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Can Finance Combat Conflict?**

Sankar De  
CAFIN, UCSC

Bharti Nandwani  
Shiv Nadar University, New Delhi

March 2016

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**Key Words:** conflict, credit supply, number of bank accounts, economic growth, channel tests.

**JEL Classification:** G21, O16.

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

Sankar De<sup>†</sup> and Bharti Nandwani<sup>‡</sup>

March, 2016

## Abstract

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

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<sup>†</sup>Corresponding author. Email: drsankarde@gmail.com, Phone: +917042662505

<sup>‡</sup>Shiv Nadar University, Greater Noida, Pin Code: 201314, India. Email: bn666@snu.edu.in.

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## 1 Introduction and motivation

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

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<sup>1</sup>Source: Global Terrorism Database

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

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

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

strategies, such as financial development, that are conducive to conflict mitigation.

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

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

Taken together, the findings offer a special insight into organization of conflicts. Conflicts of different types, including ethnic conflicts, civil wars, and extremist political insurgencies, share a critical common feature that makes all of them respond similarly to economic expansion and employment creation brought about by

financial development. Arguably, regardless of the specific type of conflict they are engaged in, rank and file insurgents have low opportunity costs of conflict participation in common. Absence of suitable employment opportunities elsewhere in the economy drives their opportunity costs low. When new jobs materialize as a result of financial development and economic expansion, their opportunity costs rise, inducing some or all of them to exit conflict. Our channel test results support this view. The insight that low opportunity costs are a pre-condition for participation in civil wars is originally due to Collier (2003). What our findings suggest is that it cuts across all forms of conflict and serves as a common thread between them.

The central contributions of the present paper are as follows. First, many conflicts, if not all, that appear to be driven by ostensibly non-economic motivations have economic underpinnings. This observation is similar in spirit to a key finding in Mitra and Ray (2012) who have documented economic motivation for Hindu-Muslim riots in India. However, what differentiates our contribution from theirs is that our results suggest that the economic underpinnings are common to conflicts of different types. They all rest on their rank and file having low opportunity costs of conflict participation. Second, following from the above, a strategy of economic expansion and growth that has the effect of raising the opportunity costs results in mitigation of conflicts of different types. In the present paper financial development is our strategy of choice though, conceivably, other economic strategies that deliver employment creation and growth could work as well. Our choice of financial development as the strategy conflict mitigation is dictated by several factors important for our study, including theoretical and empirical factors. Our model explicitly incorporates a realistic feature of conflict financing, namely that some of the funds provided for legitimate businesses get diverted to conflicts. Bank credit allows us to model this feature seamlessly. The model shows that, in spite of this diversion, an increase in credit supply causes a decline in conflict. Availability of superior

data of financial development has also motivated us to consider this strategy. For our empirical tests, the source of the data for the independent variables of interest, namely credit supply by Indian commercial banks and number of bank accounts which are the two common indicators of financial development, is Basic Statistical Returns (BSR) database of the Reserve Bank of India (RBI). BSR provides this data annually for each district-year in the aggregate as well as separately for different sectors, such as agriculture, industry, professional services etc. The quality and comprehensiveness of BSR data are excellent.

Finally, and importantly, we consider financial development to check whether economic development occurring within the market system, with banks giving credit to businesses, can mitigate conflicts without government intervention. Our findings are affirmative. Until now the policy as well as academic literatures have largely focused on government interventions as the means to conflict mitigation. The two types of options that are in principle open to a government faced with insurgency within its jurisdiction are a military response, which may take various forms such as use of paramilitary forces or launch of counterinsurgency operations, and a negotiated settlement with the insurgents. Sometimes both options are pursued simultaneously. Both approaches have well-documented limitations. All existing evidence indicates that the first option is extremely costly, particularly when it takes the form of civil wars. We have referred to some of the evidence in the opening paragraph of this paper. Further, the existing evidence on the long-term success rate of the military option is ambiguous, even ignoring concerns about causality of estimates of the impact of military operations on conflict given that it is difficult to be sure if the operations are in reaction to conflict or the result of a planned government strategy. While Berman, Felter, and Sharipo (2011) and Berman, Felter, Sharipo, and Troland (2013) find that security operations are complementary to provision of aid and were effective in reducing conflict in Iraq, Dube and Naidu (2012) find

that American aid-supported paramilitary operations in Colombia is not negatively associated with guerrilla violence. In fact, some existing studies find that counterinsurgency operations lead to increased insurgency among the local people (Benmelech, Berrebi, and Klor, 2010; Kocher, Pepinsky, and Kalyvas, 2011). Within our sample period, the "Salwa-Judam" operation launched by the government of Chhattisgarh state in central India in 2005 is a case in point. The operation is named after a paramilitary force organized by the state government that recruited tribal youths as special police officers to fight Maoist insurgency. However, our data indicates that both the frequency and intensity of conflicts in Chhattisgarh increased following the launch of Salwa-Judam. There were also many allegations of human rights violation associated with the operation, Finally, in 2011 the Supreme Court of India intervened and declared the operation illegal and unconstitutional, forcing its termination.

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

As we have indicated above, our contributions are based on a model as well as

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

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<sup>2</sup>As an example of such costs, about 40 percent of immobile capital in the agriculture, communications, and administrative sectors in Mozambique was destroyed (Breck, 2001). There are other equally staggering examples.

this negative relationship holds for all types of conflict, because the reward can fit any type. Our empirical tests consistently find a negative association between credit supply and different types of conflict. As we have indicated above, both predictions are borne out by the results of our empirical tests.

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

The paper proceeds in the following manner. Section 2 below presents a review of the relevant literature. Section 3 presents our model. The data and the variables

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

## **2 Relevant Literature**

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

Importantly for our purpose, this literature has not considered the impact of economic interventions on conflict within a market framework, which is the focus

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

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

## 3 Theoretical framework

### 3.1 The setting

In this section we present a theoretical framework for the impact of bank credit supply on conflict.

There are two sectors in the model: Industry and Conflict. There is also a financial market. There are two parties or groups,  $i$  and  $j$ . The groups may engage in both sectors. For tractability we assume that the groups do not have an initial endowment, although our results hold if this assumption is relaxed. Both groups borrow from the financial market for the express purpose of investing in the industry sector, but can divert part of the credit to invest in the conflict sector. Though monitoring is imperfect, the outcomes are observable ex post.

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

Groups  $i$  and  $j$  may also engage in conflict with a view to obtaining a reward characterized by a binary distribution;  $X$  or  $0$ .  $X$  can have many forms; political (administrative control of a geographic area), economic (control over natural resources in an area), ethnic (displacement of another community from an area), and religious (extermination of another community in an area). We assume that, regardless of the specific form of  $X$  in a given situation, possession of  $X$  generates a monetary outcome for the reward holder. Without ambiguity we denote

the monetary outcome also as  $X$ . The production function in the conflict sector is represented by  $F_i$  for group  $i$ . The output of conflict sector can be interpreted as outcomes that propel group  $i$  toward winning the conflict and capturing  $X$ , such as destruction of employable resources (manpower, capital stock etc) of group  $j$ .  $F_i : [0, \infty] \rightarrow [0, \infty]$  is strictly increasing, weakly concave, twice differentiable and Inada condition-satisfying. The production function for group  $j$ ,  $F_j$ , satisfies similar conditions.

A financial market exists where groups  $i$  and  $j$  can borrow money at an interest rate of  $r$  from a bank for industrial activity. The lending institution's objective is to break even on each credit decision. The lender is a passive player in the game between the two parties in the conflict. The lender lends  $\overline{K}_i^*$  amount of industrial credit to group  $i$ , consistent with his objective to break even. Institutional regulations as well as law of the country prevents the lender from lending directly for investment in the violent conflict sector. However, as stated above, monitoring by the lender is imperfect. Hence, both groups can divert a part of the total credit,  $\overline{K}_i^*$  to conflict without the lender's knowledge. Let  $K_i^c$  be the amount diverted to conflict by group  $i$  at date  $t$ . Therefore, the amount left to be invested in industry by group  $i$  is  $\overline{K}_i^* - K_i^c$ . Since  $f(K_i^I)$  is concave,  $f(\overline{K}_i^* - K_i^c)$  is convex in  $K_i^c$ .

Conflicts generate two types of costs for the participants. We incorporate both costs explicitly in our model. The first type is opportunity costs of loss of industrial output arising from diversion of funds. Conflicts also generate special costs due to their unique nature. A conflict of necessity involves collateral damage in the form of destruction of life and property (beyond what the parties intend to inflict on each other). The costs due to collateral damage are indirect costs as opposed to direct costs of conflict (such as costs of troops, ammunitions etc.) incurred by the warring parties. The direct costs are paid with diverted funds in our model and represented by the opportunity noted above. The indirect costs are experienced not

only by the party directly responsible for the collateral damage but also by other parties involved in the conflict (as also the rest of the society). Such costs can be substantial. We assume that the indirect cost function, denoted by  $C(K_i^c + K_j^c)$ , is strictly increasing in the total amount of capital invested in conflict by both groups. Though collateral damages are an inevitable feature of conflicts, incorporating such costs explicitly is a new contribution to modeling of conflicts. Since this is an innovative feature, at this stage we decide to consider both concave and convex indirect cost functions, and not pre-suppose a specific functional form. Which of the two functional forms is consistent with data will be known when we proceed to empirical work.

We assume the following two conditions:

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

II)  $X > \bar{K}_i^*$  and  $X > \bar{K}_j^*$ . The reward from conflict exceeds the industrial output even if the entire credit is invested in industry. Hence engagement in conflict is tempting for both groups.

## 3.2 The game

As the lender is prevented from lending for conflict sector activities, the lender considers only the borrower's output from industry in his lending decision. The lender chooses  $\bar{K}_i^*$  such that  $f_i(\bar{K}_i^*) \geq \bar{K}_i^*(1 + r)$ . This condition implies that the output from industry is sufficient to cover debt repayment. Similarly, the bank lends  $\bar{K}_j^*$  to group j such that the output from industry for group j exceeds  $\bar{K}_j^*(1 + r)$ . We

assume that if the entire funds are invested industry, the loans can be repaid and the lender's break even conditions are satisfied.

Group i has the following utility function:

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

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

$$\bar{U}_i(K_i^c, K_j^c) = f(\bar{K}_i^* - K_i^c) + \frac{F_i(K_i^c)}{F_i(K_i^c) + F_j(K_j^c)} X - r(\bar{K}_i^*) - C(K_i^c + K_j^c) \quad (2)$$

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

### 3.2.1 Convex indirect cost function

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

$$f'(\bar{K}_i^* - K_i^{c*}) + C_{K_i^{c*}}(K_i^{c*} + K_j^c) = \frac{F_i'(K_i^{c*})F_j(K_j^c)}{[F_i(K_i^{c*}) + F_j(K_j^c)]^2} X \quad (3)$$

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

similarly is

$$f'(\bar{K}_j^* - K_j^{c*}) + C_{K_j^{c*}}(K_i^c + K_j^{c*}) = \frac{F_j'(K_j^{c*})F_i(K_i^c)}{[F_i(K_i^c) + F_j(K_j^{c*})]^2} X \quad (4)$$

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

$$\frac{dk_i^{c*}}{d\bar{K}^*} = \frac{f''(\bar{K}^* - k_i^c)}{f''(\bar{K}^* - K_i^c) - C''_{K_i^c} + \frac{XF(K_j^c)[(F(K_i^c) + F(K_j^c))F''(K_i^c) - 2[F'(K_i^c)]^2]}{([F(K_i^c) + F(K_j^c)])^3}} \quad (5)$$

If the indirect cost function is convex, the sign of the denominator is negative. It follows from the concavity of  $\bar{U}_i$ .<sup>3</sup> The numerator in (5) is positive, given our assumption of strictly concave industrial production function (in  $K_j^i$ ). Hence, the sign of  $\frac{dk_i^c}{d\bar{K}^*}$  is negative.

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

### 3.2.2 Concave indirect cost function

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

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<sup>3</sup>  $\frac{\partial U_i}{\partial K_i^c} < 0$  implies that

$$f''(\bar{K}_i^* - K_i^c) - C''_{K_i^c}(K_i^c + K_j^c) + \frac{XF(K_j^c)[F(K_i^c) + F_j(K_j^c)F''(K_i^c) - 2F'[(K_i^c)^2]]}{[F(K_i^c) + F(K_j^c)]^3} < 0$$

$\bar{U}_i$  twice, we get the following expression

$$f_i''(\cdot) - C''_{K_i^c}(\cdot) + \frac{XF_j(\cdot)[F_i(\cdot) + F_j(\cdot)F_i''(\cdot) - 2F_i'[(K_i^c)]^2]}{[F_i(\cdot) + F_j(\cdot)]^3} \quad (6)$$

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

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

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

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

$$f(K_{it}^a) = K_{it}^\alpha, \text{ where } \alpha < 1$$

$$F(K_{it}^c) = \beta + K_{it}^c$$

$$C(K_{it}^c + K_{jt}^c) = \log(K_{it}^c + K_{jt}^c)$$

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

Assuming  $X=100$ ,  $\alpha = 0.5$ ,  $\beta = 1$  and  $\bar{K} = 90$  in period 1. Using python, we solve the above equation to compute the threshold value of  $\bar{K}$  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  $\frac{dk^c}{d\bar{K}}$  is negative turns out to be 32.8. Thus the range of capital investment in conflict for which the impact of credit supply on conflict is negative is [32.8,90].

### 3.3 Predictions

From the discussion above, the model offers the following two testable predictions:

I(a) If the indirect cost function of conflict is convex, an increase in credit supply reduces conflict.

I(b) On the other hand, if the function is concave, the implications are ambiguous. However, even in the latter case, the negative relationship between credit supply and conflict may hold for high levels of investment in conflict.

Later in the paper we resort to our data and test results to resolve the issue. Our test results find a negative relationship for all levels of conflict, indicating a convex indirect cost function.

II) The negative relationship between credit supply and conflict (or lack thereof) in the first prediction holds for all types of conflict. Note that the reward of conflict,  $X$ , in our model, is designed to fit all conflict types.

## 4 Data and variables

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

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

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

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<sup>4</sup>District is a unit of administration in a state/ region in India

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

Figure 1 here

#### *Dependent variables in main tests*

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

#### *Dependent variables in our channel tests*

To test the channels through which credit supply affects conflicts, we consider reduction in unemployment as a possible channel and use two measures of unem-

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

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

#### *Main independent variables*

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

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<sup>5</sup>Thick rounds are conducted quinquennially and have a large sample size whereas thin rounds have a much smaller sample size and are conducted in the years between two successive thick rounds

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

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

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

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

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<sup>7</sup>The four categories are (1) electricity, gas and water, (2) construction, (3) manufacturing and processing and (4) mining and quarrying

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

We also consider the impact of number of accounts in industry on conflict. We use the log of the number of accounts in industry as the independent variable in our tests.

#### *Control variables*

The control variables include:

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

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

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

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

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

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

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

6) Area covered under forests: source IndiaStat

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

efficient to be positive.

7) Net state domestic product: source IndiaStat

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

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

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

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

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

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

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

The definitions and summary statistics of all variables used in our empirical work are reported in tables I and II respectively. The summary statistics reported in table II indicate that 28.5 percent of the total number of observations in our sample experienced conflict defined as Conflict(G), while 35.5 percent of the district-years in our sample experienced Conflict(F). As we have noted above, the total number of observations exceeds the total number of district-years in our sample. Average industrial credit supplied in a district-year is INR 1.2 million which is about 44

percent of the total credit supply in the district year. But the standard deviation of industrial credit is very high, indicating high variability in the supply of industrial credit across district years. Note that average mining credit in a district year is INR 0.17 million, amounting to about 6 percent of the total credit and 14 percent of industrial credit supply in the average district-year.

We also look at similar summary statistics for conflicts in different regions of India. Our data (not included in a table) indicate that, compared to the rest of the country, separatist insurgency in Jammu, Kashmir, and Punjab, ethnic conflicts in north-eastern India, and Maoist insurgency in central India have a much higher incidence (0.79, 0.42, 0.19 respectively), frequency (2.14, 0.57, 0.22 respectively) and intensity (0.89, 0.48, 0.21 respectively) of conflicts. The same three measures of conflict are 0.09, 0.10, and 0.09 for the rest of India. At the same time, the industrial credit supply in the average district year is significantly less in the three regions (0.78, 0.22, 0.96 million INR respectively) than in the rest of India (2.33 million INR). The numbers are consistent with a pattern of negative relationship between industrial credit supply and conflict. The pattern appears to hold for the full sample comprising different types of conflict as well as for the separate conflict types.

\*\*\* Tables I and II here

## 5 Basic results and identification

### 5.1 Basic tests

In this sub-section, we evaluate the impact of credit supply on conflict by estimating the following regression model:

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

The dependent variable,  $Conflict(G)_{d,s,t}$  is a dummy which takes a value of 1 if

there is any report of conflict in district  $d$ , state  $s$  and time  $t$ ; 0 otherwise. The independent variable of interest,  $Icredit_{d,s,t}$  is the flow of industrial credit in district  $d$ , state  $s$  and time  $t$ .  $X_{d,s,t}$  is a vector that includes all the control variables, namely urbanization, male literacy and worker participation rate, population density, inequality, number of national highways and district roads in a district. The test model also includes state level controls, namely percentage of total area covered by forests and per capita net state domestic product. By prediction 1 of our model, the expected sign of  $\beta$ , coefficient of industrial credit supply is negative.

\*\*\* Table III here

The estimated coefficients of the regression equation are reported in column 1 of table III (coeff -0.008, p 0.00). The results show that  $Conflict(G)$  falls as more industrial credit is supplied in a district. We check that, one standard deviation increase in the industrial credit supply reduces the likelihood of conflict by 0.10. Given the average conflict level of 0.28 (table II), a reduction by 0.10 amounts to about one third reduction in the average value of conflict. In other words, the economic impact is significant, in support of prediction 1. The reported coefficients of the control variables have expected signs, except in the case of inequality. We explore the reasons after we are able to determine the sign of inequality in similar regressions later..

In this paper, we also look at the impact of industrial credit supply on the intensity of conflict as well as frequency of conflict. The results for  $Conflict(I)$  and  $Conflict(F)$  are reported in columns 2 and 3 respectively of table III. The results show that industrial credit supply also negatively impacts  $Conflict(I)$  (coeff -0.008, p 0.00) and  $Conflict(F)$  (coeff -0.21, p 0.00). We report results for  $Conflict(G)$  in all tests in the rest of the paper because it is a more general notion of occurrence of conflict than  $Conflict(I)$  or  $Conflict(F)$  and also because it gives us the weakest results in support of our hypothesis out of the three dependent

variables.

All 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 total number of observations used in each regression is 7,878 though from table II, the total number of observations for conflict is much higher (19,493). This is due to lack of availability of data for all the control variables in all district years.

## **5.2 Addressing endogeneity: Omitted variable bias**

The coefficient of industrial credit reported in table III before may be inconsistent because of endogeneity issue. Endogeneity could be due to time varying unobservable variables affecting both conflict and industrial credit supply. One possible omitted variable is the district level economic activity. Financial development has been shown to cause economic growth (Rajan and Zingales). Also, 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 our basic test model does not control for district level economic activity, our estimates are likely to be biased downwards, that is in favour of our hypothesis. To correct this problem we use a proxy for district level economic activity. An ideal proxy for it 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<sup>8</sup> 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.

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<sup>8</sup>Computed from NSS rounds

The results are reported in column 1 of table IV below.

\*\*\*Table IV here

Note that the magnitude of the coefficient of industrial credit supply is less negative (-0.0069) than the corresponding coefficient in table III (-0.008) confirming that our previous estimates were biased downwards. The sign of inequality is as expected (positive and significant). The coefficient of average monthly consumption expenditure is negative indicating, as expected, negative correlation between economic activity and conflict. We expect that the bias-corrected coefficient reflects consistent and causal impact of industrial credit supply on conflict.

### **5.3 Addressing endogeneity: Reverse causality**

There could be an endogeneity issue due to reverse causality with our basic test model. 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 be 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 influence 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 2 of table IV. The coefficient on lagged industrial credit supply is also negative and significant and is very similar in magnitude to the coefficient of current industrial credit reported in table III before. The results indicate that the results reported in table III were not confounded because of reverse causality.

However, even after addressing reverse causality industrial credit supply could still be endogenous. For instance, if banks/financial institutions base their lending decision in a district not only on the current level of conflict but also on the expected

conflict level in future. We address this issue in sub section 5.4 below.

Results in Table III and IV provide evidence in favour of the theoretical prediction of our model (Prediction 1).

## **5.4 More identification using instrumental variables**

In the previous section (subsections, 5.2 and 5.3), we have addressed two main sources of endogeneity, omitted variable bias and reverse causality, in an effort to establish causal impact of industrial credit supply on conflict. In this section, we present more evidence that our basic test model 1 is well identified. We identify a clearly exogenous policy-induced shock to industrial credit supply in our sample and verify that the changes in credit supply cause corresponding changes in conflict consistent with our prediction of negative association between them. The policy change that we consider is the introduction of Debt Recovery Tribunals (DRTs) in Indian states starting from late 1993. The DRT act, 1993, allowed the central government to establish DRTs for speedy recovery of debts in excess of INR 1 million owed to banks and financial institutions ((Visaria (2009); LilienfeldToal, Mookherjee and Visaria (2012)). Under the law the central government determine the territorial jurisdictions of DRTs. The state governments were not given any authority to influence this process (Visaria (2009)). Five DRTs were set up in 1994 with jurisdiction over thirteen states (group 1 states) and five during 1997-1999 with jurisdiction over another sixteen states (group 2 states). The phased introduction of DRTs occurred as a result of legal issues, and was entirely uncorrelated with pre-existing conflict levels in the states. Table V lists the timing of DRT introduction in group 1 and group 2 states.

\*\*\*Table V here

We exploit the phased introduction of DRTs to design our tests to verify the

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

## **5.5 First Stage**

Given that DRTs made the recovery of debts less costly, we expect DRT introduction to have a positive impact on credit supply. LilienfeldToal et al (2012) in their paper show that on an average DRTs increased credit supply for the firms in their sample. Accordingly, we expect the first stage results of regression of credit supply on the two instruments to be positive. For the first instrument, the first stage regression is designed as a difference in difference test capturing the differential impact of DRTs for group 1 states over group 2 states. Before running first stage regression, we first verify the existence of parallel trends in group 1 and group 2 states before 1994 by interacting group 1 states with eleven year dummies for 1983-1994. The results, reported in table VI below indicate that the coefficients of all interaction terms are insignificant, except in two years when they are negative. Overall, we

find no evidence of a positive pre trend in credit supply in group 1 states before DRT introduction. Note that this particular test uses fewer observations than before because the test covers a smaller sample period (1983-1996).

\*\*\*Table VI here

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

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

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

$$Icredit_{d,s,t} = \alpha_s + \gamma_t + \beta DRTduration_{s,t} + \delta X_{d,s,t} + \epsilon_{s,t}$$
<sup>9</sup>

We control for state fixed effects, year fixed effects and other control variables in both the regressions. The results, reported in columns 1 and 2 of table VII, confirm that the first stage results for both instruments are positive and significant, consistent with our prediction. The results 1.18 with 6 percent p value and 0.19 with 1 percent p value, respectively, satisfy relevance conditions.<sup>10</sup>

\*\*\*Table VII here

We also verify that the instruments satisfy exclusion restriction, namely that DRT introduction was not independently correlated with the level of conflicts in states. As we have discussed earlier, the timing of DRT introduction was driven by factors which were completely exogenous to pre existing levels of conflicts in the states. Further, LilienfeldToal et al (2012) investigate the possibility of state level factors influencing the timing of DRT introduction, and find that the timing of DRTs was not correlated with any economic, political or legal factors in the states. Their

<sup>9</sup> $X_{d,s,t}$  includes all those control variables which have been added in regression equation 13.

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

findings provide further support to exogeneity of the instruments. However, the last three years of the sample period, 2008-2010, witnessed a serious financial crisis in many countries, including India. The crisis could have affected both the conflict levels in the states (positively through reduction in the level of economic activity) and functioning of DRTs (negatively through corporate bankruptcies and excessive increase in NPAs for financial institutions). This would confound our second stage test results during 2008-2010 because DRT would no longer be exogenous after 2008. Accordingly, we reestimate our first stage regressions until 2008 and verify that strong and significant association between credit supply and DRT continues to hold (column 3 of table VII) for the sub sample period (1983-2008).

## 5.6 Second stage results

We now present IV-2SLS results of regression of conflict on credit supply (predicted from the first stage tests). Column 1 of table VIII reports the results when  $group1*post94$  is the instrument. Column 2 has DRT duration as the instrument, column 3 has DRT duration till 2008 as the instrument.

\*\*\* Table VIII here

The results reported in column 1 confirm the negative relationship between conflict and credit supply. However, the results in column 2 are insignificant. As we have argued above, DRT duration may not be exogenous after 2008. Hence in Column 3 we only consider years on and before 2008 to assess the exogenous impact of credit supply on conflict<sup>11</sup>. As expected, the reported coefficient of industrial credit supply in column 3 is negative and significant. This result allows us to make a causal claim that an increase in industrial credit supply reduces the likelihood of conflict.

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<sup>11</sup>By this exercise we only lose two years of data given our sample is from 1983-2010

Note from table VIII that the reported absolute value of credit supply coefficients in columns 1 (0.06) and 3 (0.09) are considerably higher than the corresponding OLS results reported in table III before (0.008). The results indicate that OLS estimates are biased upwards against our hypothesis. The IV results in table VIII appear to have corrected this bias. The number of observations in column 1 is fewer because the analysis is done for 1983-1996.

## **6 Tests of predictions**

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

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

To test this prediction, we compute average conflict level of each district over 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 entire sample period of 28 years 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 partition the full sample of districts into two groups with the following propor-

tions: 60/40, 50/50, 40/60, 30/70 and 20/80. In each ratio, the numerator indicates the proportion of districts in the top (that is, more conflict prone) group. We do not go below 20 percent in the top group because at this stage the bottom group will end up having too many conflict prone districts. We then estimate the differential impact of credit supply for more conflict prone and less conflict prone districts by interacting more conflict prone districts with credit supply. The test model for testing prediction 2 is

$$Conflict(G)_{d,s,t} = \alpha_s + \gamma_t + \beta Icredit_{d,s,t} + \eta Icredit * moreconflictpronedistrict + \phi moreconflictpronedistrict + \delta X_{d,s,t} + \epsilon_{d,s,t}$$

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

\*\*\*Table IX here

In Columns 1-6 of table IX we report the differential impact for districts categorised as more conflict prone and less conflict prone according to the following thresholds: 60, 50, 40, 30 and 20 percentile respectively.<sup>12</sup> In all specifications the coefficient of industrial credit is negative and significant. The coefficients of industrial credit indicates the impact of credit for less conflict prone districts. This provides us with consistent evidence that industrial credit reduces conflict in less conflict prone districts, contradicting prediction I(b). Note also that the coefficients of the interaction terms are positive and significant in all specifications. In other words, industrial credit supply has a stronger impact on conflict mitigation in less conflict prone districts than in more conflict prone districts. We conclude that the results convincingly indicate that the indirect cost function is convex, and uphold

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<sup>12</sup>In all the columns we have controlled for average monthly expenditure to control for district level economic activity.

prediction I(a).

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

To recall, prediction II states that the negative relationship between credit supply and conflict holds for all types of conflict. From our discussion in the data section before, 39 percent of the reported incidents of conflict in our sample took place in Jammu, Kashmir and Punjab in north India where civil wars in the form of violent separatist movements were the norm. 31 percent took place in Left Wing Extremism (LWE) states in central India affected by Maoist insurgency. Another 20 percent driven by ethnic conflicts took place in north-eastern India. The rest of the incidents of conflict, including religious conflicts, accounted for 10 percent of the total. To test this prediction, we test the following regression model:

$$Conflict(G)_{d,s,t} = \alpha_s + \gamma_t + \beta Icredit_{d,s,t} + \phi_1 LWE + \phi_2 NE + \phi_3 JK + \eta_1 Icredit * LWE + \eta_2 Icredit * NE + \eta_3 Icredit * JK + \delta X_{d,s,t} + \epsilon_{d,s,t}$$

We control for district fixed effects to control for time invariant district level unobserved factors that may yield spurious correlations.  $\delta X_{d,s,t}$  includes all the control variables as in test model 1. The results are reported in Table X below.

\*\*\*Table X here

The three variables in the test model are  $Icredit*LWE$ ,  $Icredit*NE$ , and  $Icredit*JK$ . The omitted category in the regression is the rest of the sample. For this category, the reported coefficient of  $Icredit$  is 0.0072, which is remarkably similar to the coefficient for the entire sample in Table IV before. Note that the coefficients of both  $Icredit*LWE$  and  $Icredit*NE$  are both insignificant. In other words, in the case of LWE and JKP states, industrial credit supply causes a similar decline in conflict as the whole sample. Interestingly, the coefficient of  $Icredit*NE$  is negative and

insignificant, implying that industrial credit supply has a stronger effect on conflict reduction than the other categories. But for all of them the association between credit supply and conflict is negative and highly significant at 1 percent level. The results vindicate prediction II strongly.

## 7 Mechanism

In the previous sections our results have documented a significant negative impact of industrial credit supply on conflict. In this section we explore the channel through which industrial credit is likely to impact conflict. We check whether industrial credit impacts conflict through employment creation in a district. Increased supply of credit to industry should boost industrial activity which is a major employment generating sector in India. Other studies (see Collier and Hoeffler(1998, 2001, 2002)) have found a negative association between employment and conflict. To test whether employment works as a channel, we estimate the following two regression equations

$$unemprate_{d,s,t} = \alpha_d + \gamma_t + \beta Icredit_{d,s,t} + \eta \bar{X}_{d,s,t} + \epsilon_{d,s,t}$$

$$unemprate_{d,s,t} = \alpha_d + \gamma_t + \beta Icredit_{d,s,t-1} + \eta \bar{X}_{d,s,t} + \epsilon_{d,s,t}$$

The two regression models above use alternatively current and lagged industrial credit supply as structural changes like unemployment<sup>13</sup> generally take some time to respond to changes in the economy. We use two notions of unemployment rate in our empirical estimation; strict unemployment and general unemployment.<sup>14</sup>

Coefficient  $\beta$  in the two regression models indicates the impact of industrial

<sup>13</sup>We use unemployment as opposed to employment in the empirical work because questions asked in NSS survey pertained to unemployment as opposed to employment

<sup>14</sup>We have constructed these variables using NSS round questionnaire. NSS questionnaire has a question on whether an individual is unemployed as per his principal activity and also a question on whether the person is unemployed on all the seven days of the week

credit supply on unemployment.  $\bar{X}_{d,s,t}$  includes average monthly consumption expenditure (as a proxy for economic activity in a district which affects both unemployment and industrial credit), literacy rate and population density. The regressions include district and time fixed effects. The results for the channel test are reported in table X below.

\*\*\*Table XI here

Columns 1 and 2 in the table report the results for general unemployment, whereas columns 3 and 4 report the results for strict unemployment. The Coefficient of industrial credit is negative and significant for both general (coeff -0.004 p 0.00) and strict unemployment (coeff -0.005 p 0.00), implying that increased industrial credit leads to fall in unemployment. The Coefficient of lagged industrial credit is also negative and significant for strict unemployment (coeff -0.003 p 0.00) and negative but not significant for general unemployment (coeff -0.0006 p 0.79). Overall the results indicate that industrial credit supply causes unemployment to fall supporting our hypothesis that unemployment is an important channel through which industrial credit reduces conflict.

Note that the tests in this part use more observations (10,698-10,956) than the tests reported before.

## 7.1 Placebo test

Our results above have established that credit supply to industry uses unemployment reduction as a channel to reduce conflict. It follows that credit supply to some other sector which does not generate employment should not have any impact on conflict. To test this proposition, we perform a placebo test. We test the impact of personal loans on unemployment and also on conflict. If our hypothesis is correct, we will not see a significant impact of personal loans on levels of either unemployment or

conflict. The results of the placebo test are reported in table XI below.

\*\*\*Table XII here

The coefficients of current and lagged personal loans in column 1 and 2, respectively are not significant (p values 0.44, 0.35 respectively), confirming that personal loans do not have any effect on unemployment. Therefore, if unemployment reduction is an effective channel to reduce conflict, personal loans should not impact conflict either. The test results reported in column 3, confirm our intuition. The regression coefficient of personal loan on conflict is insignificant (p value 0.18).

## 8 Mining Credit

We have established in previous sections that industrial credit has a causal negative impact on conflict. The industrial credit variable taken from BSR database that we use in our analysis comprises 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 (Hoelscher, Miklian, Vadlamannati(2012)). The main argument given for the association is that mining causes land dispossession for many poor people who then participate in conflicts as a means to protest against the loss of their livelihood.

Given this argument, it is interesting to see how increased credit supply to mining industry affects conflict. Therefore, in this section 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 mentioned above is available only since 1996. We estimate the following regression:

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

where Mcredit, denoting credit to mining industry, replaces Icredit in test model 1 before. The results for the full sample reported in column 1 of table XII below do

not seem to support that credit to mining industry increases conflict. The coefficient of mining is negative although statistically insignificant (p value 0.79). However, mining industry is concentrated in a limited number of states in India. In the non-mining states credit to the mining sector is negligible. Hence, the above finding could be the result of a very small proportion of mining credit in the total industrial credit (14 percent). Therefore, at the second stage of our investigation, we restrict our sample to eleven states identified as mining states by Ministry of Mines, Government of India.<sup>15</sup> The eleven states are Andhra Pradesh, Chhattisgarh, Goa, Gujarat, Jharkhand, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Rajasthan and Tamil Nadu. The test results are reported in column 2 of Table XII.

\*\*\* Table XIII here

After restricting the sample to the mining states only, the impact of mining credit on conflict appears to be negative and significant (coeff -0.006, p value 0.09), consistent with our results throughout in this paper that credit supply impacts conflict negatively.

At this stage, our findings appear to be inconsistent with other studies mentioned above that have found a positive association between mining industry and conflict. The existing research (Hoelscher et al. (2012)) has shown that mining industry is associated with conflict in some states which have both high mineral resources and high Scheduled Caste and Scheduled Tribe (ST) population. In those states land dispossession suffered by the groups mentioned above due to expansion of the mining industry contributes to conflict, as inequality between the marginalised population and the richer strata of society widens. Accordingly, we decide to examine separately the impact of mining credit on those mining states which have also experienced Maoist insurgency which typically features high participation by ST

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<sup>15</sup>Ministry of mines, Government of India in its report titled "State Wise Mineral Scenario" categorizes these states to be mineral rich

population. Our sample at this stage comprises six Indian states: Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, Maharashtra, Odisha. This sample represents intersection of two separate lists of states; namely the eleven mining states mentioned before and the nine states separately categorised as affected by Maoist insurgency by the Department of Left Wing Extremism, Ministry of Home Affairs, Government of India.<sup>16</sup>

The results of the regression tests for the six states are reported in column 3 of Table XII. Note that the coefficient of mining credit has turned positive, though is not statistically significant (p value 0.76). The result implies that increased credit to mining sector in states affected by Maoist conflict has no mitigating effect on conflict. However, this finding could be the result of a very small sample (1092). This result is weakly consistent with the finding of positive association of mining industry and conflict in Maoist insurgency states.

The control variables in all three columns mostly have expected signs. However, the coefficients of population density and forest in specification 3, negative and significant, are contrary to our previous test results. The result for population density indicates that Maoist insurgency takes place in less populated areas.

## 9 Robustness Checks

All our tests so far have used a linear specification, where the dependent variable Conflict(G) is a dummy variable. We now verify that results are robust to non linear specification in Probit models. Table XIII below reports the marginal impacts of all covariates from a Probit regression of test model 1 before. Note that our results remain unchanged. The results in table XIII confirm the negative and significant

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<sup>16</sup>The nine states are, Andhra Pradesh, Chhattisgarh, Jharkhand, Madhya Pradesh, West Bengal, Maharashtra, Odisha, Bihar and Uttar Pradesh

impact of credit supply on the probability of conflict. Also note that the results using Probit (marginal impact-0.009) and linear specifications (-0.008) are nearly identical.

\*\*\*Table XIV here

We perform another robustness check for our results reported in table III before with an alternative measure of our main independent variable. We use log of number of accounts in industrial credit in place of volume of industrial credit. Along with credit supply, number of accounts is also an important measure of financial development.<sup>17</sup> We expect increased number of accounts under industry to affect conflict in the same manner as industrial credit supply because the former also somewhat increases the coverage of industrial credit supply. Results are reported in table XIV below.

\*\*\*Table XV here

The coefficient of number of accounts is negative and significant; consistent with our prediction. Note however that one standard deviation increase in number of accounts leads to 3 percentage point fall in the likelihood of conflict whereas the effect for industrial credit supply was much higher (10 p.p). The size of the effect is smaller in the case of number of accounts probably because number of accounts do not perfectly correspond to supply of credit.

## **10 Concluding Remarks**

Using a model as well as extensive empirical tests based on district-level evidence from India over a long sample period (1983-2010), in this paper we have investigated the impact of financial development, measured both as an increase in supply

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<sup>17</sup>Data on number of accounts under industry also comes from the basic statistical returns published by the RBI.

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

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

accomplish their mission.

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Figure 1: Geographic distribution of conflicts in India

Table I: Variable definition and data source

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

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

Table II: Summary statistics

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>N</b>
Conflict(G)	0.285	0.451	19493
Conflict(I)	0.323	0.544	19258
Conflict(F)	0.355	2.466	15157
Icredit(million INR)	1.216	13.352	16739
Naccounts	8.247	1.592	17588
Mcredit(million INR)	0.181	2.47	7154
Total bank credit(million INR)	2.744	27.405	16774
Worker Participation(%)	52.268	5.059	13926
Literacy(%)	75.120	12.254	12256
Urbanisation(%)	25.293	19.408	13662
Forests(%)	21.73	20.64	19144
NSDP(per capita 1000 INR)	11.388	11.641	18306
Cexpenditure(1000 INR)	4.426	8.268	17539
Inequality	32.035	1748.582	17528
Unem(General)(%)	1.574	1.3	16970
Unem(Strict)(%)	1.503	1.087	17135

Table III: Effect of credit supply on conflict

	(1) Conflict(G)	(2) Conflict(I)	(3) Conflict(F)
Icredit	-0.0081*** (0.000)	-0.0084*** (0.000)	-0.2102*** (0.003)
Urbanisation	-0.0009 (0.516)	-0.0007 (0.661)	-0.0280 (0.545)
Worker Participation	-0.0144*** (0.002)	-0.0153*** (0.002)	0.0385 (0.855)
Literacy Rate	-0.0144*** (0.000)	-0.0138*** (0.000)	0.0625 (0.748)
Population density	0.4567*** (0.000)	0.5418*** (0.000)	9.2031** (0.015)
Forests	-0.0008 (0.810)	-0.0006 (0.812)	0.0481 (0.530)
Inequality	-0.0008 (0.423)	-0.0007 (0.420)	-0.0057 (0.754)
State Highways	0.0253 (0.102)	0.0253* (0.070)	0.4554 (0.199)
District Roads	-0.0043 (0.285)	-0.0027 (0.458)	-0.1324 (0.158)
National Highways	-0.0298 (0.414)	-0.0279 (0.401)	0.0180 (0.979)
NSDP(pc in 1000)	-0.0074*** (0.008)	-0.0078** (0.010)	-0.0635 (0.237)
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	7878	7878	7878

*p*-values in parentheses

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

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

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

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

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

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

Table IV: Addressing endogeneity concerns

	(1) Conflict(G)	(2) Conflict(G)
Icredit	-0.0070*** (0.000)	
Cexpenditure	-0.0171*** (0.002)	-0.0192*** (0.001)
Lagged Icredit		-0.0076*** (0.000)
Year FE	Yes	Yes
District FE	Yes	Yes
Observations	7878	7624

*p*-values in parentheses

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

Independent variable of interest in column 1, Icredit, is bank credit to industry

Independent variable of interest in column 2, lagged Icredit, is bank credit to industry lagged by one year

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

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

Table V: Timing of DRT establishment

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

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

	(1)
	Icredit
Group1*year2	0.0741* (0.083)
Group1*year3	0.0000 (.)
Group1*year4	-0.1017* (0.056)
Group1*year5	-0.2009 (0.262)
Group1*year6	0.0612 (0.371)
Group1*year7	0.0452 (0.226)
Group1*year8	-0.3294** (0.033)
Group1*year9	-0.0956 (0.507)
Group1*year10	-0.2007** (0.026)
Group1*year11	0.1643 (0.132)
Group1*post94	0.9846* (0.065)
Year FE	Yes
State FE	Yes
Observations	6026

*p*-values in parentheses

Dependent variable, Icredit is bank credit to industry in a district year.

Coefficient of interaction of group 1 dummy with different year dummies provide evidence for parallel trends. Standard errors are clustered at the year level

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

Table VII: Instrumental variables: First stage results

	(1)	(2)	(3)
	Icredit	Icredit	Icredit
Group1*post94	1.162* (0.064)		
Cexpenditure	0.0436** (0.046)	0.102*** (0.001)	0.0606** (0.018)
DRTduration		0.195*** (0.002)	0.194*** (0.003)
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	4841	8743	7628

*p*-values in parentheses

Controls: Present. Dependent variable, Icredit is bank credit to industry

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

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

Table VIII: Instrumental variables: Second stage results

	(1) Conflict(G)	(2) Conflict(G)	(3) Conflict(G)
Predicted Icredit(83-96)	-0.0602** (0.015)		
Cexpenditure	-0.00581** (0.039)	-0.00974 (0.126)	-0.000745 (0.803)
Predicted Icredit(83-10)		-0.0435 (0.413)	
Predicted Icredit(83-08)			-0.0836** (0.037)
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	5297	9259	8115

*p*-values in parentheses

Controls: Present. Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise  
 Independent variable, is industrial credit is credit to industry. Variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy for district level economic activity. Standard errors are clustered at the district level

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

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

	(1)	(2)	(3)	(4)	(5)
	Conflict(G)	Conflict(G)	Conflict(G)	Conflict(G)	Conflict(G)
Icredit	-0.0161** (0.018)	-0.0179*** (0.002)	-0.0170*** (0.001)	-0.0078*** (0.001)	-0.0033** (0.045)
Conflict prone (top 60)	0.1038*** (0.000)				
Top60*Icredit	0.0135* (0.051)				
Conflict prone (top 50)		0.1678*** (0.000)			
Top50*Icredit		0.0152** (0.012)			
Conflict prone (top 40)			0.2417*** (0.000)		
Top40*Icredit			0.0136** (0.010)		
Conflict prone (top 30)				0.2778*** (0.000)	
Top30*Icredit				0.0074** (0.029)	
Conflict prone (top 20)					0.2968*** (0.000)
Top20*Icredit					0.0053* (0.061)
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Observations	7878	7878	7878	7878	7878

*p*-values in parentheses

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

Coefficient of Icredit indicates impact of industrial credit supply in less conflict prone districts.

Coefficient of the interaction gives the differential impact of credit supply

on more conflict prone and less conflict prone districts. Threshold for categorizing district as conflict prone is 40th, 50th, 60th, 70th and 80th precetile in columns 1-5 respectively

Standard errors are clustered at the district level

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

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

	(1) Conflict(G)
Icredit	-0.0072*** (0.000)
LWE	-0.0174 (0.865)
NE	0.7809** (0.027)
JK	0.7458* (0.095)
Icredit*LWE	0.0029 (0.636)
Icredit*NE	-0.0248*** (0.001)
Icredit*JK	0.0008 (0.694)
Urbanisation	-0.0001 (0.931)
Worker Participation	-0.0158*** (0.001)
Literacy Rate	-0.0158*** (0.000)
Inequality	0.0007* (0.087)
Cexpenditure	-0.0169*** (0.002)
NSDP(pc in 1000)	-0.0060** (0.027)
Year FE	Yes
District FE	Yes
Observations	7878

*p*-values in parentheses

Dependent variable in column 1, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise  
 Variable LWE is a dummy variable to indicate LWE affected states. Variable NE is a dummy variable to indicate North Eastern states. Variable JK is a dummy to indicate states of Jammu Kashmir and Punjab

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

Variables Icredit\*LWE, Icredit\*NE, Icredit\*JK indicate the interaction between Icredit and LWE dummy, Icredit and NE dummy

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

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

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

	(1)	(2)	(3)	(4)
	Unem(General)	Unem(General)	Unem(Strict)	Unem(Strict)
Icredit	-0.00418*** (0.000)		-0.00511*** (0.000)	
Literacy Rate	-0.00700 (0.420)	-0.00595 (0.484)	0.00319 (0.667)	0.00414 (0.570)
Population density	2.412*** (0.000)	1.807** (0.021)	0.00351 (0.989)	-0.0703 (0.682)
Cexpenditure	-0.0171 (0.237)	-0.0204 (0.166)	0.0134 (0.291)	0.0124 (0.329)
Lagged Icredit		-0.000678 (0.781)		-0.00360*** (0.004)
Year FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Observations	10692	10485	10765	10556

*p*-values in parentheses

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

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

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

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

Standard errors are clustered at the district level

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

Table XII: Placebo test with personal loans

	(1)	(2)	(3)
	Unem(General)	Unem(General)	Conflict(G)
Personal Loan	-0.00000502 (0.189)		0.00000356 (0.180)
Literacy Rate	-0.00763 (0.382)	-0.00803 (0.359)	-0.0156*** (0.000)
Population density	2.148*** (0.000)	0.845* (0.072)	0.591*** (0.000)
NSDP(pc in 1000)	-0.00444 (0.447)	-0.00297 (0.613)	-0.00586** (0.028)
Cexpenditure	-0.0238 (0.168)	-0.0297* (0.094)	-0.0196*** (0.001)
Lagged Personal Loan		-0.00000642 (0.134)	
Urbanisation			-0.000214 (0.890)
Worker Participation			-0.0160*** (0.001)
Forests			0.00168 (0.706)
State Highways			0.0228* (0.099)
District Roads			-0.00293 (0.424)
National Highways			-0.0241 (0.593)
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	10144	9691	7571

*p*-values in parentheses

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

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

Dependent variable 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 are clustered at the district level

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

Table XIII: Impact of mining credit on conflict

	(1) Conflict(G)	(2) Conflict(G)	(3) Conflict(G)
Mcredit	-0.00119 (0.831)	-0.00646* (0.093)	0.00677 (0.761)
Urbanisation	0.00117 (0.764)	-0.0193 (0.220)	-0.0182 (0.179)
Worker Participation	-0.0114 (0.445)	-0.0263 (0.336)	-0.0451** (0.035)
Literacy Rate	-0.0238*** (0.000)	-0.0210** (0.029)	-0.0345** (0.018)
Population density	1.052*** (0.000)	5.859 (0.226)	0.600 (0.544)
Forests	0.00861* (0.088)	0.150 (0.160)	-0.0870 (0.250)
Inequality	0.0113** (0.017)	0.0150* (0.064)	0.0190 (0.110)
Cexpenditure	-0.0390*** (0.000)	-0.0371*** (0.000)	-0.0509*** (0.000)
State Highways	0.0342 (0.195)	0.0567** (0.023)	-0.0112** (0.036)
District Roads	-0.00708 (0.272)	-0.0116** (0.042)	0.00456*** (0.005)
National Highways	-0.0251 (0.660)	0.01000 (0.873)	-0.0408*** (0.000)
NSDP(pc in 1000)	-0.00455 (0.129)	-0.00417 (0.365)	-0.00613 (0.224)
ST share			0.00156 (0.970)
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Observations	3652	1654	1092

*p*-values in parentheses

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

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

variable cons expenditure denotes the average household consumption expenditure, it has been used 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 are clustered at the district level

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

Table XIV: Robustness check with probit specification

	(1) Conflict(G) margins_b/p
Conflict(G)	
Industrial Credit	-.0092087*** .0003422
Urbanisation	-.0012614 .5285781
Worker Participation	-.0170887*** .0002873
Literacy Rate	-.0101178*** 9.97e-06
population Density	1.612715** .0278023
Forests	.0353116** .0351346
State Highways	.0556809** .0128196
District Roads	-.0116425** .0408154
National Highways	-.08099* .0794383
NSDP(pc in 1000)	-.0043612 .1008825
Constant	.2495224
Observations	5758

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 XV: Robustness check with number of credit accounts

	(1) Conflict(G)
Naccounts	-0.0134 (0.226)
Urbanisation	-0.000537 (0.726)
Worker Participation	-0.0155*** (0.001)
Literacy Rate	-0.0151*** (0.000)
Population density	0.352 (0.132)
Forests	-0.00681 (0.447)
Inequality	0.000608 (0.214)
Cexpenditure	-0.0153*** (0.002)
State Highways	0.0243 (0.108)
District Roads	-0.00407 (0.306)
National Highways	-0.0235 (0.601)
NSDP(pc in 1000)	-0.00614** (0.023)
Year FE	Yes
District FE	Yes
Observations	7961

*p*-values in parentheses

65

Dependent variable, Conflict(G) takes a value of 1 in case of death/property damage; 0 otherwise  
Independent variable of interest is noof accounts which is the number of accounts under industry  
variable cons expenditure denotes the average household consumption expenditure, it has been used as a proxy  
for district level economic activity.

Standard errors have been clustered at the district level

# Sankar De

## Contact information

Phone: +91 7042662505

E-mail: [drsankarde@gmail.com](mailto:drsankarde@gmail.com)

## Personal

Marital Status: Single.

Nationality: Indian. Permanent resident of the USA.

## Education

PhD, University of California, Berkeley, USA.

MBA, Indian Institute of Management, Calcutta, India

BA, Presidency College, University of Calcutta, India

## Employment

2013 - 2015	Professor, Department of Economics, and Director, Centre for Emerging Societies, Shiv Nadar University, India
2004 - 2013	Professor and Founding Executive Director, Center for Analytical Finance Indian School of Business, Hyderabad, India.
1997 - 2004	Executive Director, Center for Professional Development in Finance (CPDF), Berkeley, USA, and Adjunct Faculty, Haas School of Business, Berkeley, USA
1994 - 1996	Visiting Professor, Haas School of Business, University of California, Berkeley, USA
1992 – 1994	Visiting Professor, Indian Institute of Management, Calcutta
1989 – 1992	Associate Professor, University of Wisconsin – Madison
1986 – 1988	Assistant Professor (Visiting), Southern Methodist University
1982 – 1986	Assistant Professor, University of Texas at Austin

## Honorary positions

President, Asian Finance Association (2012 – 2014)

Director, Asian Finance Association (2010 - present)

Fellow, Wharton Financial Institutions Center (2006 – present)

## Academic affiliations

Member, Program Committee, American Finance Association, 2010

Member, Program Committee, Financial Intermediation Research Society (2009 - present)

Member, Review Committee, IFMR, 2009

Member, American Economic Association

Member, American Finance Association

Member, Econometric Society

Member, Western Finance Association

### **Professional affiliations**

Member, Reserve Bank of India Technical Advisory Committee on Monetary Policy (2012 – 14)  
Member, Committee on Economic Policy, Confederation of Indian Industries (2010 -

### **Teaching records**

#### **Programs**

Undergraduate, MBA, and Ph.D. classes in finance and economics. High teaching ratings at all levels and all institutions (including UC-Berkeley) and several honors.

#### **Courses**

Financial Management  
Corporate Finance  
Mergers and Acquisitions  
Role of Institutions in Financial Markets

#### **Executive teaching**

Citigroup  
International Monetary Fund  
Barclays Global Investors

### **Research records**

#### **Interests/expertise**

Role of institutions in financial markets  
Emerging capital markets (special focus on access to finance for underserved sectors)  
Behavioral finance and small investors  
Financial development and economic inequality  
Financial development and conflict

### **Academic publications**

#### **Books and monographs**

Capital Markets in India, Sage Publications, jointly with Rajesh Chakrabarti (editors), 2010  
India's Financial System (jointly with Franklin Allen and Rajesh Chakrabarti), Nomura Occasional Series on Contemporary Capital Markets, 2008

#### **Book chapter**

Law, Institutions, and Finance in China and India, *Emerging Giants: China and India in the World Economy*, Oxford University Press (jointly with F Allen, R Chakrabarti, QJ Qian, and M Qian), 2011

#### **Journal articles (refereed)**

Financing Firms in India (jointly with Franklin Allen, Jun Qian, Meijun Qian, and Rajesh Chakrabarti), *Journal of Financial Intermediation*, 2012.

Legal Liabilities and Market for Audit Services (jointly with P. K. Sen), *Journal of Business Finance and Accounting*, 2001

On Revelation of Private Information in Stock Market Economies, (jointly with M. Berliant), *Journal of Mathematical Economics*, 1998.

Is Auditor Moral Hazard the Only Reason to Ban Contingent Fees for Audit Services? (jointly with P. K. Sen), *International Journal of Auditing*, 1997.

Effects of Competition on Bidder Returns (jointly with M. Fedenia and A. Triantis), *Journal of Corporate Finance*, 1996 (lead article).

Managerial Reaction to Takeover Bids: A Theory of Strategic Resistance (jointly with P. Knez), *Journal of Economics and Management Strategy*, 1994.

Contingent Payments and Design of Debt Contracts, (jointly with J. Kale), *Financial Management* special issue on "Security Design", 1993, (invited article).

Rights Versus Underwriting: Optimality of Equity Issue Strategies, (jointly with P. Nabar), *Research in Finance*, 1992.

Diversification Patterns and Long-Term Corporate Performance, " *Managerial Decision and Economics*, 1992 (lead article).

Economic Implications of Imperfect Quality Certification, (jointly with P. Nabar), *Economics Letters*, 1991.

Medium of Payment in Corporate Acquisitions: Evidence from Interstate Bank Mergers, (jointly with Marcia Millon Cornett), *Journal of Money, Credit and Banking*, 1991.

Bidder Returns from Corporate Takeovers: Evidence from Interstate Bank Mergers, (jointly with Marcia Millon Cornett), *Journal of Banking and Finance*, 1991.

Optimality of Coupon-Bearing Debt Under Asymmetric Information, (jointly with J. Kale), *Economics Letters*, 1990.

Benefits of Interstate Banking: The Evidence from Shareholder Returns, (jointly with D. Duplichan), *Proceedings of Fourth International Symposium on Money, Banking, and Insurance*, 1990.

### **Working papers**

Financial Development and Conflict Mitigation: Can Finance Combat Conflict (jointly with Bharti Nandwani), 2016: SSRN link <http://ssrn.com/abstract=2697110>

How Much Does a Bank Account Help the Poor? An Investigation with Instrumental Variables (jointly with Gitanjali Sen), 2016: SSRN link <http://ssrn.com/abstract=2714214>

Borrowing Culture and Debt Relief: Evidence from a Policy Experiment (jointly with Prasanna Tantri), 2015: SSRN link <http://ssrn.com/abstract=2396368>

Are Banks Responsive to Exogenous Shocks in Credit Demand? District – level Evidence from India (jointly with Siddharth Vij), 2015  
SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1964105](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1964105)

Are Investors Ever Rational? (jointly with Saptarshi Mukherjee), 2012:

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2156047](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2156047)

Are Out-of-Pocket Costs Over-weighted Relative to Opportunity Costs? A Disposition Effect-Based Investigation, (jointly with Rahul Chhabra), 2012

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1962241](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1962241)

Behavioral Biases, Investor Performance, and Wealth Transfers between Investor Groups (jointly with Rahul Chhabra, Naveen Gondhi, and Bhim Pochiraju), 2011

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=2022992](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2022992)

Finance, Growth, and Inequality: Channels and Outcomes, (jointly with Subrata Sarkar, Manpreet Singh, and Siddharth Vij), 2011

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1713605](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1713605)

Accounting for contemporaneous and time dependence in panel data", 2011

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1787125](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1787125)

Credit Rationing in Informal Markets: The Case of Small Firms in India, 2011

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1786139](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1786139)

Employment Protection Laws and Income Inequality, (jointly with Manpreet Singh, Krishnamurthy Subramanian, and Siddharth Vij), 2011

Is Zero Return a Natural Benchmark for Investors? An Investigation with Individual Trading Records, (jointly with Naveen Gondhi and Bhim Pochiraju), 2011

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1846474](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1846474)

Inter-Firm Credit: Do Informal Relationships Help? (jointly with Manpreet Singh), 2010

Relational Contracts and Courts, (jointly with Manpreet Singh), 2009

SSRN Link: [http://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=1493646](http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1493646)

Financial System Capacities of China and India, (jointly with Franklin Allen, Jun Qian, Meijun Qian, and Rajesh Chakrabarti), 2008

### **Refereeing/reviewing**

Journal of Development Economics

Financial Management

Journal of Economics and Management Strategy

Journal of Financial and Quantitative Analysis

Review of Economics and Statistics

Dryden Press

Irwin Press

McGraw-Hill Press

### **Recent non-academic articles**

Times of India

Wall Street Journal (Asia)

Knowledge@Wharton

Ideas for India

### **Recent conference presentations**

Growth and Development Conference, Indian Statistical Institute Delhi, December 2015  
Growth and Development Conference, Indian Statistical Institute Delhi, December 2014  
Asian Finance Association Conference, Bali, June 2014  
CAFIN conference, University of California – Santa Cruz, April 2014  
IGIDR Emerging Markets Finance Conference, Mumbai, December 2013  
Asian Finance Association Conference, Nanchang, China, July 2013  
Financial Intermediation Research Society (FIRS) conference, Dubrovnik, June 2013  
Asian Econometric Society Conference, Delhi, December 2012  
Financial Intermediation Research Society (FIRS) conference, Minneapolis, June 2012  
IGIDR Emerging Markets Finance Conference, Mumbai, December 2011  
Financial Intermediation Research Society (FIRS) conference, Sydney, June 2011  
Academy of Behavioral Finance and Economics Conference, Los Angeles, September 2011  
Growth and Development Conference, Indian Statistical Institute Delhi, December 2011  
Growth and Development Conference, Indian Statistical Institute Delhi, December 2010  
Winter Research Workshop, Indian School of Business, December 2010  
Asian Finance Association Conference, Hong Kong, July, 2010  
Growth and Development Conference, Indian Statistical Institute Delhi, December 2009  
CAFS Conference, Chulalongkorn University, Bangkok, November, 2009.  
Joint ISB-SIFR-Wharton Emerging Markets Conference, Stockholm, September, 2009  
Financial Crisis Conference, HKUST, Hong Kong, July, 2009  
Summer Research Conference 2009 in Finance, ISB, July 2009.  
Financial Intermediation Research Society (FIRS) conference, Prague, May 2009

### **Recent invited presentations**

CAFRAL, Reserve Bank of India, October 2015  
Delhi School of Economics, October 2015  
Indian Statistical Institute, Delhi, September 2015  
Indian Statistical Institute, Delhi, October 2013  
Journal of Financial Stability Conference, Bali, September, 2013  
World Bank Finance Research Center, June 2013  
Hong Kong University of Science and Technology, Hong Kong, April 2012  
International Growth Centre India Development Policy Conference, December 2011  
Asian Finance Association, Hong Kong, July, 2010  
International Growth Centre (London School of Economics and Oxford University) India research launch conference, Delhi, March, 2010  
Institute for Financial Markets and Research (IFMR), December, 2009  
Tel Aviv University, Israel, November, 2009  
Hebrew University, Israel, November, 2009.

### **Recent media coverage of research**

The Economic Times: [Disposition effect & over-confidence trigger investor losses in stock markets: Sankar De, ISB professor](#)

Financial Express: [Indian retail investors tend to lose in stock markets: ISB](#)  
Business Standard: <http://www.business-standard.com/india/news/retail-investors-tend-to-lose-in-stock-markets-says-isb-study/494187/>  
Moneylife: <http://www.moneylife.in/article/indian-retail-investors-tend-to-lose-in-stock-markets-isb/29947.html>  
Indian Express: [Indian retail investors tend to lose in stock markets: ISB](#)  
Outlook India: [Indian Retail Investors Tend to Lose in Stock Market: ISB](#)  
NDTV Profit: [Indian retail investors tend to lose in stock markets: Indian School of Business](#)  
Financial Chronicle: [But retail investors lose Rs 5,584 cr/year](#)  
Moneycontrol.com: [http://www.moneycontrol.com/news/features/indian-retail-investors-tend-to-losestock-markets-isb\\_788789.html](http://www.moneycontrol.com/news/features/indian-retail-investors-tend-to-losestock-markets-isb_788789.html)  
Opinion piece in Business Standard:  
<http://myimpact.impactmeasurement.co.in/impact/clip.php?id=3524986a56e5154f3dad5bad0d8bb60d&id2=9c058240ef2752e73d433eb4e246e2d6>  
Businessline<http://www.thehindubusinessline.com/markets/stock-markets/indian-retail-investors-are-more-irrational-traders-study/article4156830.ece>  
Smart Investor: <http://www.thehindubusinessline.com/markets/stock-markets/indian-retail-investors-are-more-irrational-traders-study/article4156830.ece>  
Equitymaster: <http://www.thehindubusinessline.com/markets/stock-markets/indian-retail-investors-are-more-irrational-traders-study/article4156830.ece>  
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Andhra Jyothy:  
<http://myimpact.impactmeasurement.co.in/impact/clip.php?id=8cddbca639a1dac1e8d2d67bf08d29ef&id2=9c058240ef2752e73d433eb4e246e2d6>  
Zee news [http://zeenews.india.com/business/news/finance/indian-retail-investors-tend-to-lose-in-stock-markets-isb\\_65382.html](http://zeenews.india.com/business/news/finance/indian-retail-investors-tend-to-lose-in-stock-markets-isb_65382.html)  
Article.win.com  
[http://article.wn.com/view/2012/11/29/Disposition\\_effect\\_overconfidence\\_trigger\\_investor\\_losses\\_in/](http://article.wn.com/view/2012/11/29/Disposition_effect_overconfidence_trigger_investor_losses_in/)  
RetailAsia.com <http://www.retailinasia.com/article/careers/human-resource/2012/12/indian-retail-investors-are-more-%E2%80%98irrational%E2%80%99-traders-study>  
<http://www.businessworldads.in/indian-retail-investors-are-more-irrational-traders-study/>  
Blog: <http://silverlinemoments.blogspot.in/2012/12/5584-crore-loss-aversion-overconfidence.html>  
Blog:<http://jkahlon.blogspot.in/2012/12/indian-retail-equity-investors-tend-to.html>

## **Awards/honors**

### **Education**

University of California, Berkeley, award for academic excellence among foreign students, 1979-80.

Newhouse Award (awarded by University of California, Berkeley, for academic excellence among foreign students), 1978-79.

J. N. Tata Endowment Scholarship (a competitive scholarships program open to Indian students for graduate studies abroad), 1976.

**Teaching**

Several citations and honors, including Finalist, annual MBA teaching award, Haas School of Business, University of California, Berkeley, 1995, 1996.

Cited as among the best business school professors in Business Week's annual guide to the best business schools in the USA, 1997.

**Research**

Financial Management Association annual research award (1988) for "An Examination of Stock Market Reactions to Interstate Bank Mergers" (jointly with Marcia Millon Cornett)

**Advising/consulting****Assignments**

Merger, consolidation, and restructuring of corporations;  
Valuation, capital budgeting and corporate diversification;  
Investment banking regulations

**Organizations**

Securities Exchange Commission (SEC)  
Ford Foundation;  
Citigroup (South Asia);  
International Monetary Fund