in conflict. Thus, in case of no bail out, there would be more conflict in the society because the opportunity cost of participation in conflict is small.

Now, we work out the condition under bank will have an incentive to bail out group j. Bank knows that in case j wins, it will be in a position to repay so it assesses whether to extend the loan in case j fails. The condition which will ensure that bank will bail out j is $f(f(\overline{K} - K_j^c) - \hat{K_j^c}) > 2\overline{K}(1+r)$. According to this condition, even when group j fails it can repay the loan amount in period 2 with the help of industrial output from the last period. But given that $f(\overline{K} - K_j^c) < \overline{K}(1+r) < f(\overline{k})$, the above mentioned condition is very less likely to hold.

So, even when we introduce dynamic set up and drop the assumption of exogenous credit supply, the theoretical prediction remains the same as static case. Supply of credit in economy reduces the likelihood of conflict. Although in the second period, investment in conflict reduces for j as compared to period 1, but the reduction is dramatic when j gets bailed out. We test the predictions of our theoretical model in the following section.

4 Data and Variable construction

To test the theoretical predictions of our model in data, we look at episodes of conflicts in Indian districts[5] from 1983-2010. For the other productive sector in the economy (as described in our model) we focus on industrial sector and we look at data on industrial credit supply in Indian districts from 1983-2010. Data sources and construction of our dependent, independent and control variables are described

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

in detail below.

Dependent variables

Our main dependent variable Conflict (G), is a dummy variable which takes a value of 1 if there is conflict; 0 otherwise. Data on conflict comes from Global Terrorism Database (GTD) which has district level information on conflict since 1976. The Global Terrorism Database (GTD), made available by The National Consortium for the Study of Terrorism and Responses to Terrorism (START) is an open-source database including information on terrorist events around the world. We choose GTD over South Asian Terrorism Portal (another common data source on conflict) for data on conflict because as opposed to South Asian Terrorism Portal, GTD has data starting from 1983, the year in which our credit data begins. However, GTD has data on terrorist attacks and religious violence too apart from conflict. For our analysis we drop the incidents of religious violence and terrorism.[6]

GTD gives detailed information about the conflict incident including information on the number of people killed, whether there was any property damage due to the incident, target of the incident, weapons used, summary of the incident etc. We define Conflict(G) as any violent event which caused damage to either human life or property. So, Conflict(G) is a dummy which takes a value of 1 if there was any conflict, zero otherwise. According to this definition of conflict, 27 percent of the sample suffered incidents of conflict and in about 50 percent of them there has been property damage, as reported in table 1 of summary statistics.

We also use Conflict(I) as one of our dependent variables. Conflict(I) is a cate-

[6]The type of violence of the incident can be easily inferred from the data as it has information on the perpetrator group and the nature of the incident.

gorical variable which indicates the intensity of conflict and has been constructed using information on number of people killed available in GTD. We assign Conflict(I) as 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, 4 if number is above 50. The other dependent variable that we consider is Conflict(F) which has also been constructed using GTD. Conflict(F) is the total number of incidents of conflict in a given district year and thus indicates the frequency of conflict in a district year.

To test the channels through which credit supply effects conflict, we use general unemployment, strict unemployment and land inequality as our dependent variables. General, Strict unemployment and land inequality have been constructed using National Sample Survey (NSS) data. NSS is a large household survey conducted quinquennially in India. We use data from four thick rounds[7], namely 43rd conducted in 1987-88, 55th conducted in 1999-2000, 61st conducted in 2004-05 and 66th conducted in 2009-10. During the time period of our study, NSS conducted one more thick 50th round in 1993-94, but this round doesn't identify households up to district level. Hence we use a thin 51st round conducted in 1994-95.

Using data from the above mentioned rounds, We compute land inequality by computing the gini coefficient of household land possession for each district for the above mentioned five years. We then linearly interpolate the gini coefficient to get the value of land inequality for all the years (1983-2010) in a district.
General unemployment has been constructed using a question on unemployment in principal activity in the NSS questionnaire. General unemployment gives us the

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

percentage of people unemployed according to their principal activity. Strict unemployment has been constructed using a question on unemployment in weekly activity in the NSS questionnaire. Strict unemployment gives us the percentage of people unemployed according to their weekly activity.

Independent variables

The main independent variable of interest for our empirical analysis is credit to industrial sector (in millions) because we have considered industry as the other productive sector in the economy. The reason for considering industry and not agriculture or service sector as the other productive sector is that people engaged in agriculture sector rely heavily on informal source of funding. Since we only have data on credit supply by banks, considering credit supply to agriculture by banks would highly underestimate the total credit received by this sector. The reason for not focusing on service sector is that service sector is fully developed in only urbanized districts. Since, Lakshmi Iyer(2009) has shown that conflict is somewhat more common in rural districts than urban districts in India, considering service sector would cause selection problem and would bias our results.

So, we restrict attention to industrial sector and focus on credit to industry from 1983-2010. Data on credit supply to industry has been computed using Basic Statistical Returns (BSR) published by the central bank of India, Reserve Bank of India (RBI). BSR gives district wise data on the stock of credit according to different occupations in a district in a particular year. Since we are interested in evaluating the impact of credit supply to industry on conflict, we compute the flow of credit in a district. In order to compute the supply (flow) of industrial credit, we compute the difference in the stock of credit over two consecutive years. We observe that there are some district-years with negative flow of credit, so we code these districts as having zero supply of industrial credit. Summary statistics reported in table 2 show that average industrial credit supplied to a district-year is 1.2 millions which is about 44 percent of the total credit supply to a 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 mining industry also has been computed using BSR published by RBI. Mining industry is one of the four broad categories of industries covered under industry section in BSR data.[8] But credit data on these four categories is available only after 1996. So, while considering the impact of mining credit on conflict, we restrict the sample to years 1996-2010. Note that average mining credit in a district year is 0.17 million which is 6 percent of the total supply of credit.

We also look at the impact of number of accounts under industry on conflict. BSR has district wise data on number of accounts according to different occupations. We use the log of the number of accounts under industry to carry out our analysis.

Controls

Data on most of the control variables like worker participation rate, literacy rate, urbanisation (proportion of population living in urban areas in a district), population density and Scheduled Tribal (ST) population have been taken from the Indian

[8]the four categories are namely electricity gas water, construction, manufacturing processing and mining quarrying

Population Census of 1991, 2001 and 2011. Data on number of district roads, national and state highway has been taken from Pradhan Mantri Gram sadak Yojana website. Variable, Forest is the proportion of area covered by forests in a state . Data on forest and net state domestic product (nsdp) has been taken from India stat. We have used average consumption expenditure to control for district level economic activity. This variable has been computed using NSS data for 5 thick rounds. Since we only have 5 rounds of NSS data available with us, we linearly interpolate average consumption expenditure for non NSS years.

Definition of all the variables used in our empirical work has been provided in Table 1.

5 Results

5.1 Empirical Strategy

In this section we empirically test the predictions of our theoretical model. Our model predicts that if the cost function is convex more supply of credit to industry should lead to a fall in the likelihood of conflict (Result 1). Whereas, if the cost function is concave then supplying credit to industry would lead to fall in conflict only when the investment in conflict crosses a certain threshold (Result 2).

However, we don't know the nature of the actual cost function. We test this using the two predictions from our model in the data on conflict in Indian districts from 1983-2010. If on an average industrial credit supply reduces conflict, then this would lend support to our result 1 but even then we cannot rule out that cost due to conflict is concave. To test for concavity of cost we'll need to also see the impact of industrial credit supply on conflict after a given threshold level of investment in conflict.To start with, we evaluate the impact of credit supply on conflict for the full sample (Result 1). We test this by estimating the following regression model:

$$conflict_{d,s,t} = \alpha_d + \gamma_t + \beta industrialcredit_{d,s,t} + \delta X_{d,s,t} + \epsilon_{d,s,t} \tag{18}$$

The main dependent variable $conflict_{d,s,t}$ is a dummy which takes a value of 1 if there is any event of conflict in district d, state s and time t; 0 otherwise. The independent variable of interest $industrialcredit_{d,s,t}$ is the flow of credit to industry in district d, state s and time t. $X_{d,s,t}$ includes control variables like urbanization, male literacy and worker participation rate, population density, percentage of total area covered by forests,per capita net state domestic product, number of national highways and district roads in a district.
All the regressions include district fixed effects to control for 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 estimated coefficient of industrial credit in equation 13 would give us the impact of industrial credit supply on conflict. Our model predicts the estimated sign of β to be negative on an average. Along with industrial credit, we have also added other control variables which we think would influence conflict[9]. Variables, male literacy and worker participation rate have been added because Collier and Hoeffler (1998, 2001, 2002) in their paper have shown that higher literacy and employment rate is associated with low levels of conflict. We also expect higher work partic-

[9]based on our judgement and existing literature on covariates of conflict in India

ipation and literacy rate to be negatively associated with conflict because we feel higher literacy and work participation rate would increase the opportunity cost of participation in violent activities.

We have added Urbanisation because it has been believed by some (Lakshmi Iyer, 2009) that conflict is mainly a rural phenomena and that urban districts have had less incidents of conflict than rural districts. Hence, we expect the coefficient on urbanisation to be negative.

We have also controlled for population density because it is possible that districts with high population density have high incidents of conflict due to competition for limited resources. Variable Forest has been added because Fearon and Laitin(2003) in their paper show that places with high proportion of area under forests have high levels of conflict. So, in line with their prediction we also expect the sign of the coefficient on forest to be positive probably because difficult terrain and forest areas are conducive to insurgent activities.

We have added net state domestic product to control for the impact of state income on conflict which would determine the strength of its counter conflict operations. Variables national highways and district roads in a district determine how accessible the district is which would influence insurgent activities and counter conflict operations.

5.2 Main Results

The estimated coefficients of equation 18 are reported in column1 of table 3.

The results show that the likelihood of occurrence of conflict falls as more industrial credit is supplied in a district. One standard deviation increase in the industrial credit supply reduces the likelihood of conflict by 0.10. Given the average conflict level of 0.27, a reduction by 0.10 means almost one third reduction in the average value of conflict. Industrial credit thus not only has a statistically negative impact but also economically significant impact on conflict.The negative and statistically significant coefficient of industrial credit provides evidence in support of result 1

The coefficient on other control variables are quite consistent with our predictions in the empirical strategy subsection. The coefficient on urbanisation,literacy and worker participation rate is negative as predicted. Our results also indicate that states with high proportion of area under forests have high levels of conflict, in line with our prediction. The coefficient of population density is positive and significant probably due to competition for a given set of resources. The coefficient of nsdp is negative and significant consistent with our predictions.

Our dependent variable in column 1 of table 3 is a dummy variable indicating the presence of insurgent activities. In this paper, we also look at the impact of industrial credit supply on the intensity of conflict by estimating the following two equations.

$$conflict(I)_{d,s,t} = \alpha_d + \gamma_t + \beta_1 industrialcredit_{d,s,t} + \delta X_{d,s,t} + \epsilon_{d,s,t} \tag{19}$$

$$conflict(F)_{d,s,t} = \alpha_d + \gamma_t + \beta_2 industrialcredit_{d,s,t} + \delta X_{d,s,t} + \epsilon_{d,s,t} \tag{20}$$

Conflict(I) is a categorical variable indicating the intensity of conflict according to the number of people killed in the conflict event. Variable Conflict(F) captures the frequency of conflicts in a district d and in a particular year y. The results for both the equations are reported in column 2 and column 3 respectively of table 3.

Results show that industrial credit supply negatively impacts the index and the frequency of conflict. The negative coefficient on industrial credit supply in both the columns indicate that industrial credit supply has a negative impact not only on the likelihood of conflict but also on the intensity of conflict. One standard deviation rise in the supply of industrial credit reduces the frequency of conflicts in a district by 3. However we keep Conflict(G) variable as our main dependent variable of interest in most of our tests because we feel it is a more general notion of occurrence of conflict than conflict index (based on the number of people killed) or frequency.

5.3 Endogeneity concerns

The estimation of the above regression equations assume industrial credit supply to be exogenous. But the coefficient on industrial credit is likely to be inconsistent because of endogeneity issue. Endogeneity could be due to time varying unobservable variables effecting both conflict and industrial credit supply. One important and in most likelihood the only variable effecting both conflict and industrial credit supply is the district level economic activity.
Economic activity has been established to be positively correlated with credit supply. Also, existing literature on conflict has shown a negative link between income and conflict.(see Collier and Hoeffler 2002; Fearon and Laitin 2003; Miguel, Stayanath and Sergenti 2004).

Since we haven't controlled for district level economic activity in our regression equations our estimates are likely to be biased downwards. To address this problem we use a proxy for district level economic activity. An ideal proxy for district level economic activity would be district level GDP. However, data on district level GDP is not available for all the districts for the time period 1983-2010. So, we proxy for the district level economic activity using average monthly household consumption expenditure[10] in a district. Average monthly consumption expenditure has been widely used as a proxy for income which is a fairly good indicator of economic activity. So, now after adding average monthly household consumption expenditure we should get consistent estimates of the impact of credit supply to industry on conflict. The results are reported in table 5 below.

As before, industrial credit is negative and significant but now, the coefficient of industrial credit supply in table 5 gives the consistent and causal impact of increasing industrial credit supply on conflict. Notice, the magnitude of the coefficient on lagged industrial credit supply has become less negative confirming that our previous estimates were biased downwards. The coefficient of average monthly consumption expenditure is negative pointing to the negative correlation between economic activity and conflict.

Although we have addressed omitted variable problem by proxying for district level economic activity (Table 4) there might still be endogeniety issues in estimating the impact of industrial credit supply on conflict due to reverse causality. It is possible that the level of conflict in a district has an impact on the supply of credit. The environment of fear and instability created by conflicts might effect lending behaviour of banks causing the point estimates to b e inconsistent.

To correct this, we use lagged industrial credit as an independent variable in place of current industrial credit. Since, it is unlikely that conflict at time t will effect

[10]computed from NSS rounds

credit supply in previous periods, inclusion of lagged credit supply addresses reverse causality problem. The estimates with lagged industrial credit supply are reported in column 1 of table 4.The coefficient on lagged industrial credit supply is also negative and significant confirming the negative impact of industrial credit supply on conflict. This confirms that results in table 3 were not confounded because of reverse causality.
Results in Table 3, 4 and 5 provide evidence in favour of the theoretical prediction of our model (Result 1).

6 More Identification: Instrumental Variable Technique

In the previous subsection, we tried to address two main sources of endogeneity to claim causal impact of industrial credit supply on conflict. Reverse causality problem was addressed using lagged industrial credit as the main independent variable and omitted variable concern was addressed using consumption expenditure as a proxy for district level economic activity. However, even after addressing 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, then simply lagging credit supply would not solve reverse causality issue. Similarly, if there are other district level time varying omitted variables apart from economic activity which effect both industrial credit supply and conflict, then by simply proxying for economic activity would not solve endogeneity issue.

To be able to cleanly identify the causal impact of industrial credit supply on conflict, we make use of instrumental variable technique. We exploit the phased introduction of Debt Recovery Tribunals (DRTs) in Indian states in late 1993 for our instrument. DRT act, 1993 allowed the central government to establish debt recovery tribunals for speedy recovery of debts due to banks and financial institutions ((Visaria (2009); LilienfeldToal, Mookherjee and Visaria (2012)). This was done as part of financial sector reforms of the early 1990s to aid banks to reduce their non performing loans. This law allowed banks and financial institutions to file suits for claims larger than rupees 1 million. Before this law, all debt recovery suits were tried in civil courts, according to the Code for Civil Procedure which usually took really long time. But DRTs streamlined procedures that allowed cases to move through the process more quickly.

The DRT law allowed the central government to establish tribunals across the entire country and to determine their territorial jurisdiction; state governments were not given any formal authority to influence this process. Five states received tribunals in 1994 with jurisdiction over twelve states. However, as reported in Visaria (2009), the introduction was halted in 1994, in response to a case filed by the Delhi Bar Association, the Delhi High Court ruled that the DRT law was not valid. However in 1996, after the countrys Supreme Court issued an interim order in favor of the law, DRT establishment was resumed. New DRTs were set up starting in 1996. By 1999, most Indian states had received a DRT. Table 6 lists the timing of DRTs establishment in different states. States which received DRT before 1996, we call them group 1 states and and the ones which received after 1996, we call them group 2 states.

The events described above suggest that the timing of DRT establishment was driven by reasons plausibly exogenous to the level of conflict in states. This implies that establishment of DRTs should effect conflict only through credit supply. Exploiting this, we use two alternative instruments for credit supply namely, duration of DRTs and the establishment of DRTs in group 1 states. Duration of DRT indicates the total number of years for which DRT has been in place in a given state-year. Since DRT was introduced in 1994 and given that our sample is till 2010, the maximum value of DRT duration variable is 16 and minimum is 0 (for years prior to DRT establishment) . Naturally, since group 1 states got DRT earlier (1994) than group 2 states, the value of duration for group 1 states is higher. Our second instrument is the interaction between group 1 states and post 1994 year dummy (post 94 is 1 for years after 1994 and zero otherwise) but in this case we restrict our analysis till 1996, reason for this will be explained in detail in the next sub section. This interaction term captures the differential impact of DRT in group 1 states till 1996.

6.1 First Stage

We expect the coefficient of both the instruments in the first stage regression to be positive. Given that DRTs made the recovery of debts easy and faster, we expect it to have a positive impact on credit supply, specifically industrial credit supply. Also, Toal, Mookherjee and Visaria (2012) in their paper show that on an average DRTs increased credit supply for firms for the period 1993-2003. Given this and our intuition, we expect first stage results to be positive and significant. So, DRT as an instrument will allow us (if the first stage results are strong) to isolate the exogenous variation in credit supply, which we can then use to estimate the causal impact of credit supply on conflicts.

For the first instrument, first stage is like the difference in difference impact of introduction of DRTs on credit supply. Since we want to capture the differential impact of DRTs for group 1 states, we stop our sample at 1996 because group 2 states also got treated after 1996. The first stage regression equation for group1*post96 instrument is

$$industrialcredit_{d,s,t} = \alpha_s + \gamma_t + \beta group1 * post94_{s,t} + \eta group1_s + \delta X_{d,s,t} + \epsilon_{s,t} \tag{21}$$

Note that one of the very important assumption of difference in difference technique is the existence of parallel trends in treatment and control groups before treatment gets implemented. In order to check parallel trends in credit supply in the two groups, I check for the presence of differential impact of DRT on credit supply before 1994 by interacting group 1 states with year dummies before 1994. If the coefficients of these interactions are not significant, then this would indicate parallel trends in treatment and control groups. Results are reported in table 17. Note that although the coefficient on the two interaction terms is positive and significant, this result is against our suspicion of pre exisiting positive credit supply trend in group 1 states.

For our second instrument, DRT duration, the first stage is the regression of industrial credit supply on DRT duration after controlling for state fixed effects, year fixed effects and other control variables.

$$industrialcredit_{d,s,t} = \alpha_s + \gamma_t + \beta DRTduration_{s,t} + \delta X_{d,s,t} + \epsilon_{s,t} \tag{22}$$

[11]Results, reported in columns 1 and 2 of table 7, confirm that first stage results for both the instruments are consistent with our prediction. The coefficient on both DRT duration and the interaction term is positive and significant indicating that

[11] $X_{d,s,t}$ includes all those control variables which have been added in regression equation 13.

both our instruments have positive influence over credit supply. Establishment of DRT, therefore has a positive impact on industrial credit supply, this result implies a strong first stage for our instruments. Apart from a strong first stage, we also need to show that both our instruments satisfy exclusion restriction. For these instruments to satisfy exclusion restriction, DRT establishment must not be correlated with level of conflict in states.

We expect exclusion restriction to hold for both our instruments. Given that the timing of DRT establishment was driven by factors which were completely exogenous to pre existing levels of conflict as described earlier, there is no reason to expect DRT to have an independent impact on conflict. Toal, Mookherjee and Visaria (2012) investigate the possibility of state level factors to influence the timing of DRT establishment. But they find that the timing of DRTs was not corelated with economic, political or judicial environment. This also provides corroboration to our argument of validity of the instruments. However, we suspect violation of exclusion restriction for DRT duration instrument after 2008. This is because financial crisis which occurred in 2008 could have an influence over the working of DRT .[12] Financial crisis could also potentially impact conflict probably because of fall in employment and unstable economic environment.

Figure 1 plots the trend in conflict and industrial credit over 1983-2010[13]. Expectedly, we can see that industrial credit supply sharply falls after 2007 and a large part of this fall can be explained by the financial crisis. But also notice, that conflict also starts rising after 2007. This increase in conflict can also be correlated with

[12]For e.g. after financial crisis, it is possible that the cases filed with DRTS increased from before and this increase in pressure on DRTs affected its working and efficiency.

[13]for each year, a red (blue) point in the graph indicates the average industrial supply (conflict) over the sample.

financial crisis. So then in that case, DRT would have an independent influence over conflict through all those factors which happened as a result of financial crisis of 2008. To make sure that our instrument is perfectly valid, we also present a specification in which we restrict our analysis till 2008. Column 3 of table 6 present first stage regression results for DRT duration only till year 2008. We find that the coefficient of DRT duration is positive and significant which once again confirms that our first stage results are strongly positive and significant.

6.2 Second stage results

Now that we have argued as well as shown that both DRT duration and the interaction between group 1 states and post 94 dummy seem valid instruments for industrial credit supply, we present IV-2SLS results of the regression of conflict on credit supply (predicted from the first stage). Column 1 of table 8 reports the results when interaction term is instrument, column 2 has DRT duration as the instrument, column 3 has DRT duration till 2008 as the instrument.

Result reported in column 1 confirm the negative relationship between conflict and credit supply but column 2 indicates no negative and significant impact of credit supply on conflict. However we are not confident of the result in column 2 because we suspect DRT to effect conflict after 2008 because of 2008 financial crisis. Hence in Column 3 we only look at years on and before 2008 to assess the exogenous impact of credit supply on conflict[14]. As expected, the coefficient of industrial credit supply is negative and significant. This results allowas us to make a causal claim that increase in industrial credit supply reduces the likelihood of conflict. Also, the result indicates that DRT duration does not seem to be a good instrument post 2008

[14]by this exercise we only lose two years of data given our sample is from 1983-2010

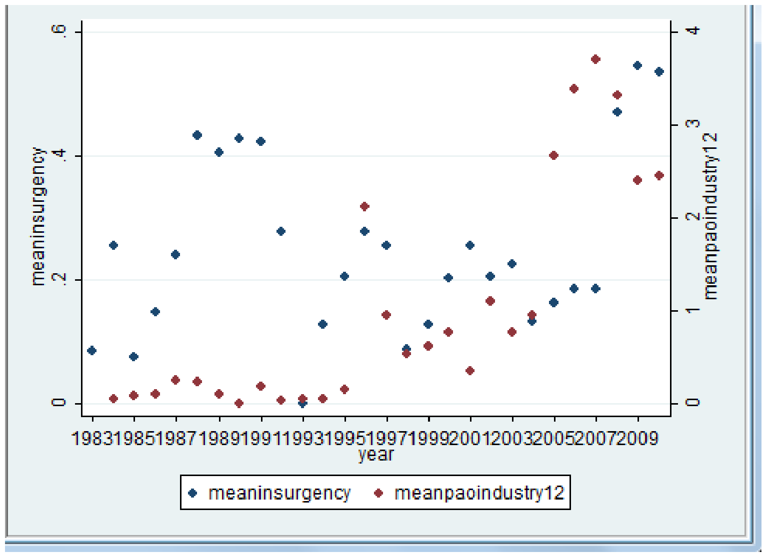

Figure 1: Map

and probably this is the reason why we don't see significant negative significant impact of predicted credit supply for the full sample.

In column 3 with the interaction term as the instrument, the coefficient of credit supply is again negative and significant. This further provides evidence that credit supply reduces the likelihood of conflict. Note that the absolute value of coefficient of predicted credit supply in columns 1 and 3 is quite high as compare to OLS results in table 3 (0.008). This indicates that our OLS estimates are biased upwards and we seem to have corrected for it by these two instruments. Also, note that since our OLS results are baised upwards, they provide us with the lower bound on effect of credit supply on conflict.

7 Robustness Checks

Since our main dependent variable, conflict is a dummy variable, we would like to make sure that results in case of linear specification (Table 3,4 and 5) are robust to probit specification too. The marginal impacts in case of probit regression is reported in table 6 below. As before results in table 6 confirm the negative and significant impact of credit supply on the probability of conflict. Also note that the results using probit and linear specifications are nearly identical, so from now on we restrict our attention to the linear specifications.

We perform another robustness check for our results in table 3 by using log of number of accounts under industry as the dependent variable instead of industrial credit supply. Along with credit supply, number of accounts is also an important measure of financial development. [15] Our previous result has shown that more credit supply to industry, by increasing access to credit has a negative impact impact on conflict. Increasing number of accounts under industry would also somewhat increase the coverage of industrial credit supply. So, we would also expect increased number of accounts under industry to also effect conflict in the same manner as industrial credit supply. Results are reported in table 7.

The coefficient of number of accounts is negative and significant; consistent with the effect of industrial credit supply on conflict. Note however that one standard deviation increase in number of accounts leads to 3 percentage point fall in the likelihood of conflict whereas the magnitude of the effect for industrial credit supply was much higher (10 p.p). The size of the effect is small probably because number of accounts do not perfectly translate into supply of credit which is why we retsrict our analysis to industrial credit supply.

[15] Data on number of accounts under industry also comes from the basic statistical returns published by the RBI.

7.1 Testing Result 2

We now proceed to test another important prediction of our theoretical model (Result 2). Result 2 stated that industrial credit supply would negatively impact the likelihood of conflict only when capital invested in conflict crosses a threshold. That is, only districts to the right of the threshold will experience a fall in conflict when industrial credit supply increases. If we find evidence in support of result 2, then this would confirm that the cost due to conflict is infact concave.

To test this prediction we divide the districts into more conflict prone and less conflict prone districts based on the existing conflict levels. In order to characterize districts as conflict prone, we compute the average conflict level in a district over 1983-2010. Thus, each district gets a number between zero and one which is its average conflict level over the sample period. We then look at the distribution of these average conflict levels and we call a district as more conflict prone if the average conflict level for that district is higher than a pre decided threshold.

Similarly we call a district less conflict prone if the average conflict level for this district is below the threshold. We consider various threshold points to categorize districts into conflict and non conflict prone districts. We start with considering 40th perecentile[16] (of the distribution of average conflict values) as the threshold, districts which lie to the left of this threshold would be called less conflict prone and districts which lie to the right would be called more conflict prone. We then increase the threshold levels to 50, 60, 70 and 80th percentile. We then estimate the differential impact of credit supply for more conflict prone and less conflict prone

[16]We start with 40, because average conflict level is 0 till the 40th percentile of the distribution. So districts lying below the 30th percentile of the distribution have not experienced any conflict at all

districts (by interacting more conflict prone districts with credit supply). In all the spcifications we have controlled for state fixed effects to control for time invariant state level unobserved factors which effect conflict proneness of a district.

In Columns 1-6 of table 6 we report the differential impact for districts categorised as more conflict prone according to the following thresholds: 60, 50, 40, 30 and 20 percentile respectively.[17]. In all the specifications industrial credit is positive and significant. The coefficient of industrial credit gives us the impact of credit on less conflict prone districts. This provides a very strong evidence that for less conflict prone districts supply of industrial credit helps in reducing conflict. This indicates that the cost due to conflict is convex in the data. Also, notice that the coefficient of interaction term in all the specifications is positive and significant. This shows that bank finance has a strong negative impact on conflict in less conflict prone districts as opposed to more conflict prone districts.

Our results in tables 6 empirically confirms that increase in credit supply leads to a stronger fall in conflict for district which are less conflict prone and that we find evidence of convex cost due to conflict.

8 Mechanism

In the previous section our results established significant negative impact of industrial credit supply on conflict . In this section we explore the channel through which industrial credit is likely to have an impact on conflict.

We hypothesize that industrial credit impacts conflict through reducing unemploy-

[17]In all the columns we have controlled for average monthly expenditure to control for district level economic activity.

ment in a district.The main line of argument is that increased supply of credit to industry in a district boosts industrial activity which is one of the largest employment generating sector. Thus, credit supply to industry is likely to have a positive spillover effect on employment generation. Following this argument, we expect employment generation due to the supply of industrial credit to be an important and plausible channel because unemployment has been established to have a negative correlation with conflict (see Collier and Hoeffler(1998, 2001, 2002)).

Though the argument seems logical, whether it is realistic needs verification with the data. To test employment as a channel, we estimate the following regression equations.

$$unemprate_{d,s,t} = \alpha_d+\gamma_t+\beta induscredit_{d,s,t}+\eta consexpend_{d,s,t}+\delta populationdensity_{d,s,t}+\epsilon_{d,s,t} \tag{23}$$

$$unemprate_{d,s,t} = \alpha_d+\gamma_t+\beta induscredit_{d,s,t-1}+\eta consexpend_{d,s,t}+\delta populationdensity_{d,s,t}+\epsilon_{d,s,t} \tag{24}$$

Coefficient β will give us the impact of industrial credit supply on unemployment. We also add average monthly consumption expenditure to control for economic activity in a district which effects both unemployment and conflict. We have added district fixed effects and time fixed effects to control for the unobserved factors effecting credit supply and to control for the macroeconomic shocks to unemployment, respectively.

Along with current year's industrial credit supply we also evaluate the impact of lagged industrial credit because structural changes like unemployment[18] generally take some time to respond to changes in economy. We use two notions of unem-

[18]we use unemployment as opposed to employment in the empirical work because questions asked in NSS survey pertained to unemployment as opposed to employment

ployment rate in our empirical estimation. We have termed them as strict unemployment and general unemployment. General unemployment gives us the percentage of people unemployed according to their principal activity whereas strict unemployment gives us the percentage of people unemployed on all seven days of the week[19].

Since we have only five thick rounds of NSS data availbale with us, unemployment rate for non NSS years have been linearly interpolated. The results for the channel test is reported in table 9. Columns 1 and 2 present the results for general unemployment whereas Columns 3 and 4 present the results for strict unemployment. Coefficient of industrial credit is negative and significant for both general and strict unemployment (Col. 2 and 4) implying that increased industrial credit leads to fall in unemployment. Coefficient of lagged industrial credit is also negative for strict unemployment. Results show that in the three out of four cases, industrial credit supply causes unemployment to fall supporting our hypothesis that industrial credit effects conflict through employment channel. Thus, we have established that unemployment is an important channel through which industrial credit reduces conflict.

8.1 Placebo Test

Our results have shown that industrial credit reduces the incidence of conflict by reducing unemployment. If our channel argument holds, then credit supply to any sector which does not generate employment should not have any impact on the conflict. To test this, we perform placebo tests of the impact of personal loans on conflict and unemployment. If employment actually is the channel through which

[19] We have constructed these variables using NSS round questionnaire. NSS questionnaire has a question on whether an individual is unemploymed as per his prinicipal activity and also a question on whether the person is unemploymed on all the seven days of the week

credit supply decreases conflict then, we should not see any impact of personal loans on conflict because personal loans are not likely to have any effect on unemployment.

The results of the placebo tests are presented in Table 10. The coefficient of lagged personal loan and personal loan in column 1 and 2, respectively is not significant confirming that personal loans do not have any impact on unemployment. We have shown that personal loans do not effect unemployment, so now according to our unemployment channel personal loans should also not reduce conflict. Results in column 3 confirm that increased supply personal loans do not help in reducing conflict, since the coefficient of lagged personal loans is not significant. Our placebo test confirms that unemployment is an important channel through which credit supply reduces conflict.

9 Mining

So far, our results have established that supplying more credit to industry reduces the likelihood of conflict. The industrial credit variable that we focus on in our analysis comprises of credit to four industrial sectors, namely electricity gas water, construction, manufacturing processing and mining quarrying. Out of these four categories mining industry has been positively linked with conflict in some states by few researchers, e.g. Hoelscher, Miklian, Vadlamannati(2012). The main argument given for the association is that mining causes land disposession of many poor people. These people then participate in conflicts as a means to protest against the loss of their livelihood.

If the above argument holds then it would be interesting to see how increased credit supply to mining industry effects conflict. To test the impact of mining credit on conflict, we focus only on the mining category of the industrial credit. But this reduces our sample size because the data on disaggregation of industrial credit into the four industries is available only after 1996. Results in Column 1 of Table 11 however does not seem to support that credit to mining industry heightens the chances of conflict. The coefficient of mining is negative although statistically insignificant indicating no impact of mining on conflict.

But it is possible that we are getting this result because mining credit is a very small proportion of total industrial credit in the full sample. Mining industry is concentrated in few states and for non mining states credit to mining sector is negligible. So, we now restrict the analysis of mining credit on conflict to only mining states. Ministry of mines, in its report titled ”State Wise Mineral Scenario” categorizes 11 Indian states to be mineral rich (Andhra Pradesh, Chhattisgarh, Goa, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharshtra, Odisha, Rajasthan, Tamil Nadu). We focus on only these eleven states to test the imapct of mining credit on conflict.

Results are reported in column 2 of Table 11. Even after restricting the sample to only mining states we don't find any impact of mining credit on conflict. As before the coefficient of mining is negative though statistically insignificant. So, this might lead us to conclude that mining credit doesn't have any association with conflict even in mineral rich states. But Hoelscher, Miklian, Vadlamannati(2012) in their paper have shown that mining is associated with conflict in only those states which have both high mineral deposits and high Scheduled Caste and Scheduled Tribe (ST) population. This is because in these states land disposession due to mining further widens the inequality between marginalised and poor sections of society like STs and the powerful elite.

We now test the impact of mining credit on those mineral states which have also experienced Maoist insurgency. Department of Left Wing Extremism, Ministry of home affairs categorizes nine states as being effected by Maoist insurgency (Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, West Bengal, Maharshtra, Odisha, Bihar and Uttar Pradesh). These states have seen high participation of STs in insurgent activities and some of them are also rich in minerals. So, it would be interesting to focus our analysis on the mineral rich states effected by Maoist insurgency. The results of the regression of mining credit on Maoist insurgency in mineral rich states are reported in column 3 of Table 11.

Coefficient of mining credit is positive but not statistically significant. This result implies that increased credit to mining sector in maoist conflict states has no/weak positive effect on conflict. Thus, credit to mining sector might not always be helpful in reducing conflict especially in Maoist insurgency effected states with high mineral deposits. Although this result is somewhat consistent with the findings of Hoelscher, Miklian, Vadlamannati(2012), it demands further investigation on the reasons for no effect on conflict. Next section looks at the channels which explain the positive impact of credit to mining on conflict.

9.1 Mechanism

In this sub section, we explore the channels through which mining credit leads to increase/no impact in conflict. Mining industry being an employment generating sector is likely to have a negative impact on conflict through reducing unemployment, but it is also documented that mining industry has caused land disposession at a large scale. It is possible that in these states forceful land acquisition from poor and marginalised sections by large companies have led to an increase in land inequality which has fuelled conflict.

We hypothesise that there are two opposite channels at work due to increased mining credit in these states. First channel could be the decrease in unemployment rate caused by mining credit which is likely to reduce conflict whereas the second channel could be the increase in land inequality which is likely to increase conflict.
To test the first channel we regress the two notions of unemployment, general and strict unemployment on current and lagged mining credit. Table 12 reports the regression results, only current mining credit seems to have a negative and significant impact on general unemployment. In other specifications, we don't find any evidence of negative impact of mining credit on unemployment. Thus, our results show that mining credit had a very weak impact on reducing unemployment.

We test our second channel by regressing land inequality in a district d and year y on current and lagged mining credit. Results are reported in Table 13. As we can see the coefficient of both current and lagged mining credit is positive and significant implying that increased supply of mining credit increases land inequality in a district. Since the coefficient is positive for both current and lagged mining credit, we have a strong evidence of increase in land inequality due to increased credit to mining industry.
Thus, the channel test for the two opposite channels provides us with a plausible reason of no effect/increase in conflict due to increased mining credit. Mining credit has a very weak, though negative impact on unemployment whereas it has strong positive impact on land inequality. Thus mining credit in Maoist effected states does harm by increasing land inequality and it benefits weakly by reducing unem-

ployment. The net effect of the two channels therefore could be no impact/weak positive impact on conflict.

10 conclusion

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 use multiple measures of conflict and an exhaustive list of control variables that have been shown by other papers to influence conflicts. The test results overwhelmingly support our models prediction that financial development mitigates conflicts. The observed effects are significant statistically as well as economically. Further, we find that, the effects are stronger in less conflict-prone 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. However, credit supply to mining industries in mineral-rich districts in India provides an exception to our results. In this case two opposing channels, employment growth and rising inequality in land distribution, appear to offset each other. Barring this case, our results make a strong case for more financial development within a market framework as a means to combat conflicts in affected areas. The policy prescription challenges conventional wisdom in the subject.

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Table 1: Variable definition ad data source

Variable	Definition	Data source
Conflict(G)	Dummy variable, takes a value of 1 if there was a death or property damage due to insurgent activity; 0 otherwise	Global Terrorism Database
Deaths	Number of people killed due to insurgent activities	Global Terrorism Database
Property Damage	Dummy variable, takes a value of 1 if there was a property damage due to insurgent activity; 0 otherwise	Global Terrorism Database
Conflict(F)	Total number of conflict incidents in a given district in a given year	Constructed using Global Terrorism database
Conflict(I)	Captures the intensity of conflict based on the total number of people killed	Constructed using Global Terrorism database
Industrial Credit	Bank credit supply to industry	Basic Statistical Return published by Reserve Bank Of India
Mining Credit	Total bank credit supply to Mining and quarrying	Basic Statistical Return published by Reserve Bank Of India
Personal Loan	Bank credit supply for personal use	Basic Statistical Return published by Reserve Bank Of India
Total bank Credit	Total bank credit supply (all occupations combined)	Basic Statistical Return published by Reserve Bank Of India
Lagged Industrial Credit	Bank credit supply to industry lagged by one year	Basic Statistical Return published by Reserve Bank Of India
Lagged Mining Credit	Bank credit supply to Mining and quarrying lagged by one year	Basic Statistical Return published by Reserve Bank Of India

Worker Participation Rate	Percentage of people employed out of total labour force	Census India
Literacy Rate	Percentage of people employed out of total population	Census India
urbanisation	Percentage of population living in urban areas	Census India
st	Percentage of Scheduled tribal population in a district	Census India
Forests	Percentage of total area covered by forests in a state	Open Government Database Website
per capita SDP	Per capita net state domestic product	India Stat
Average Household Expenditure	Average monthly consumption expenditure of a household in a district	National Sample Survey Rounds
General Unemployment	Percentage of people unemployed according to their principal activity	National Sample Survey Rounds
Conservative Unemployment	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
Land inequality	Gini coefficient of land possession in a district	constructed using National Sample Survey Rounds
Avg Land holding	Average land possessed by a household in a district	National Sample Survey Rounds

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Conflict(G)	0.273	0.445	0	1	20357
Deaths	2.337	5.532	0	187	5548
Property Damage	0.48	0.5	0	1	5548
Industrial Credit	1.216	13.199	0	692.859	17197
noof accounts	8.252	1.591	0	14.848	18056
Mining credit	0.175	2.398	0	171.227	7617
Total bank Credit	2.749	27.085	0	1532.358	17235
Worker Participation	52.316	5.064	28.989	81.66	14273
Literacy Rate	75.314	12.225	27.653	99.705	12581
Urbanisation	25.338	19.326	0.802	100	14004
Forests	21.677	20.504	3.97	85.91	19919
NSDP(pc in 1000)	11.527	11.717	1.003	97.524	19027
Cons expenditure	4.436	8.193	-102.259	281.347	18419
Unem(General)	1.573	1.299	0.148	5.096	17831
Unem(Strict)	1.503	1.09	0.202	4.345	17998

Table 3: Effect of credit supply on conflict

	(1) Conflict(G)	(2) Conflict(I)	(3) Conflict(F)
Industrial Credit	-0.0082***	-0.0086***	-0.2416***
	(0.000)	(0.000)	(0.003)
Urbanisation	-0.0009	-0.0007	-0.0256
	(0.516)	(0.654)	(0.567)
Worker Participation	-0.0144***	-0.0153***	0.0161
	(0.002)	(0.002)	(0.939)
Literacy Rate	-0.0146***	-0.0143***	0.0314
	(0.000)	(0.000)	(0.870)
population Density	0.7282***	0.8507***	18.4479*
	(0.001)	(0.001)	(0.075)
Forests	0.0162***	0.0191***	0.6150**
	(0.001)	(0.001)	(0.026)
State Highways	0.0233	0.0227*	0.3683
	(0.122)	(0.092)	(0.293)
District Roads	-0.0039	-0.0022	-0.1125
	(0.312)	(0.531)	(0.220)
National Highways	-0.0161	-0.0115	0.4125
	(0.680)	(0.754)	(0.582)
NSDP(pc in 1000)	-0.0078***	-0.0083***	-0.0513
	(0.005)	(0.005)	(0.320)
Constant	0.8752	0.6447	-52.3967
	(0.150)	(0.339)	(0.258)
Observations	8201	8201	8201

p-values in parentheses

District FE:YES, Year FE: Yes

Dependent variable in column 1, Conflict(G) takes a value of 1 if there's conflict; 0 otherwise

Conflict(I) in column 2 is a categorical variable constructed on the basis of number of people killed

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

independent varibale of interest is industrial credit

standard errors have been clustered at the district level

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

Table 4: Addressing endogeneity concerns

	(1)
	Conflict(G)
Industrial Credit	-0.0069***
	(0.000)
Urbanisation	-0.0001
	(0.927)
Worker Participation	-0.0156***
	(0.001)
Literacy Rate	-0.0153***
	(0.000)
population Density	0.5111***
	(0.000)
Forests	0.0017
	(0.691)
Cons expenditure	-0.0166***
	(0.001)
State Highways	0.0239
	(0.108)
District Roads	-0.0039
	(0.314)
National Highways	-0.0270
	(0.549)
NSDP(pc in 1000)	-0.0060**
	(0.024)
Constant	2.3576***
	(0.000)
Observations	7975

p-values in parentheses

District FE:YES; Year FE: Yes

Dependent variable, Conflict(G) is a dummy which takes a value of 1 if there's conflict; 0 otherwise

independent varibale of interest is industrial credit which 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

standard errors have been clustered at the district level

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

Table 5: Addressing endogeneity concerns

	(1)
	Conflict(G)
Lagged Industrial Credit	-0.0076***
	(0.000)
Urbanisation	0.0001
	(0.962)
Worker Participation	-0.0160***
	(0.001)
Literacy Rate	-0.0153***
	(0.000)
population Density	0.5383***
	(0.000)
Forests	0.0020
	(0.636)
Cons expenditure	-0.0186***
	(0.000)
State Highways	0.0260*
	(0.088)
District Roads	-0.0045
	(0.267)
National Highways	-0.0281
	(0.487)
NSDP(pc in 1000)	-0.0059**
	(0.024)
Constant	1.9002***
	(0.000)
Observations	7737

p-values in parentheses

District FE:YES; Year FE: Yes

Dependent variable, Conflict(G) is a dummy which takes a value of 1 if there's conflict; 0 otherwise

independent varibale of interest is lagged industrial credit which is credit to industry lagged by one year

standard errors have been clustered at the district level

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

Table 6: Timing of DRT establishment

City of DRT	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 16 1999	Maharashtra, Goa

Table 7: First Stage Results

	(1)	(2)	(3)
	Industrial Credit	Industrial Credit	Industrial Credit
group1post94	1.186*		
	(0.066)		
group1	0.0981		
	(0.436)		
Urbanisation	0.0137*	0.0373***	0.0326***
	(0.052)	(0.000)	(0.000)
Worker Participation	-0.00313	0.000883	0.00307
	(0.344)	(0.875)	(0.595)
Literacy Rate	-0.0116*	-0.0182***	-0.0169***
	(0.094)	(0.001)	(0.004)
population Density	-0.0143	0.0953	0.0819
	(0.756)	(0.272)	(0.382)
Forests	0.00208*	-0.0831**	-0.0482
	(0.076)	(0.014)	(0.187)
Cons expenditure	0.0246*	0.101***	0.0571**
	(0.058)	(0.001)	(0.032)
DRTduration		0.194***	0.194***
		(0.002)	(0.003)
Constant	0.588	-2.339***	-1.027*
	(0.188)	(0.001)	(0.066)
Observations	4861	8920	7793

p-values in parentheses
State FE:YES; Year FE: Yes
Dependent variable, industrial credit is 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 have been clustered at the year level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Second stage Results

	(1) Conflict(G)	(2) Conflict(G)	(3) Conflict(G)
predicted indcred	-0.0678**		
	(0.015)		
Urbanisation	0.00556***	0.00675***	0.00731***
	(0.000)	(0.002)	(0.000)
Worker Participation	-0.00956***	-0.00914***	-0.00757***
	(0.001)	(0.000)	(0.001)
Literacy Rate	-0.00114	-0.00601***	-0.00424***
	(0.298)	(0.000)	(0.000)
population Density	-0.0455**	-0.0517**	-0.0369**
	(0.032)	(0.018)	(0.025)
Forests	-0.00578***	-0.0374***	-0.0481***
	(0.005)	(0.000)	(0.000)
Cons expenditure	-0.00507*	-0.00742	-0.000319
	(0.067)	(0.235)	(0.921)
predicted indcred		-0.0633	
		(0.214)	
predicted indcred			-0.0901**
			(0.031)
Constant	0.891***	1.266***	1.142***
	(0.002)	(0.000)	(0.000)
Observations	5383	9510	8354

p-values in parentheses

State FE:YES; Year FE: Yes

Dependent variable, Conflict(G) is a dummy which takes a value of 1 if there's conflict; 0 otherwise

Inpependent variable, is industrial credit is credit to industry

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 have been clustered at the district level

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

Table 9: Robustness Checks 1:Probit Results

	(1)
	Conflict(G)
	margins_b/p
Conflict(G)	
Industrial Credit	-.009239***
	.0003335
Urbanisation	-.001227
	.5362917
Worker Participation	-.0175464***
	.0001822
Literacy Rate	-.0096794***
	.0000228
population Density	1.609103**
	.0276177
Forests	.0352508**
	.0346236
State Highways	.0546748**
	.0132994
District Roads	-.0113613**
	.043002
National Highways	-.0808062*
	.0787201
NSDP(pc in 1000)	-.0043894*
	.097104
Constant	
	.2443216
Observations	5755

District FE:YES; Year FE: Yes

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 have been clustered at the district level

Table 10: Robustness Checks:2

	(1)
	Conflict(G)
noof accounts	-0.0224**
	(0.031)
Urbanisation	-0.00138
	(0.359)
Worker Participation	-0.0142***
	(0.002)
Literacy Rate	-0.0142***
	(0.000)
population Density	0.516**
	(0.021)
Forests	0.0101*
	(0.088)
State Highways	0.0212
	(0.163)
District Roads	-0.00351
	(0.367)
National Highways	-0.000150
	(0.997)
NSDP(pc in 1000)	-0.00793***
	(0.004)
Constant	0.897
	(0.162)
Observations	8295

p-values in parentheses

Dependent variable, Conflict(G) takes a value of 1 if there's conflict; 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

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

Table 11: differential impact of credit supply on conflict prone districts

	(1)	(2)	(3)	(4)	(5)
	Conflict(G)	Conflict(G)	Conflict(G)	Conflict(G)	Conflict(G)
Industrial Credit	-0.0157**	-0.0174***	-0.0167***	-0.0075***	-0.0031*
	(0.018)	(0.003)	(0.001)	(0.001)	(0.060)
conflict prone_40	0.1011***				
	(0.000)				
interaction_40	0.0132*				
	(0.050)				
conflict prone_50		0.1648***			
		(0.000)			
interaction_50		0.0148**			
		(0.013)			
conflict prone_60			0.2375***		
			(0.000)		
interaction_60			0.0134**		
			(0.010)		
conflict prone_70				0.2829***	
				(0.000)	
interaction_70				0.0071**	
				(0.036)	
conflict prone_80					0.2981***
					(0.000)
interaction_80					0.0047*
					(0.098)
Constant	2.6683***	2.6006***	2.4445***	2.1693***	1.9850***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	7975	7975	7975	7975	7975

p-values in parentheses

State FE:YES; Year FE: Yes

Dependent variable, Conflict(G) takes a value of 1 if there's conflict; 0 otherwise

Independent variable of interest is industrial credit which is credit to industry in less conflict prone districts

coefficient of the interaction gives the differential impact of credit supply

on conflict prone and non 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 have been clustered at the district level

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

Table 12: test for unemployment as a channel

	(1) Unem(General)	(2) Unem(General)	(3) Unem(Strict)	(4) Unem(Strict)
Lagged Industrial Credit	-0.000641		-0.00361***	
	(0.792)		(0.004)	
Literacy Rate	-0.00610	-0.00679	0.00408	0.00336
	(0.473)	(0.433)	(0.573)	(0.648)
population Density	1.708**	2.278***	-0.0855	-0.00812
	(0.032)	(0.000)	(0.599)	(0.972)
Cons expenditure	-0.0210	-0.0177	0.0118	0.0128
	(0.151)	(0.217)	(0.348)	(0.310)
Industrial Credit		-0.00411***		-0.00509***
		(0.001)		(0.000)
Constant	2.247***	3.007***	3.151***	3.157***
	(0.000)	(0.001)	(0.000)	(0.000)
Observations	10695	10880	10766	10953

p-values in parentheses
District FE:YES; Year FE: Yes
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 have been clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Placebo Test

	(1) Unem(General)	(2) Unem(General)	(3) Conflict(G)
Personal Loan	-0.00000263		0.00000354
	(0.442)		(0.181)
Worker Participation	0.0585***	0.0581***	-0.0160***
	(0.001)	(0.002)	(0.001)
Literacy Rate	-0.00684	-0.00693	-0.0153***
	(0.441)	(0.436)	(0.000)
population Density	2.061***	0.744	0.590***
	(0.000)	(0.140)	(0.000)
Cons expenditure	-0.0231	-0.0288	-0.0197***
	(0.180)	(0.103)	(0.001)
NSDP(pc in 1000)	-0.00947	-0.00776	-0.00599**
	(0.101)	(0.183)	(0.023)
Lagged Personal Loan		-0.00000356	
		(0.352)	
Urbanisation			-0.000164
			(0.915)
Forests			0.00188
			(0.679)
State Highways			0.0227*
			(0.098)
District Roads			-0.00291
			(0.423)
National Highways			-0.0247
			(0.582)
Constant	-1.446	-0.510	2.417***
	(0.235)	(0.713)	(0.000)
Observations	10329	9907	7665

p-values in parentheses
District FE:YES; Year FE: Yes
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
standard errors have been clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Impact of mining credit on conflict

	(1) Conflict(G)	(2) Conflict(G)	(3) Conflict(G)
Mining credit	-0.000490	-0.00448	0.0187
	(0.924)	(0.217)	(0.430)
Urbanisation	0.000392	-0.0204	-0.000894
	(0.915)	(0.180)	(0.900)
Worker Participation	-0.0148	-0.0337	-0.0382**
	(0.314)	(0.200)	(0.018)
Literacy Rate	-0.0245***	-0.0220**	-0.0398***
	(0.000)	(0.018)	(0.000)
population Density	0.982***	5.466	-0.933***
	(0.000)	(0.270)	(0.000)
Forests	0.0105*	0.138	-0.0535***
	(0.078)	(0.205)	(0.000)
Cons expenditure	-0.0315***	-0.0259***	-0.0375***
	(0.000)	(0.001)	(0.000)
State Highways	0.0324	0.0509**	0.00571
	(0.182)	(0.031)	(0.175)
District Roads	-0.00640	-0.00986*	-0.000401
	(0.279)	(0.061)	(0.726)
National Highways	-0.0258	0.00900	-0.0585***
	(0.665)	(0.890)	(0.000)
NSDP(pc in 1000)	-0.00416	-0.00422	-0.00444
	(0.147)	(0.339)	(0.186)
st			-0.00892
			(0.189)
Constant	2.634**	-4.204	9.768***
	(0.033)	(0.614)	(0.000)
Observations	3762	1728	1981

p-values in parentheses
District FE:YES; Year FE: Yes
Dependent variable, Conflict(G) takes a value of 1 if there's conflict; 0 otherwise
Independent variable of interest is mining which is credit to mining industry
variable cons expenditure denotes the average household consumption expenditure, it has beenused as a proxy for district level economic activity. Sample size in this table reduces as compared to previous tables because credit data on mining and quarrying classification is available after 1996
standard errors have been clustered at the district level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Impact of mining credit on unemployment

	(1) Unem(General)	(2) Unem(General)	(3) Unem(Strict)	(4) Unem(Strict)
Mining credit	-0.0787**		-0.0139	
	(0.011)		(0.455)	
Literacy Rate	0.0208	0.0230	0.0346***	0.0339***
	(0.148)	(0.154)	(0.001)	(0.002)
population Density	3.358***	3.581***	-1.948***	-2.085***
	(0.000)	(0.000)	(0.000)	(0.000)
Cons expenditure	0.0542***	0.0513***	-0.00843	-0.00717
	(0.000)	(0.001)	(0.423)	(0.474)
NSDP(pc in 1000)	0.0136	0.0155*	-0.0137**	-0.0164***
	(0.121)	(0.098)	(0.013)	(0.004)
Lagged mining credit		-0.0283		-0.00356
		(0.662)		(0.903)
Constant	-1.974**	-87.11***	-0.475	49.98***
	(0.013)	(0.000)	(0.413)	(0.000)
Observations	2666	2498	2667	2500

p-values in parentheses

District FE:YES; Year FE: Yes

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

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

Independent variables of interest are mining which is credit to mining industry and

lagged mining credit which is credit to mining industry 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 have been clustered at the district level

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

Table 16: Effect of mining credit on land inequality

	(1) Land inequality	(2) Land inequality
Mining credit	0.00000780^{+}	
	(0.085)	
urbanisation	-0.000141	0.000123
	(0.905)	(0.921)
Work Participation Rate	-0.00255	-0.00309
	(0.454)	(0.392)
Literacy Rate	0.000824	0.000630
	(0.516)	(0.623)
per capita SDP	-0.000000527	-0.000000717^{+}
	(0.212)	(0.089)
schedule5	-0.329*	-0.334*
	(0.000)	(0.000)
population Density	-0.000307*	-0.000316*
	(0.000)	(0.000)
Avg Land holding	-0.0875*	-0.0834*
	(0.001)	(0.001)
Average Household Expenditure	0.00000128*	0.00000149*
	(0.032)	(0.011)
Lagged Mining credit		0.00000872*
		(0.012)
Constant	0.999*	1.037*
	(0.000)	(0.000)
Observations	2380	2223

p-values in parentheses
District FE:YES
Year FE: NO
$^{+}$ $p < 0.10$, * $p < 0.05$

Table 17: Checking common trends

	(1) Industrial Credit
group1year2	0.0797*
	(0.078)
group1year3	0.0000
	(.)
group1year4	-0.1036*
	(0.061)
group1year5	-0.2037
	(0.262)
group1year6	0.0681
	(0.312)
group1year7	0.0593
	(0.102)
group1year8	-0.3144**
	(0.035)
group1year9	-0.1103
	(0.471)
group1year10	-0.1990**
	(0.027)
group1year11	0.1635
	(0.132)
group1post94	0.9964*
	(0.066)
Constant	0.3194*
	(0.060)
Observations	6048

p-values in parentheses

State FE:YES; Year FE: Yes

Dependent variable, industrial credit is credit to industry

coefficient of interaction of group 1 dummy with different year dummies provide the evidence for parallel trends

standard errors have been clustered at the year level

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