Default and Punishment: Incentives and Lending Behavior in Indian Banks

Abhijit Banerjee, Shawn Cole, Esther Duflo*

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Abstract

We analyze a model of lending in which loan officers face both an incentive to lend, and the possibility of penalties for making loans that go bad. The model predicts the following: loan officer incentives will be flat, and firms may face credit constraints in equilibrium. Outside monitoring may alleviate these credit constraints, but may also lead to incentives to "evergreen," i.e. bail out failed borrower when the probability of being punished for default increases. We test these predictions using a dataset of all commercial bank loans in India from 1981 to 2003, combined with a data set on the investigation and discovery of fraud by the "central vigilance commission", a federal body charged with investigating default. We find evidence that following the discovery of a fraud in a particular bank branch, vigilance activities greatly increases. This in turn results in reduced lending: the amount of credit declines sharply at the affected bank branch, as well as neighboring branches. This effect is large, and persists in part for up to two years. Bank risk-taking also declines following an inspection.

*MIT (banerjee@mit.edu), Harvard Business School (scole@hbs.edu), and MIT (eduflo@mit.edu), respectively.

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1 Introduction

While the idea that firms, especially in developing countries, are often credit constrained is now widely accepted, we have less understanding of the causal mechanisms that lead to their being constrained. In particular, while standard models of credit market failures emphasize information asymmetries between the banks and their clients, a more recent literature has started to emphasize the fact that agency problems *within* the bank might limit and distort the pattern of lending. The basic idea in this literature is that bankers do not lend their own money; they lend money that belongs to depositors. Moreover typically they do not even own equity in the bank, and therefore have relatively little direct financial stake in the survival of the bank. Yet bankers get to take decisions that can potentially cost the bank much more than what the bank pays them. In the circumstances, it is not surprising that banks put a lot of emphasis on monitoring of loan officers and limiting their discretion, as way to control the potential for moral hazard.

Stein (2002), the first to theorize this phenomenon, models the incentive problem within banks as one of getting the bankers to reliably reveal the "soft" information they have about their potential loan clients. He argues that as banks become larger and it becomes more difficult for the bank's equity holders to verify the information being used to take lending decisions, lending to firms about which there is not a lot of hard information available (such as small firms) will shrink. This is consistent with the finding in Berger, Demsetz and Strahan (1999) and Berger et al (2005) that after consolidations banks are less likely to lend to small businesses.

While this evidence quite suggestive, it does not directly prove that there are incentive problems within banks: We cannot entirely rule out the possibility that it is the result of something else that is related to the size of the bank. More direct evidence of agency problems comes from Hertzberg, Liberti and Paravisini (2008) who show that a policy of rotating the officer who is in charge of a particular loan after a fixed period leads to more bad news being revealed about the recipients of the loans. They argue that this reflects the fact that loan officers try to suppress bad news about firms that they have previously lent to. However their data does not permit them to look whether this translates into an effect on the volume or direction of lending.

The contribution of this paper is to empirically demonstrate that these agency problems do have an effect on loan volumes. Our empirical setting is the banking sector in India. Most banks in India, though corporatized, have a substantial degree of public ownership. Because of this when a loan goes bad in any of these banks there is some chance that the loan officer who initiated the loan will be investigated for criminal embezzlement of public funds under the government's anti-corruption laws. A federal body, the Central Vigilance Commission, is in charge of these investigations, and while investigations are rare, and convictions even rarer, bankers claim that the possibility of being investigated very seriously.

In this paper we study theoretically and empirically what we would expect to happen to lending when the probability of being investigated by the vigilance commission increases temporarily. The model developed in Section 3 makes several predictions: first, optimal incentives for loan officers will be flat, consistent with what is observed in these banks. Second, if collusion between borrowers and loan officers is sufficiently cheap, there will be credit constraints in equilibrium. Third, we study the introduction of an outside monitor. Increasing the penalty for collusion can potentially alleviate credit constraints. However, a period of high enforcement may in fact encourage "evergreening", or "gambling for revival": lending to firms which are about to default in the hope that they will receive a good draw in the next period and get out of their bad situation.[1]

To empirically investigate these predictions, we exploit an unusual data set, made available at the Reserve Bank of India. The data set contains information (date, type, location, and punishment) on all the frauds reported to the Reserve Bank of India between 1980 and 2006. We use it in conjunction with quarterly and annual information on lending at the branch level for a panel of over 43,000 bank branches in the country followed for several years.

We start by showing that when a fraud is discovered by the Central Vigilance Commission in a particular branch in a particular year, the discovery of other frauds in the same branch increases by a factor of 27 in that year, compared to previous years. This suggests a clear persistence in vigilance activity: the probability of being punished for default is larger in a bank branch in the year following the investigation of a fraud. We exploit this within an event-study approach, where we study how lending behavior in a particular branch changes after the

[1] This model of evergreening is in the spirit of Rajan (1994).

discovery of a fraud in the years following the discovery, compared to other branches. We find that credit drops significantly in the year of the investigation but continues to drop several years into the future, and eventually lending levels end up 20% below where they would have been.

These results provide credible evidence that bankers are influenced by considerations other than the quality of the borrower in deciding how much to lend–in particular the fear of being investigated leads them to lend less. This does not directly tell us anything about whether the extent of monitoring in the Indian system is constrained optimal, given the demonstrated potential for moral hazard: the loans that are cut back may well be particularly bad along some dimension that we do not observe. Vigilance activity also affects the sectoral allocation of credit, as branches shift credit from riskier to less risky sectors. Finally, vigilance activity affects other branches of the same bank in the same town. However there is some, admittedly imperfect, evidence suggesting that the cut back might come with its own inefficiencies. We find some evidence that this decline is driven by a reduction of high-quality loans, and we find evidence suggestive of ever-greening.

The evidence that the loan officers are not always trying to maximize either the bank's objective function or some other social objective (neither of which presumably changed on the date of the investigation), is also consistent with the evidence in Banerjee and Duflo (2008) for one Indian bank, showing that there is no correlation between a firms's performance and the increment in its lending limit. It is also help explain the strong correlation betwen corruption and lending, found for example in Beck, Demirguc-Kunt and Levine (2006).

The remainder of this paper proceeds as follows. In Section 2 we provide a brief description of banking in India, and a discussion of the debate on the relationship between corruption and lending. We develop a model of the loan allocation decision by a honest agent subject to incentives to lend and to avoid default in section **??**, and describe the data in the following section. We then use the data to learn something about the parameters of the model,in Section 5. Finally, section presents the empirical results, testing the model's predictions about the relationship between fraud discovery, lending, default, and the riskiness of decisions taken by banks. Finally, Section 7 concludes.

2 Context and Overview

In this section, we briefly describe the context in which banks operate, including anecdotal evidence on the claim that fear of prosecution causes loan officers to behave very conservatively.

We focus on government-owned banks because they dominate the Indian financial system. Public sector banks include both government founded banks (such as the Bank of India), as well as banks nationalized by the government in 1969 and 1980. In the 1990s, several formerly public banks were partially privatized, and foreign banks had entered, primarily in large cities. While public sector banks market share has declined since then, in 2006 government-owned banks provided 71% of bank credit in the economy.

Corruption in lending is a major policy concern, in India and elsewhere. Cole (2008) shows that lending follows a political cycle. Khwaja and Mian (2005) document political corruption of loans in Pakistan. In India, since public sector banks are owned by the government, employees of the bank are treated by law as public servants, and thus subject to government anti-corruption rules. In particular, any default is in principle subject to investigation by the Central Vigilance Commission, a federal authority which maintains an arms-length relationship with the banks, but is empowered to prosecute loan officers.

Bankers have expressed concern that it is very easy to be charged with corruption. Some feel that any financial loss to a government owned bank would automatically lead to investigation, with the burden of proof on the banker to prove her or his innocence. The quote below is fairly typical.

> [Bankers] say that government officials, who are clueless about banking economics, are posted as vigilance officials and there is the threat of a vigilance inquiry each time a bona fide lending decision results in a bad account. Bankers say that they are flush with funds, but credit is not taking off because of fear psychosis. A top banker said: "You become averse to risks in such an environment. Many of us are turning to narrow banking and stick to gilts.[2]"

The Reserve Bank of India (RBI), the Indian equivalent of the Federal Reserve has also

[2] Frontline (Hindu), 15(10), May 9-22, 1998. Accessed at http://www.hinduonnet.com/fline/fl1510/15101090.htm on October 20, 2007.

argued that another result of this fear is bankers reluctance to settle non-performing loans (RBI 2000, p. 29), for fear of being charged with corruption. In 2000, the Indian banking system had among the highest percentage of assets in default of any banking system in the world.

A working group on banking policy set up by the Reserve Bank of India, and chaired by M.S. Verma, noted in 2000:

> The [working group] observed that it has received representations from the managements and the unions of the banks complaining about the diffidence in taking credit decisions with which the banks are beset at present. This is due to investigations by outside agencies on the accountability of staff in respect of some of the N[on] P[erforming] A[ssets]. The group also noticed a marked reluctance at various levels to take any credit decision. (Tannan 2001, p. 1579).

In response to criticism from bankers, economists, and others, the Central Vigilance Commission introduced in 1999 a special chapter of the vigilance manual, on vigilance in public sector banks. While this new chapter was meant to reassure bankers, the language would probably not reassure anyone with experience working in a multinational bank. The manual reads, for example, that "every loss caused to the organization, either in pecuniary or non-pecuniary terms, need not necessarily become the subject matter of a vigilance inquiry. . . once a vigilance angle is evident, it becomes necessary to determine through an impartial investigation as to what went wrong and who is accountable for the same." (p. 5)

Interviews with public sector bankers revealed widespread concern: the legal proceedings surrounding charges of corruption can drag on for years, leaving individuals charged with corruption in an uncertain state. Even if an individual is exonerated, she may have been relieved of her duties, transferred, or passed over for promotion during the time of investigation. In theory (as well as practice), even one loan gone bad may be sufficient to start vigilance proceedings. The possible penalties stand in stark contrast to rewards. While banks are constantly urged by the Reserve Bank of India to loan as much as possible, there are no explicit incentives for making good loans, or ways to penalize officers who make conservative decisions.

Not surprisingly, the Central Vigilance Commission disputes the claim that there is a "fear psychoses," and, to bolster their position, released in 2000 a "critical analysis" of vigilance activity in public sector banks in 1999. The analysis reveals that in 1999, the Central Vigilance Commission received 1,916 references, 72% of which were credit-related, of which 55% resulted in recommendations for major punishment.

Thus, compared to the volume of lending, the probability to be investigated for a fraud is actually extremely small. Moreover, their 2000 report states "Out of every 100 cases coming before it, the Commission would advise major penalty proceedings in 28 cases, minor penalty proceedings in 32 cases, and administrative warning/exoneration in 40 cases." (p. 9). The author of the report, a CVC official, argued that this level of activity should not be enough to cause "fear psychoses": "These figures reveal that a person is not damned the moment his [sic] case is referred to the Commission...These statistics appear to indicate a very fair and objective approach on the part of the Commission to the cases that were referred to it." (CVC 2000 p. 10).

Nevertheless, the "fear of lending" arguments made by the bankers seem to have been serious enough to convince the government: In April 2004 (after the period covered by this study), lower-level loan officers were removed from the jurisdiction of the Central Vigilance Commission. Our data covers the period before this changes, when even low level loan officers could still be charged by the CVC.

3 Some simple theory

In this section, we describe the problem of bank trying to design incentives for its loan officers as well as its borrowers. The original source of the incentive problem comes from the possibility of collusion between the banker and the borrower, which allows the borrower to default even when he has the money. To discourage this, the bank has to punish the loan officer for loans that end up in default, but this can create another incentive problem: no one wants to lend, lest the loan goes into default. The incentive design problem is the problem of balancing these different sources of potential cost for the bank.

3.1 The basic setup

Each bank has money to lend out and the (gross) opportunity cost of a one unit of loans is ρ. There is a large population of potential borrowers. Borrowers can be bonafide (type B) or malafide (type M) in proportion ξ and $1 - \xi$.

Type M borrowers simply take the money, eat it and default. Type B borrowers live for two periods and in principle can invest in both, though if he does not invest in the first he cannot invest in the second. The investment project in period 1 requires I_1 units of investment while the project in period 2 requires at least $\underline{I_2} > I_1$ but it is possible to invest as much as $\overline{I_2} > \underline{I_2}$.

Borrowers come to the bank because they have no money and cannot save. Therefore in period 1 they want to borrow I_1 and period 2 they want to borrow $\overline{I_2}$.

In each period, the investment project succeeds with probability π.When the project fails, there are no revenues. When it succeeds it generates a (gross) return $R > \rho$ per unit of investment.

However the fact that he has been successful does not mean that the borrower will repay the bank. He can simply say that he invested and failed and the bank will not have the hard evidence to prove in a court of law that this was not true.

This is one place that hiring a banker can help: A banker who is keeping an eye on the project knows how to prove in a court of law that the borrower is lying and this makes it too costly for the borrower to lie unless he can get the loan officer to collude with him.

We do not rule out collusion between a type B borrower and his banker: indeed we assume that there is collusion whenever the total surplus that they can generate by colluding is greater than the sum of their outside options. However we assume that there is a cost, $F < \rho I_1$, involved in getting the banker to agree to report that the firm failed when it did not: This is a cost that the borrower and the banker jointly pay whenever they collude to pervert the truth.

This cost F is in effect the reason why the bank may be able to prevent collusion. Given that the banker is in a position to expose the borrower if he lies, the borrower can only lie when he can get the banker to collude, which leads to a loss in surplus of F for the two of them. Therefore as long $F > 0$, introducing a banker into the story makes it harder for the borrower to strategically default.

F can be seen as the cost of the banker's conscience. But it could equally be the cost of getting the records that the banker has about the loan aligned with the "false" records that the borrower has prepared: without their matching the bank would have hard evidence that the banker was lying and punish him so severely that it would not be worth it for him.

We do not introduce a corresponding cost for the case where the banker and the borrower collude to report that the project succeeded when it did not. This is not essential for any of our results

Finally we rule out collusion between type M borrowers and the banker: in other words, the equivalent of F for colluding with malafide borrowers is too large to make collusion worthwhile. This may be because it is just too easy for the bank to generate hard evidence that the banker colluded with a malafide borrower: after all, there is no project to show in this case.

We assume that at the beginning of his life the borrower signs a binding two-period contract with the bank and all his credit comes from this one bank. However there is ex ante competition between banks which ensures that the bank makes zero profits in expectation in equilibrium. In other words the bank maximizes

$$\text{expected revenue from lending - expected wages of bankers - } \rho.\text{total lending}$$

and in equilibrium this number is supposed to be zero. We are therefore assuming that the bank is risk-neutral and has no time preference. We make the same assumption about bankers and borrowers.

The bank then assigns this loan to a banker–this is the only loan the banker handles. The contract with the banker is also a two period contract, but he need not be employed in the second period if the bank does not want him. The banker's outside option is to earn zero. However there is a floor on how little bankers can be paid as long as he is employed, in any state of the world, *unless the bank has hard evidence that the banker committed fraud*. Call this minimum amount $w > 0$. Therefore bankers earn rents when they are employed. However w is small enough that

$$w + \rho I_1 < (1 - \pi) RI_1.$$

Because $I_2 > I_1$ for all feasible I_2,

$$w + \rho I_2 < (1 - \pi) RI_2$$

The project is therefore postive NPV in both periods.

3.2 Information and incentive problems

There are two central information problems in this model. First the bank does not observe the type of the borrower. Second, the bank does not observe whether the project succeeded or not. It only observes whether the loan was repaid or not.

The banker, on the other hand, observes the borrower's type. He also observes whether the project succeeds. He can then report success to the bank or collude with the borrower and report failure.

If the banker observes failure, he can report it to the bank, or he can collude with the borrower to report success. This is only feasible in the first period, because then it is possible for the borrower to repay the loan out of his second period loan. This is what we call evergreening.

3.3 The social optimization problem

The social optimization problem quite straight-forward, absent incentive constraints. No loans should be given to type M borrowers but since the project generates positive surplus in both periods type B borrowers should invest as much as they can in both periods.

Since we assumed that the project generates positive surplus even after paying the banker, this remains true even when we introduce an incentive problem for type B borrowers but assume that the banker has no incentive issues. Then the borrower knows that he cannot get away with defaulting and therefore investing in both periods remains the (constrained) socially optimal outcome.

3.4 The bank's problem

In the constrained case discussed above, where the banker has no incentrive problems but the borrower does, it is trivial to check that the bank will implement the constrained social optimum: it will hire a banker, pay him w and in a zero-profit equilibrium, will offer nothing to a type M borrower while offering a type B borrower a loan of I_1 in period 1 at a (gross) interest rate $r_1 = \frac{1}{\pi}\left(\rho + \frac{w}{I_1}\right)$ and a loan of I_2 in period 2 at a interest rate $r_2 = \frac{1}{\pi}\left(\rho + \frac{w}{I_2}\right)$.

Once the banker needs to be given incentives, the problem becomes much less straightforward, as the borrower and banker can potentially collude.

3.4.1 Incentive instruments

To describe the contract between the bank, banker and borrower, note that there are several scenarios the bank may observe. The banker may not lend at all, or he may lend in the first period but not the second period. For each period for which there is lending, the banker reports an outcome to the bank, either success or failure. Thus, in the first period, the loan officer may report N, S, or F to the bank. In the second period, if the loan officer lends, he will again report success or failure.

We allow the bank a fairly general set of wage contracts. For payment in the first period, the bank offers $\left\{w_N^1, w_S^1, w_F^1\right\}$, depending on whether the loan officer lends, and what the reported outcome is. If the loan officer lends in the first period, the bank makes an additional wage payment, which may be conditioned on the outcome of both the first and second periods: $\left\{w_{SS}^2, w_{SF}^2, w_{FS}^2, w_{FF}^2, w_N^2\right\}$, where SF indicates that the loan was reported sucessful in the first period and reported a failure in the second, etc.

The bank need not employ the loan officer in the second period: denote the probability that the banker continues to be employed in the second period by $\mu(\widetilde{I}_1)$,where $\widetilde{I}_1 \in \{0, I_1\}$ denotes first period investment. This captures the idea that the banker is not very useful in the second period if there is no first period investment and therefore may be "fired". However note that in order to decide that the loan is not be given, the banker needs to be employed in period 1 and therefore $w_{1N} \geq w$. Moreover it is obvious that since the bank needs the banker to collect on the loan $\mu(I_1) = 1$.

As far as the borrower is concerned, the contract specifies the probability (τ_S^2 or τ_F^2) he can borrow in the second period conditional on having borrowed in the first as well as the amount (I_{2S} or I_{2F}) and the interest rate he is offered in both periods (r_1, r_{2S}, r_{2F}). He needs no incentives in the case where he does not get to borrow in period 1.

We start by describing the incentive compability constraints faced by the loan officer in the second period, and then consider those faced by the loan officer in the first period. A key feature of the model is the notion of bailouts, in which a loan officer can renew a failed loan in the hopes that the firm succeeds in its second project, and is able to repay the loan.

3.4.2 Incentive to report in the second period

Assume that the firm got a loan in the first period and its success or failure was truthfully reported to the bank. Then the only incentive problem comes from the possibility of reporting that the firm failed when in fact it succeeded. Given that collusion is always an option (assuming that in the absence of collusion the banker just does his job), to prevent this the bank must ensure that the loan officer tells the truth. There are two constraints, depending on what happened in the first period:

$$\begin{aligned} w_{2FS} + I_{2F}(R - r_{2F}) &\geq w_{2FF} + I_{2F}R - F \\ w_{2SS} + I_{2S}(R - r_{2S}) &\geq w_{2SF} + I_{2S}R - F. \end{aligned}$$

these can be re-written

$$F \geq I_{2F}r_{2F} - (w_{2FS} - w_{2FF}) \qquad (\mathrm{ICC}^2_{FS})$$

$$F \geq I_{2S}r_{2S} - (w_{2SS} - w_{2SF}) \qquad (\mathrm{ICC}^2_{SS})$$

It is of course possible that the borrower did not reveal the truth in period 1. If he said that he failed when he succeeded and still got a loan in the second period, he is no different from someone who really failed. The interesting case is when he said that he succeeded when he failed. This is the case of evergreening. If the loan was $\widetilde{I}_2$ the actual amount invested was $\widetilde{I}_2 - r_1 I_1$. But he has to repay an amount $\widetilde{I}_2 r_2$. However since **??** does not depend on the amount actually invested in period it remains the correct representation of the incentive constraint.

3.4.3 Incentive to report in the first period

In the first period, a successful firm may claim to have failed or a failed firm can claim to have succeeded. To prevent the first problem we need that

$$\begin{aligned} & w_{1S} + I_1(R - r_1) + \tau_{2S}[\pi(w_{2SS} + I_{2S}(R - r_{2S})) + (1-\pi)w_{2SF}] \qquad (\mathrm{ICC}^1_S) \\ \geq\ & w_{1F} + I_1 R - F + \tau_{2F}[\pi(w_{2FS} + I_{2F}(R - r_{2F})) + (1-\pi)w_{2FF}] \end{aligned}$$

In writing down this expression we have assumed that there is no strategic default in the second period, which will be true if ICC^2_{FS} and **??** hold.

Falsely claiming success becomes an issue because the first period loan can be repaid using money from the second loan, provided the second project is profitable enough. Two cases require analysis; in case 1, a project funded by an evergreened loan is sufficiently productive to repay the bank:

$$R(I_{2S} - I_1 r_1) \geq I_{2S} r_{2S}$$

Under this assumption, it is always going to be optimal to avoid any strategic default in the second period and therefore the condition for getting the loan officer to reveal the failure can be written as:

$$\begin{aligned} & w_{1F} + \tau_{1F}[\pi(w_{2FS} + I_{2F}(R - r_{2F})) + (1-\pi)w_{2FF}] \\ \geq \quad & w_{1S} + \tau_{1S}[\pi(w_{2SS} + (I_{2S} - I_1 r_1)R - I_{2S} r_{2S})) + (1-\pi)w_{2SF}] \end{aligned} \tag{ICCB^1_F}$$

In the second case,

$$R(I_{2S} - I_1 r_1) < I_{2S} r_{2S}$$

and therefore the loan will never be repaid in full. Therefore the banker knows that if he reveals that the firm has succeded in the second period (and nevertheless the loan is not repaid) then the bank will have hard evidence that he had in fact lied about the firm's first period success and he can be severely punished. Assume that the punishment is severe enough that he never wants to choose this option. Therefore he must always announce that the firm failed in the second period.[3] To get him to reveal that the firm failed in the first period it must be that

$$\begin{aligned} & w_{1F} + [\pi(w_{2FS} + I_{2F}(R - r_{2F})) + (1-\pi)w_{2FF}] \\ \geq \quad & w_{1S} + [\pi(I_{2S} - I_1 r_1)R - F)) + w_{2SF}] \end{aligned} \tag{ICCN^1_F}$$

since in the second period he will always report failure.

[3] It is true that the bank might be better off allowing i.e not punishing partial default in this case even though it knows that the banker cheated because it gets at least some money. However allowing partial default might also encourage borrowers who have been successful in both periods to opt for partial default in the second period. The trade off depends on how partial the partial default is. We do not deal with this poissibility because it involves soime extra notation and the basic inisght, that evergreening might lead to default (partial or otherwise) remains the same.

3.4.4 Incentive to lend in the first period

Would the banker want to lend to a type B in the first period? If he does not lend he gets $w_{1N} + \mu(0)w_{2N}$. Now the bank has no reason to make this any more than the absolute minimum it can be since it wants investment. So it will set $w_{1N} = w$ and $\mu(0) = 0$.

Given this, the banker will always lend since he can always make sure that gets at least w in both periods by reporting truthfully in both periods.

3.4.5 Analysis

The first step is to note that there is never any reason to reward the banker for failure. Keeping the expected amount paid to the banker in any particular scenario–say $\pi w_{2SS} + (1-\pi)w_{2SF}$– fixed, raising w_{2SS} and lowering w_{2SF} always (weakly) improves incentives. Hence we must have $w_{1F} = w_{2SF} = w_{2FF} = w$.

Next note that the bank's payoff from a second period loan to someone who has reported failure in the first period, is $\pi[I_{2F}r_{2F} - (w_{2FS} - w)] - I_{2F}\rho - w$. From ICC^2_{FS} $I_{2F}r_{2F} - (w_{2FS} - w)$ is also what enters the incentive constraint for second period reporting. Finally rewriting ICC^1_S, ICCB^1_F and ICCN^1_F slightly, it is evident that $I_{2F}r_{2F} - (w_{2FS} - w)$ is what enters those expressions as well. Hence for any fixed value of I_{2F}, from the point of view of incentives and its earnings, the bank is therefore indifferent between all combinbations of r_{2F} and w_{2FS} that keep $I_{2F}r_{2F} - (w_{2FS} - w)$ constant. However lower values of r_{2F} are more attractive to borrowers (the borrower always has the option of paying off his debt at the rate r_{2F} and not colluding with the banker, hence a lower interest rate is always better for him). Therefore ex ante competition between banks will drive r_{2F} down till $w_{2FS} = w$. By exactly the same logic, it must be that $w_{2SS} = w$ and $w_{1S} = w$.

Result 1: All incentives are provided through the interest rate: $w_{1S} = w_{1F} = w_{2SS} = w_{2SF} = w_{2FS} = w_{2FF} = w$.

This tells us that flat incentives for bankers emerge as optimal when there is limited scope for punishing them (so that giving them incentives involve paying them extra) and there is a lot of collusion between the banker and the borrower. Giving incentive to both by lowering the interest rate is more effective in attracting borrowers and equally effective in reducing strategic defaults. This is interesting because flat incentives is what we see.

Armed with this set of preliminary results we can prove the main result of this section:

Result 2: The bank will implement the constrained optimal outcome in which there is investment I_1 in the first period and whether or not the first period project fails the amount invested in period 2 is I_2 ($\tau_{2S} = \tau_{2F} = 1, I_{2S} = I_{2F} = I_2$) if and only if $2\pi F \geq 2w + (I_1 + I_2)\rho$.

Proof: Using Result 1, we can rewrite ICC^2_{FS} and ICC^2_{SS} in the simplified form

$$F \geq I_2 r_{2F} \qquad (\text{EICC}^2_{FS})$$

$$F \geq I_2 r_{2S}. \qquad (\text{EICC}^2_{SS})$$

SimilarlyICC^1_S, ICCB^1_F and ICCN^1_F can be rewritten as

$$F + \pi I_2 r_{2F} \geq I_1 r_1 + \pi I_2 r_{2S}, \qquad (\text{EICC}^1_S)$$

$$I_1 r_1 R + I_2 r_{2S} \geq I_2 r_{2F}, \qquad (\text{EICCB}^1_F)$$

$$I_1 r_1 R + F \geq I_2 r_{2F} \qquad (\text{EICCN}^1_F)$$

The total amount paid by the borrower to the bank (which is the total interest earning of the bank) is

$$\pi I_1 r_1 + \pi^2 I_2 r_{2S} + (1 - \pi) I_2 r_{2F}$$

Suppose there is a solution to the bank's optimization problem where EICC^1_S does not bind. Then we can always increase $I_1 r_1$ and reduce $I_2 r_{2F}$ keeping the bank and the the borrower indifferent, while at the same time relaxing the incentive constraints, EICC^2_{FS} and EICCB^1_F or EICCN^1_F. Therefore there is always an optimum where EICC^1_S binds.[4]

Next assume EICC^1_S binds to get

$$\frac{F - I_1 r_1}{\pi} = I_2 r_{2S} - I_2 r_{2F}$$

Substituting this into the expression $I_1 r_1 R + I_2 r_{2S} - I_2 r_{2F}$

$$I_1 r_1 R + \frac{F - I_1 r_1}{\pi} > 0$$

since $\pi R > \rho > 1$. In other words when EICC^1_S exactly binds, EICCB^1_F is not binding, so we can ignore it. In the case of EICCN^1_F it follows immediately from the fact that $F \geq I_2 r_{2F}$ that we can always ignore it. We therefore focus on EICC^1_S, EICC^2_{FS}, EICC^2_{SS}.

[4] It should be acknowledged that this might require r_{2F} to be less than 1 or even negative, though this is not true of the specific solution we actually derive.

The total expected interest earning of the bank is $\pi[I_1 r_1 + \pi I_2 r_{2S} + (1-\pi) I_2 r_{2F}]$, which, from EICC^1_S, EICC^2_{FS} is less than $2\pi F$. Therefore the optimal pattern of investment is not viable if

$$2\pi F < 2w + (I_1 + I_2)\rho$$

Conversely if

$$2\pi F \geq 2w + (I_1 + I_2)\rho,$$

then we can always set $r_{2F} \leq F/I_2, r_{2S} \leq F/I_2$ and $r_1 \leq F/I_1$ and still satisfy EICC^1_S and the zero profit constraint

$$\pi[I_1 r_1 + \pi I_2 r_{2S} + (1-\pi) I_2 r_{2F}] = 2w + (I_1 + I_2)\rho$$

To see assume that EICC^1_S binds and using that replace $I_1 r_1 + \pi I_2 r_{2S}$ in the zero profit constraint by $F + \pi I_2 r_{2F}$, to get that

$$\begin{aligned} \pi I_2 r_{2F} &= 2w + (I_1 + I_2)\rho - \pi F \leq \pi F \\ \textit{or } I_2 r_{2F} &\leq F \end{aligned}$$

It follows that the values of r_1 and r_{2S} that satisfy both these constraint must satisfy

$$I_1 r_1 + \pi I_2 r_{2S} = F + \pi I_2 r_{2F} \leq F(1+\pi)$$

Therefore it is always possible to find values of r_1 and r_{2S} satisfying $r_{2S} \leq F/I_2$ and $r_1 \leq F/I_1$, that also satisfy the zero profit constraint. ■

This result simply says that if the cost of collusion F is low enough, the bank cannot lend the efficient amount. As a by-product it also tells us when this happens that the maximum amount of lending that is possible in the second period is I_2^m which satisfies $2\pi F = 2w + (I_1 + I_2^m)\rho$.

3.5 Bringing the police in

When collusion is too easy, the only way to get enough lending is to improve monitoring. We have assumed all along that there are severe punishments available, but they can only be used when there is hard evidence that fraud was committed. The problem is that the bank has to find a way to get hold of this hard evidence.

Hiring another banker to monitor the first banker is one way and all banks do this. However if collusion between the two bankers is cheap enough then this will not help: now the loan must cover another person's salary but the improvement of incentives will be small (because collusion is easy).

The alternative is to report default as a potential case of fraud to the police (which is what the CVC is in effect). The advantage is in part the advantage of an arm's length relationship, which makes collusion a harder. But it is also that the police (or the CVC) may be in a better position to investigate fraud since they have the right to question the borrower and look into his finances.

The disadvantage is that the police will typically have their own views of when and how much they should investigate. This is especially true when there are firewalls in place between the bank and the police in order to prevent collusion. In the rest of this section we will assume that the intensity of policing is an exogenous parameter and examine its effects on lending, etc.

3.5.1 The benefits of policing

Assume that when there is default there is some probability that the police investigate the default as a case of fraud. If it is proved to be fraud, the banker is severely punished–the ex ante expected cost conditional of having committed fraud is denoted by P_t in period t. However there is a harassment cost even if he is exonerated–we denote the expected cost for a banker whose loan has gone into default in the absence of any fraud (the project failed) by αP_t.

This imposes some additional costs on the banker even if he never commits fraud. However recall that he was earning rents to start with: As long as π is high enough, and P_t is not too large this will not make him unwilling to lend.

It is easily checked that the introduction of policing does not change the logic of Result 1 and we should still have that wage incentives are not used. Using this, the conditions for implementing the optimal outcome–EICC$^2_{FS}$ and **??** can be rewritten as

$$F + P_2 \geq I_2 r_{2F} \qquad (\text{PICC}^2_{FS})$$

$$F + P_2 \geq I_2 r_{2S}. \qquad (\text{PICC}^2_{SS})$$

while EICC_S^1, EICCB_F^1, and EICCN_F^1 can be re-written as

$$\begin{aligned} F + \pi I_2 r_{2F} + P_1 &\geq I_1 r_1 + \pi I_2 r_{2S}, && (\text{PICC}_S^1) \\ I_1 r_1 R + I_2 r_{2S} &\geq I_2 r_{2F} + \alpha P_1, && (\text{PICCB}_F^1) \\ I_1 r_1 R + F + P_2 &\geq I_2 r_{2F} + \alpha P_1 + (1-\pi)\alpha P_2 && (\text{PICCN}_F^1) \end{aligned}$$

These expressions should be self evident, with possible exception of the last inequality. Recall that this is the case where the banker will have to commit fraud in the future to cover up the current bailout of a failed loan. The P_2 on the left comes from this possibility. The $(1-\pi)\alpha P_2$ on the right comes from the fact that in the second period there is some probability of default even if the banker commits no fraud. This term usually cancels with the corresponding term on the left of the inequality, because in all the other incentive constraints it is assumed that there will be no fraud in the future.

An argument parallel to the argument in the proof of Result 2 shows that the first constraint in PICC_S^1 can always be assumed to bind at an optimum. Rewriting that constraint as:

$$\frac{F + P_1 - I_1 r_1}{\pi} = I_2 r_{2S} - I_2 r_{2F}$$

we can show that

$$I_1 r_1 R + I_2 r_{2S} - I_2 r_{2F} - \alpha P_1 = \frac{I_1 r_1 \pi R + F + P_1 - I_1 r_1 - \alpha \pi P_1}{\pi} > 0$$

as long as $\alpha < 1$. Hence as long as $\alpha < 1$, as before, we can ignore the no bailout constraint in the case where bailout does not automatically lead to default.

In the case where it does lead to default in the second period, note that reducing $I_2 r_{2S}$ and raising $I_1 r_1$keeping $I_1 r_1 + \pi I_2 r_{2S}$ constant, relaxes the incentive constraints while keeping both the bank and the borrower's payoffs unchanged. Combined with the fact that we can assume that $F + \pi I_2 r_{2F} + P_1 = I_1 r_1 + \pi I_2 r_{2S}$ in any optimum, this tells us that we can make $I_1 r_1$ as close to $F + \pi I_2 r_{2F} + P_1$ as we like even without making $I_2 r_{2S}$ negative. Substituting $F + \pi I_2 r_{2F} + P_1 = I_1 r_1$ into $I_1 r_1 R + F + P_2$ gives us

$$(1 + R)F + \pi R I_2 r_{2F} + R P_1 + P_2)$$

which is obviously greater than

$$I_2 r_{2F} + \alpha P_1 + (1-\pi)\alpha P_2.$$

Therefore we can also ignore the no-bailout constraint in this case as well.

Result 3: The no-bailout constraint can be ignored in optimally designed contract.

This is not just a useful analytic step towards solving for the optimal contract but also an important result in itself: it tells us that in the world of this model bailouts are not a feature of the optimally designed contract. In other words, it is never the case that They may happen (as we will see) but only because the contract is not optimal in that environment.

The intuition for this result comes from the fact that bailing out is inefficient. By concealing failure, the borrower ends up underinvesting and for that reason it is easy to persuade him not to do so.

The final step in characterising the optimal contract is to mimic the proof of Result 2 to derive (the proof is exactly the same as in the previous case and is therefore omitted):

Result 4: The bank will implement the constrained optimal outcome in which type B investors invest I_1 in the first period and whether or not the first period project fails, invests an amount I_2 in period 2 ($\tau_{2S} = \tau_{2F} = 1, I_{2S} = I_{2F} = I_2$) if and only if $2\pi F + \pi P_1 + \pi P_2 \geq 2w + (I_1 + I_2)\rho$.

This tells us that by appropriately choosing the value of P_1 and P_2, it is always possible to implement the optimal outcome.

3.5.2 The costs of policing

As mentioned above, the problem with policing is that the police does not coordinate its decisions with the bank. Specifically the data suggests that the equivalent of P_1 and P_2 are low in normal times: investigations for fraud are rare. However when the police does investigate one loan in a branch the likelihood that it will investigate another is actually quite high. In other words, P goes up for some time before going down. Specifically denote P in normal times by P^n in both periods and assume that when there is an ongoing investigation it goes up to $P^H \gg P^n$ for the current period before going down to $P^h, P^H > P^h > P^n$ in the next period and to P^n subsequently.

Assume also that in normal times the contract the bank is offering is optimal but the investigation is unexpected and therefore when it hits, the existing contracts with the firms do not change. However any contracts that are offered to "young" borrowers in the current period can adjust to the new environment.

Given that P_1 and P_2 have gone up suddenly, the no fake default constraint does not bind and hence Result 3 need not hold. In fact since the contractual terms are fixed, it is easy to imagine a situation where P_1 goes up enough that $I_1r_1R + I_2r_{2S} < I_2r_{2F} + \alpha P_1$ or $I_1r_1R + F + P_2 < I_2r_{2F} + \alpha P_1 + (1-\pi)\alpha P_2$, so that the relevant no bailout condition no longer holds. Moreover in case 2 (which is when bailouts lead to future default) the relevant no bailout condition ($I_1r_1R + F + P_2 \geq I_2r_{2F} + \alpha P_1 + (1-\pi)\alpha P_2$) makes it clear that bailouts are most likely to happen when P_1 goes up sharply but P_2 either does not go up or goes up much less, since the increase in P_2 tends to undo the effect of the increase in P_1. This is of course exactly the nature of CVC investigations.

The intution behind this result is simple: Since bailouts in this case just postpone the default, the fact that a default tomorrow is much less likely to be investigated than a default today is natural inducement to bailout.

Result 5: An unexpected temporary increase in P can lead to bailouts especially if it is likely to falls back towards the norm in the next period. The default rate will fall when the investigation begins. In the case where bailouts automatically lead to default, the immediate fall in defaults will be followed by an increase in the next period, as all the postponed defaults happen.

For the "young" borrowers in the period when the investigations begin, it is possible to adjust the contract to take into account the changed environment. Nevertheless if α is high enough and $P^h \gg P^n$, the fact that there will be an onerous investigation of defaults even if there is no fraud might discourage bankers from lending. They may prefer to claim that all firms are type M and wait out the period.

Result 6: Borrowers who are starting in the period of the investigation may not get a loan from the bank in that period if P^h is high enough and in that case, will not borrow in the subsequent period as well.

4 Data and Descriptive Analysis

This study takes advantage of an unusually rich collection of datasets, collected by the Reserve Bank of India.

The fraud-level data set contains information on frauds and suspected frauds reported to the Reserve Bank of India. Upon discovery of a fraud or suspected fraud, banks are required to file a report with the Reserve Bank of India. In principle, the dataset should have an entry for every fraud reported; however, in the early 2000s, the dataset was transferred to a new electronic records-keeping system, and not all of the older frauds were transferred. For each fraud, we observe the date the fraud occurred, the date the fraud was detected, the branch at which the fraud occurred, and the size of the fraud. Other optional fields include the outcome of the investigation, what punishment was meted out, and whether criminal charges were filed. Unfortunately, these fields are not mandatory, and are populated for a very small number of frauds. Summary statistics are given in Table 1. In total, we observe 862 credit-related frauds, the vast majority of them committed between 1990 and 2002, the period covered by our data set. Of those, 323 are labelled as "extension of credit for illegal gratification" and most of the others are "other credit related" fraud. The large majority of the frauds take place in the public banks (which is not surprising since most credit is provided by public banks).

To start providing a sense of this data, Table 2 presents evidence on where frauds tend to be detected. We estimate a cross-sectional linear probability model, with the dependent variable equal to 100 if a fraud was detected in that branch at any point between 1980 and 2005:

$$y_b = \alpha + X_b\beta + \varepsilon_b, \tag{1}$$

where X_b is a set of branch characteristics.

Results are presented in Table 2. Column (1) reports results from Equation (1), for all 56,446 branches in the sample. As there were only 898 credit-related frauds observed in that period, the magnitude of the coefficients is low. There is a strong positive association between the size of the city in which the branch is located, along with the size of the bank branch, as measured by the log of total credit outstanding in 1998. Being located in a larger credit market (as measured by loan size) is also positively correlated with the detection of a fraud. Curiously, the correlation between the level of corruption in a state (as measured by Transparency International India) and the discovery of fraud is negative. This may indicate that fraud is more likely to be *detected* in states with lower levels of corruption. In the simple cross-section, there is a weak negative relationship between corruption and the quality of intermediation (as measured by the share of nonperforming credit, or the percentage of loans late). Columns (2) and (3) present equation (2) with district and credit-market fixed effect, respectively. Most results stay qualitatively similar.

Bank heterogeneity matters as well: in a simple regression of credit fraud on bank fixed-effects, the bank fixed-effects are significant at the 1% level. In the analysis below, we systematically control for bank-branch fixed effect, to control for systematic differences between branches were fraud tends to be discovered and other branches.

We combine this fraud database with two databases of bank credit, one at quarterly frequency, one at annual. The quarterly dataset gives the aggregate amount of lending and deposits of each bank branch, in India, from June 1991 to May 2006.[5] The dataset is an unbalanced panel. Our regressions include 56 quarters, covering approximately 43,000 bank branches, for a total of 2.5 million observations.

The second set of credit data is a loan-level, annual data set. Each year, every bank branch in India is required to provide information on every loan in its portfolio to the Reserve Bank of India. This information includes the size of the loan, interest rate, and performance status, as well as various characteristics of the borrower, including industry (at the three-digit level), rural/urban status, etc. We analyze the aggregated data only (aggregations are described below).[6] At the branch level, annual credit growth is available for 11 years, totaling 408,555 observations.

The two datasets are complementary: the higher frequency of the quarterly dataset allows for better measurement: frauds are of course discovered throughout the year, and with quarterly data, we are better able to pin down the short- and medium-term effects of the discovery of fraud. The quarterly data also provide a longer time series, 15 years. To delve deeper

[5]In this work, we include all scheduled commercial banks (public, private, and foreign), but exclude Rural Regional Banks, which are not scheduled commercial banks, and therefore not subject to the same set of regulations.

[6]Banks were allowed to report loans smaller than Rs. 25,000 (ca. $625) in an aggregated fashion until 1999, at which point loans below Rs. 200,000 (ca. $5,000) were reported as aggregates.

into the effects of vigilance activity, we use the annual dataset, which includes information on the repayment status of loans and the industries to which banks lend.

Both the quarterly and annual datasets identify bank, branch, credit market, district, and date. Approximately 10% of the credit data is missing: this occurs when a bank does not report required information.

Taken together, this data form, to our knowledge, one of the richest data sets on fraud in the banking sector, and its implication for lending. Due to the highly confidential nature of the data, all data analysis was performed at the Reserve Bank of India, either by one of the researchers on site, or using codes that was provided by us.

5 Fraud Discovery and Punishment

5.1 The Impact of the Discovery of a Fraud on Vigilance Activity

To test the main predictions of the model, our empirical strategy will be to exploit the increase in the probability of being investigated or punished for default after a fraud has occurred in a particular branch. In the model, the probability that the regime of high inspection continues into the next period is an important parameter: it makes sense for a loan officer to bail out a firm during a "high inspection regime" if she expects that the probability of inspection will be lower in the future. Thus, this section focuses on how the probability of fraud detection evolves over time following the discovery of a fraud in one particular branch.

As we already noted, the probability of detection is very low: the probability of any given branch reporting a suspected fraud is only 1.2% over the entire 15-year period of our data. In any given year, the unconditional probability of vigilance activity is 8 basis points. However, there is very large serial correlation in inspections. To understand how an investigation affects the subsequent probability of a detection ocurring, we estimate the following model:

$$D_{b,t} = \alpha + \sum_{n=1}^{5} D_{b,t-n} + \varepsilon_b \tag{2}$$

where $D_{b,t}$ is a dummy variable taking the value of 1 if the branch reports a suspected fraud in year t, and 0 otherwise. Regression results are displayed in Panel B, for a lag structure including 1-5 lags. Two results stand out: first, if a fraud was detected in a given year, the probability of detection in the subsequent year, relative to a branch in which no fraud was detected, is substantially increased. The coefficient on $D_{b,t-1}$ is .023, indicating an increased probability of 2.3 percentage points. Relative to the baseline probability of 8 basis points, this represents a an increase by a factor of 29 times. Second, the probability of heightened vigilance drops by half the following year, and remains at that level after two years. After three years, however, the probability of detection is very low, indistinguishable from the probability of detection in a branch with no history of fraud detection.

Part of the increase in the probability of detection certainly comes from the fact that the same set of people are likely to have committed more than one fraud. The investigation of one fraud reveals all the older ones. In fact, this is probably what prompts the vigilance team to investigate this branch thoroughly. But as they do so, it is also likely that they investigate the lending activities of others in the bank. Thus, we take this data to suggest that fraud discovery in a bank creates a large increase in the probability of subsequent investigation, which persist for about two years. In the next section, we will investigate how lending decisions respond to this temporary increase in vigilance activity.

5.2 Vigilance and Penalties

One way to discourage evergreening may be to provide larger penalties for larger defaults. In the model of policing above, the penalties, P_1, and P_2, were independent of loan size.

While it is difficult to get data that precisely pins down the shape of the penalty function, comparing the penalties in our dataset, which includes frauds of various sizes, with penalties imposed for major penalties, provides good evidence than penalties do not vary with the size of the loan.

In 2000, in order to stigmatize corruption, the CVC decided to publish on its website the names, and penalties, of senior-level officers who had been found guilty of corruption. While the specifics of the fraud committed were not disclosed, because the bankers worked at the highest level, the frauds likely involved very large sums. Of the 76 bank officials for whom data was made public, the distribution of penalties was:

Outcome	Frequency
Criminal Charges Filed	1
Censured	2
Obligatory Retirement	4
Dismissed	21
Pay Reduction	46

This distribution corresponds closely to the sets of penalties in our dataset, whose average loan size is quite small. This, in our mind, provides strong evidence that the penalty for fraud is not commensurate with the amounts involved, let alone convex: a large part of the cost seems to be the investigation itself, which appears to be quite traumatic for low-level loan officers. But the punishments, even for large frauds, mainly involved a pay reduction. This of course begs the question of why the penalty function is not made more convex: this could be achieved by not prosecuting a loan officer until several of their loans appear to have a suspected fraud, and by handing out much more severe punishment once someone is actually investigated and proven guilty. It may be particularly tempting for bankers accused of large fraud to bribe the CVC investigators. Thus, the need to maintain an arm's length relationship between the bank administration and the CVC may be the reason why the penalty function cannot be convex.

6 Empirical Tests of the Model

6.1 Lending Decisions

We now turn to testing a central prediction of our model: does vigilance activity reduce lending activity? To investigate this question, we treat the discovery of a fraud in a branch as an "event" and study how lending in this bank changes after the discovery of the fraud, compared to other unaffected branches.

6.1.1 Branch-Level Effects

We use an event-study (difference-in-difference) methodology to measure the impact of vigilance activity on lending. This strategy compares how lending evolves in branches that are affected by fraud investigations, to other similar branches that are not.

The base specification uses quarterly lending data, at the branch-level. Denote y_{obct} as the change in log credit at bank branch office o, belonging to bank b, in credit market c, at time t. The estimated equation is thus:

$$y_{obct} = \alpha_o + \sum_{k=-8}^{8} \beta_k D_{o,t,k} + \beta_{\geq 9} D_{o,t,\geq 9} + \gamma_t + \varepsilon_{obct}, \tag{3}$$

where y_{obct} is log credit growth, defined as $\log(credit_{obc,t}/credit_{obc,t-1})$.[7] $D_{o,t,k}$ indicate the *detection* of the fraudulent act. Thus $D_{o,t,0}$ is set to one if a fraud occurs in branch office o in quarter t, and zero otherwise, while $D_{o,t,-3}$ is set to 1 if a fraud will occur in branch office o at time $t+3$. $D_{o,t,\geq 9}$ is dummy variable indicating a fraud was committed nine or more quarters previous to quarter t in branch office o. a_o and γ_t denote branch and quarter fixed-effects, respectively, which we include in the preferred specification.

Table 4 reports results from the baseline specification, for the sample of frauds coded as "extension of credit for illegal gratification" or "other, credit related." Under the null hypothesis that vigilance activity does not affect lending, the coefficients β should be zero.[8] Column (1) reports results from Equation (3) without branch or time fixed effects. Column (2) adds quarter fixed effects (γ_t); column (3) adds branch fixed effects (a_0); and column (4) presents the results with quarter and branch office fixed effects. Column (4) is the preferred specification, as the branch fixed effects control for all unobserved time-invariant heterogeneity, while the quarter fixed effects control for aggregate changes in credit at the national level.

This regression is perhaps best understood graphically: Figure 1 displays the coefficients from the preferred specification for each event time (eight quarters prior to an event, seven quarters prior, etc...) The blue line gives the point estimate, while the yellow lines give the 95-percent confidence interval. The line therefore traces how credit evolves prior to the discovery of a fraud, and following a fraud.

A clear pattern emerges. The corrupt loan is discovered at time zero. Prior to this discovery, credit typically evolves at a rate no different than at other branches, with the exception

[7] We use log credit growth, rather than log credit, because credit is highly serially correlated, and because credit growth may be more relevant than the stock of credit.

[8] The average size of a fraudulent loan is a quite small relative to the branch portfolio, so there is no mechanical relationship between discovery of fraud and the amount of lending.

of "six months prior" and "three months prior," when the growth rate is above average (this may have been what prompted the investigation, or this may be a symptom of fraudulent activity). Following the discovery of fraud, credit growth drops precipitously, relative to other branches: by 1.36 percent relative to branches in which a fraud is not discovered in the quarter of discovery (column (4)). In the subsequent quarter, credit growth is 3.73 log points below unaffected branches. This is a very large effect: the average growth rate in credit is 3.5% per quarter, meaning that following an investigation, the credit growth is stagnant. Credit continues to grow at a slower pace following the discovery of the fraud, with a cumulative effect of nearly twenty percent less credit lent by an affected branch after two years. The final coefficient, $D_{o,t\geq 9}$, is negative and significant, suggesting that credit continues to decline (relative to other branches) even two years after the discovery of the fraud.

Even though our dependent variable is change in log credit, specification 3 is likely to suffer from serial correlation. Running a regression with branch and quarter fixed effects, and 2.5 million observations, correcting for non-independence of error terms in SAS taxes the available computer facility, so the majority of the regressions presented in this paper are currently presented with unadjusted standard errors.[9] However, in an appendix table we present the baseline specification, with corrected and uncorrected standard errors. Correcting the standard errors has little effect on the measured precision of the estimates: only one "pre" coefficient is statistically distinguishable from zero, the "post" coefficients remain negative and similar in size, though three of the eight are not statistically distinguishable from zero. The t-statistic on the effect one quarter after discovery of the fraud remains very high, approximately 5.5.

Table 5 estimates equation (3) with a longer series of post-event dummies, tracing the effect up to two years later. The results for the branch-level identification are presented in column (1). Including sixteen post dummies reduces the sample size by two years of fraud discovery, but provides a longer picture of the effect. The results are nearly identical: the effect of discovery of fraud is negative and significant for the first eleven quarters following discovery, with a cumulative effect of 21 percent less credit.

What explains the persistence of the effect on lending, despite the fact that the increase in the vigilance activity in the branch stops relatively quickly? Our model predicts some temporal

[9] This is due to time constraints. Subsequent versions of this paper will have corrected standard errors.

propagation of shocks. First, mechanically, the volume of loans will be reduced as the vigilance officer discovers evergreening. Second, as loan officers fear increased scrutiny, they reduce the size of loans to new firms. Because the informativeness of a failure is increasing in the size of the loan, loan officers on average learn less about new firms in the vigilance period; then, even when the monitoring threat has reduced, the optimal loan size is smaller. However, firms in our model live only two periods, and the model cannot explain as much persistence. In reality, firms live longer than two periods, and thus the effect may persist longer. The firms who were kept alive by successive evergreening, and who were cut from the portfolio during the vigilance period, may in particular have otherwise continued to receive credit for a very long time. It is therefore difficult to conclude whether this persistence is a good thing or a bad thing. Another reason for the stickiness of the effect may be because the investigation remains salient in the minds of loan officers, even as the probability of investigation decreases dramatically.

6.1.2 Spillover Effects of Vigilance Activity

In this section, we investigate whether the investigation has spillover effects to other branches in the same area: do other branches of the same banks in the town also stop lending when a particular branch is investigated following the discovery of a fraud? How about other banks in the same town?

To interpret these results, we first need to investigate whether discovery of fraud in a branch increases the probability a fraud will be discovered in other branches of the same bank in the next year, and other branches in the same town. We investigate this question by augmenting equation (2) with a dummy for whether a fraud was discovered in another branch of the same bank in the same town in the previous year, and a dummy for whether a fraud was discovered in another branch in the town in the previous year. Both effects are significant, although they are smaller than the direct effect: when a branch of the same bank in the same town, the probability of inspection increases by 0.9 percentage point (about half the size of the direct effect). The increase is only 0.2 percentage point if another branch of the same branch, but in a different town, was investigated, although the increase number remains significant.

Since there was an effect on the probability of inspection, we may expect an effect on lending on those branches as well.

These effects can be identified by extending the framework above. First, to simplify notation a little, define the $\phi()$ function as a set of dummy variables that indicate an event window for a particular category (e.g., bank branch, or town):

$$\phi(Category) = \sum_{k=-8}^{16} \beta_k D_{k,category} + \beta_{\geq 9} D_{\geq 9,category}$$

Thus, ϕ (branch) indicates a series of 25 dummy variables, in the same fashion as the dummy variables introduced above in equation 3. (Here we extend the window from 8 quarters before through 16 quarters after, along with a dummy for more than 16 quarters following the discovery of a fraud.) Similarly, ϕ (Town) is a set of 25 dummy variables comprising an event window around a fraud being discovered in a particular town: the indicator $D_{c,t,0}$ is 1 for all branches within a town if a fraud was discovered that quarter at any branch within that town. Finally, ϕ (TownBank) gives a set of dummy variables, where the event is discovery of a fraud at any branch office of that particular bank in that town.

To estimate the effect of discovery of fraud at a particular branch on that branch, other branches within its network, and the aggregate supply of credit in the credit market, we estimate the following equation:

$$y_{obct} = \alpha_o + \phi(branch) + \phi(banktown) + \phi(town) + \gamma_t + \varepsilon_{obct} \tag{4}$$

Table 6 presents regression 4, including 16 lags after the discovery of the frauds. The seventy-two coefficients of interest (24 for each set of dummies) are presented in columns (1), (2), and (3). The most important effect is clearly at the affected branch, consistent with what we had estimated before: these coefficients are all negative and significant following the discovery of fraud. Consistent with the probability of detection results, there is also an immediate decline in other branches of the same bank as the bank in which the fraud was discovered (column (2)): credit declines by 0.76 percent. The effect is somewhat lower than half of the direct effect on the bank branch. This effect is short-lived, however. There does not appear to be a marked increase in lending by other branches in response to the reduced supply of credit. This again is consistent with the much lower impact of lending on those branches. Interestingly, we do not see an *increase* in lending by the other branches, which could have happen if all the clients of the branch that stopped lending moved to other banks.

These results are of independent interest. They also provide some reassurance that the results are indeed due to the causal effect of the increase in the probability being investigation for fraud, since, from the point of view of other branches in the same town, the discovery of a fraud in another branch is an exogenous event.

6.2 Repayment and Risk-Taking

Section 6 clearly established that credit in a branch (and indeed, a town) declines following the discovery of a fraud. In addition, the model predicts that banks will prefer to lend to safer firms.

To conduct this analysis, we use the loan-level data, which are annual credit data, available from 1992-2003. While these loan data are remarkably comprehensive (recall we have a separate observation for each loan above a relatively low threshold), they are unfortunately not a panel, meaning we cannot link loans from one year to the next. (We can, of course, link the loan to the branch, and link the branch from year to year.)

We first replicate the results found at the quarterly level in the annual data, using a window of two years. The results are presented in Table 7. The effects at the branch level are very similar: in the year of a fraud discovery, annual credit growth declines by two percent relative to other bank branches. In the subsequent years, the annual effect is close to six percent, which is roughly consistent with the two-percent quarterly effect. Loan growth prior in branches in which fraud is about to be discovered is no different than growth in branches in which no fraud will be detected. Column (1) presents the results without bank branch fixed effects, while column (2) gives the results with branch fixed effects. Both estimates include year fixed effects.

6.2.1 Branch Risk-Taking

The quantity of credit lent declines rapidly following the discovery of a fraud. What happens to the composition of lending? We first focus on the riskiness of loans made by loan officers: if lenders are afraid that a bad loan may land them in hot water, they may prefer to lend to borrowers who are less likely to default. We do not observe the credit rating of the borrower (for this time period, there is no formal credit rating institution, and this data set does not include data on the credit-worthiness of the borrower). Instead, we exploit the fact that some industrial sectors are riskier than others. We calculate how risky each industrial sector is, measuring the percentage of loans in that sector that are late in repayment. This measure could vary from zero to 100:

$$sharelate_i = 100 * \frac{\text{Value of Lending in Industry that is Non-Performing in 1992}}{\text{Lending in Industry in 1992}}.$$

We then take the share of credit lent by each branch o to industry I, to come up with a predicted portfolio riskiness :

$$branchrisk_{ot} = \sum_{i \in \text{Industries}} \frac{\text{Value of Branch lending to Industry}}{\text{Value of all Branch Lending at time t}} * sharelate_i$$

Note that $branchrisk_{ot}$ is not determined by the share of loans late at branch o: rather, it measures the share of loans with late repayment predicted by the industrial composition of lending.

Table 8 reports how $branchrisk_{ot}$ varies following the discovery of an alleged fraud. Column (2) presents equation (3) with branch and year fixed effects. Two years prior to the discovery of fraud, the measure of risk exposure is no different than branches in which a fraud is not about to be discovered. One year prior to the fraud, the level of risk taking is elevated. However, one year following the discovery of fraud, the riskiness of the loan portfolio drops substantially, with $branchrisk_{ot}$ falling approximately eight percentage points. The standard deviation of branchrisk_{ot} is approximately seven percentage points, so this represents a significant drop.

6.2.2 Loan Repayment

Credit drops substantially following discovery of a fraud, as does the risk-taking behavior of bank branches. What happens to the quality of loans made by an affected branch?

Because we do not observe a panel of loans, we cannot differentiate loans made prior to discovery of fraud from loans made after discovery. Instead, we focus on the growth in total credit, and the growth in bad credit.

The effect on aggregate credit is presented in columns (1) and (2) of Table 9. Columns (2) and (4) include branch fixed effects. Column (3) shows that the total amount of credit marked as late is much higher in the year in which the fraud is discovered, drops in the following year, and again increases slightly above the steady state in the following year. The increase in the year of the discovery is probably mechanical: as the CVC team investigates the bank, they identify a number of loans that are to be written off. The reduction of default in year $t + 1$, followed by an increase the following year, is consistent with the ever-greening predicted by the model: in year $t + 1$, the loan officer ever-greens to avoid default, and this tends to reduced default (even though that coefficient is not significant). However, some of the firms that were artificially supported then fail by the following year, which leads to a sharp increase in default by year $t+2$, before things go back to normal in year $t+3$. It is interesting that this time series pattern fits the model so closely.

6.3 An Attempt At Reform

On January 1, 1999, the Central Vigilance Commission, in response to criticism mentioned above, introduced a special chapter of the Vigilance Manual. The goal of this chapter was to clarify the standards and procedures of investigation of employees of public sector banks. This suggests a natural experiment: if the manual changed the incentives faced by loan officers, the effects of investigation should change.

To test this, we estimate equation (3) using two sets of D variables: one set for the period before January 1, 1999, and one set for the period after 1999. Results are presented in Table 10. The results suggest that the new vigilance chapter did not change the effect of a vigilance investigation: the β coefficients are very similar in the pre-and post-reform period. Panel B gives the cumulative effect of three years following the discovery of the fraud (the value $\beta_0+\beta_1+\beta_2+\beta_{\geq 3}$). The cumulative effect prior to the reform is -8.15, which is indistinguishable from the cumulative effect following the reform, of -7.64.

The inefficacy of the manual was predicted in early 2002 by a Public Sector Bank Manager in the newspaper "The Hindu:"

> A deeper examination would clearly show that a separate manual is unlikely to improve the matter of oppressive levels of accountability in PSBs. To recall a similar

Governmental supervision, in 1992 when the country was almost on the verge of insolvency and industrial growth was at low levels, one of the constraints to growth was identified as controls on creation of new industrial capacity. The then Finance Minister did not substitute one licensing policy by another, but abolished licensing requirements for all but a handful of industrial sectors. The results of this bold action are there for all to see.[10]

7 Conclusion

This paper derives and tests a model of bank lending behavior, in the face of outside supervision. We then test this model using an unusual data set from India, which combines data on almost all the credit frauds detected over two decades and the universe of loans over a long period. The data largely support the main predictions of the model: lending declines following vigilance activity, bankers shift to less risky industries, and defaults follow a very specific pattern: after the initial increase due to the vigilance activity, they decline to levels below the "normal" level of default, only to increase again to high levels in the following year.

These findings are confirmed using two independent datasets on vigilance activity, in quarterly, and annual fraud data. The most precise estimate comes from quarterly branch loan data: immediately following an investigation, lending falls 4% relative to non-affected branches, and this effect is quite persistent, lasting over two years. The effect occurs primarily at the affected branch, but spills over to other branches of the same bank in the same credit market (which appears to be also affected by heightened vigilance). Other bank branches in the market did not increase lending to "replace" the missing credit. There is no systematic increase (or decrease) in credit prior to discovery of a fraud, implying that the observed effects may have a causal interpretation. Thus, in a very real sense, the bank officers are correct: fear of prosecution causes lending officers to act substantially more cautiously than their peers, who are not affected by recent discovery of fraud.

Determining whether these effects are efficient or inefficient is more difficult. We present suggestive evidence that vigilance activity is linked to "under-lending." Given that prior research

[10] R. Viswanathan, The Hindu, Jan 12, 2002

provides evidence of credit constraints in precisely this context, vigilance activity may indeed be inefficient. First, the fact that vigilance activity affects aggregate lending at the bank level, is hard to reconcile a bank-wide slowdown in credit following the charge of a single (albeit prominent) individual. Second, the effect is found in other branches belonging to the same bank in the same town. Third, the size of the credit declines are much larger than the amount of money involved in the fraud, and are very persistent. Finally, we see that the lending strategy taken by the affected branch changes substantially. Rather than "root out" a corrupt officer and continue to lend to the optimal mix of borrowers, bank branches affected by a vigilance activity shift lending towards safer industries.

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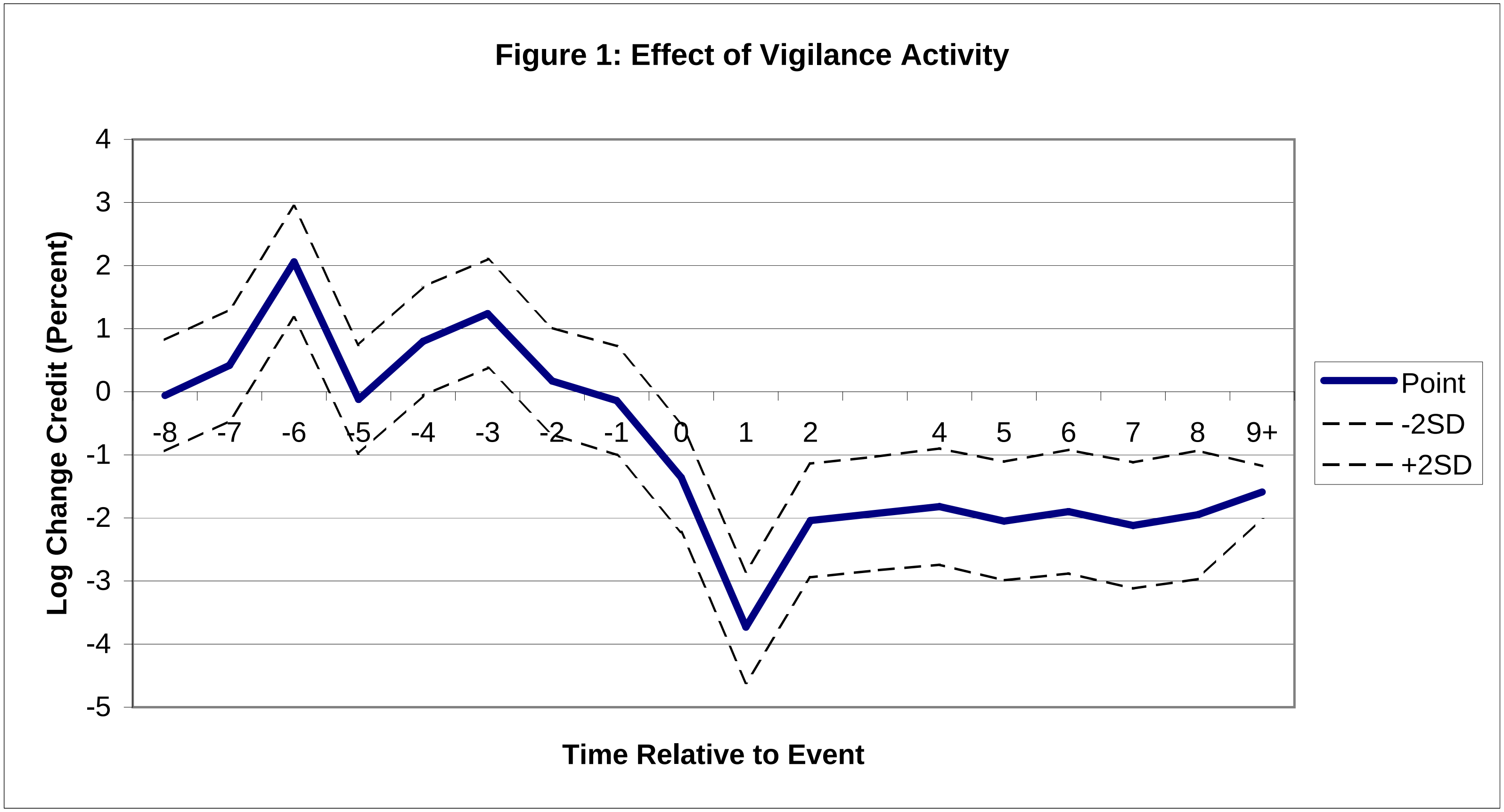
Figure 1: Effect of Vigilance Activity
Log Change Credit (Percent)
4
3
2
1
0
-1
-2
-3
-4
-5
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
4
5
6
7
8
9+
Time Relative to Event
Point
-2SD
+2SD

Table I
Vigilance Allegations Summary Statistics

This table provides summary statistics of credit-related vigilance allegations reported to the Reserve Bank of India, between the period 1980-2002. Requiring a bribe to give a loan would fall under extension of credit for illegal gratification, while reckless lending would be categorized as other credit-related fraud. Panel A describes the temporal distribution of the credit-related allegations. Panel B indicates the share of reports that originated in government-owned banks over the time period. Panel C provides information on the size distribution of frauds, in nominal Indian Rupees. and USD.

Panel A: Scope of Vigilance Allegations				
		Detected in the:		
	Total	1980s	1990s	2000s
Number				
Extension of credit for illegal gratification	323	46	126	151
Other credit-related fraud	539	45	86	408
Total	862	91	212	559
Share in Public Sector Banks				
Extension of credit for illegal gratification	0.9	0.89	0.87	0.92
Credit-Related Other	0.8	0.91	0.8	0.78

Panel C: Size of Failed Loan				
	Overall	1980s	1990s	2000s
Average Size (Rs. 1000s)	506.4	98.2	210.2	701.8
Average Size (US Dollars 1000s)	14.5	2.8	6.0	20.1
Minimum (USD)	0	0	0	0
25th Percentile (USD)	94	102	112	90
Median (USD)	312	357	468	265
75th Percentile (USD)	1,314	1,247	1,748	1,104

Panel D: Credit Summary Statistics				
		N	Mean	Std. Dev
Quarterly Credit Data				
Change in Log Credit		2,493,537	3.50%	2.78%
Annual				
Change in Log Credit		405,227	12.45%	
Change in Log (Late Credit)		245,774	-3.04%	
Share of Loans Late		365,909	15%	
Distribution of 1992 Loan Sizes (USD 1000s)				
Average	$598			
Minimum	$0			
25th Percentile	$61			
Median	$105			
75th Percentile	$170			

Table II
Predictors of Vigilance Activity

This table provides the results from an OLS regression in which the dependent variable is set to 1 if a fraud was discovered in that branch between 1980 and 2005. Each column represents one regression. The independent variables include log branch size (measured by aggregate credit), the share of credit in the branch reported as nonperforming, as well as credit market characteristics: the population density (measured from 1-9), the number of bank branches, and the log size of the credit market. The State Corruption Index is increasing in perceived corruption at the state level. There are approximately 550 districts in India. The Reserve Bank of India defines 35 thousand credit markets.

Dependent Variable	Fraud Detected at Branch		
Log Branch Size	0.60 ***	0.63 ***	0.75 ***
	(0.06)	(0.06)	(0.08)
Share of Credit Nonperforming	0.48 *	0.39	0.77
	(0.27)	(0.29)	(0.51)
Population Density in Credit Market	0.33 ***	0.30 ***	
	(0.07)	(0.08)	
Number of Bank Branches	0.00 ***		
	(0.00)		
Log Size of Credit Market	-0.16 **	-0.22 ***	
	(0.07)	(0.08)	
State Corruption Index	-24.63 **		
	(11.98)		
Fixed Effects	None	District	Credit Market

Table III
Persistence of Vigilance Activity

This table reports coefficients from panel regressions estimating the persistence of vigilance activity at the bank branch level. The dependent variable is whether vigilance activity occurred in branch b in year t, while the independent variables are indicators for whether vigilance activity occurred in the branch in previous years. The penultimate column includes a dummy for whether vigilance activity occurred in a branch of the same bank in the previous year (e.g., for a branch of Canara Bank in Bangalore, was there an investigation at any Canara Bank branch in Bangalore in the previous year), while the final column the measure indicates whether there was vigilance activity in any branch in that credit market (town) in the previous year.

Dependent Variable	Fraud Detected in Branch This Year						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fraud detected in branch last year	0.024 ***	0.024 ***	0.025 ***	0.026 ***	0.027 ***		
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)		
Fraud detected in branch 2 years ago		0.012 **	0.012 **	0.012 **	0.011 **		
		(0.005)	(0.005)	(0.005)	(0.005)		
Fraud detected in branch 3 years ago			0.020 ***	0.020 ***	0.019 **		
			(0.007)	(0.008)	(0.008)		
Fraud detected in branch 4 years ago				-0.002	-0.002		
				(0.003)	(0.003)		
Fraud detected in branch 5 years ago					-0.001		
					(0.003)		
Fraud detected *bank-town* in previous year						0.012 ***	
						(0.001)	
Fraud detected in *town* in previous year							0.004 ***
							(0.000)
N	623,434	578,903	534,372	489,841	445,310	623,490	623,490

Table IV
The Effect of Vigilance Activity on Lending

This table presents regressions relating quarterly credit growth to vigilance activity, at the bank branch level, for all bank branches in India over the period 1990-2005. The dependent variable is log change in credit, while the right hand side variables are event time indicators around the quarter in which vigilance activity occurs. "Vigilance Activity" is a dummy variable taking the value of 1 if a vigilance activity occurs at a specific branch in a specific quarter. The "Quarter + (-) N" dummy is equal to 1 at time t if vigilance activity occurs at that branch at time t-(+)N, for example Quarter-1 indicates the quarter one month prior to vigilance activity

Dependent Variable	Log change in credit			
	(1)	(2)	(3)	(4)
Quarter -4	1.72 ***	1.38 ***	1.11 *	0.8 *
	(0.56)	(0.43)	(0.57)	(0.44)
Quarter - 3	1.61 ***	1.83 ***	0.96	1.24 ***
	(0.55)	(0.43)	(0.57)	(0.44)
Quarter - 2	1.69 ***	0.74 *	1.05 *	0.17
	(0.55)	(0.43)	(0.56)	(0.43)
Quarter - 1	0.21	0.41	-0.41	-0.14
	(0.55)	(0.43)	(0.57)	(0.44)
Vigilance Activity	0.04	-0.75 *	-0.65	-1.36 ***
	(0.56)	(0.44)	(0.58)	(0.44)
Quarter + 1	-3.11 ***	-3.13 ***	-3.8 ***	-3.73 ***
	(0.57)	(0.44)	(0.58)	(0.45)
Quarter + 2	-0.47	-1.48 ***	-1.11 *	-2.04 ***
	(0.58)	(0.45)	(0.59)	(0.46)
Quarter + 3	-1.96 ***	-1.39 ***	-2.6 ***	-1.93 ***
	(0.59)	(0.45)	(0.60)	(0.46)
Quarter + 4	-0.31	-1.29 ***	-0.93	-1.82 ***
	(0.60)	(0.47)	(0.62)	(0.47)
Quarter + 5	-2.05 ***	-1.54 ***	-2.65 ***	-2.05 ***
	(0.61)	(0.48)	(0.63)	(0.48)
Quarter + 6	0.55	-1.47 ***	0.04	-1.9 ***
	(0.63)	(0.49)	(0.65)	(0.50)
Quarter + 7	-2.66 ***	-1.73 ***	-3.14 ***	-2.12 ***
	(0.64)	(0.50)	(0.66)	(0.51)
Quarter + 8	-1.49 **	-1.55 ***	-1.97 ***	-1.95 ***
	(0.66)	(0.51)	(0.68)	(0.52)
Quarter > 8	-1.17 ***	-1.36 ***	-1.36 ***	-1.59 ***
	(0.13)	(0.10)	(0.27)	(0.21)
N	2,493,542	2,493,542	2,493,542	2,493,542
Quarter Fixed Effects		Yes		Yes
Branch Fixed Effects			Yes	Yes

Table V

Long-run Persistence of Vigilance Activity on Lending

This table presents a regression relating quarterly credit growth to vigilance activity, at the bank branch level, for all bank branches in India over the period 1990-2005. The dependent variable is log change in credit, while the right hand side variables are event time indicators around the quarter in which vigilance activity occurs. For clarity, the coefficients from one regression are reported in three columns.

Quarter - 8	-0.533	Quarter + 1	-3.074 ***	Quarter + 9	-2.170 ***
	(0.487)		(0.586)		(0.720)
Quarter - 7	-0.337	Quarter + 2	-2.102 ***	Quarter + 10	-1.660 **
	(0.489)		(0.613)		(0.750)
Quarter - 6	1.841 ***	Quarter + 3	-1.655 ***	Quarter + 11	-2.380 ***
	(0.500)		(0.630)		(0.760)
Quarter - 5	0.033	Quarter + 4	-1.412 **	Quarter + 12	-0.790
	(0.503)		(0.650)		(0.770)
Quarter -4	0.727	Quarter + 5	-1.470 **	Quarter + 13	0.390
	(0.517)		(0.670)		(0.780)
Quarter -3	1.022 *	Quarter + 6	-1.750 ***	Quarter + 14	-1.730 **
	(0.530)		(0.680)		(0.800)
Quarter - 2	0.300	Quarter + 7	-1.870 ***	Quarter + 15	-1.490 *
	(0.543)		(0.690)		(0.810)
Quarter - 1	0.444	Quarter + 8	-1.710 **	Quarter + 16	-2.070 ***
	(0.555)		(0.700)		(0.800)
Fraud Detected	0.226			Quarter > 16	-0.920 **
	(0.574)				(0.460)
Quarter Fixed Effects	Yes				
Branch Fixed Effects	Yes				
N				1,421,749	

Table VI
Spillover Effects of Fraud on Lending

This table presents a regression testing for spillovers of vigilance activity onto related branches. All three columns present coefficients from one regression. The coefficients are estimates from the event window. The dependent variable changes in log credit from affected branches. "Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific quarter (column 1), in another branch of the same bank in the same town (column (2), and of any other bank branch in the same town. The "Quarter + (-) N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-(+)N.

Time Window		Affected branch	Non-affected branch of bank	Non-affected branch in same town
		(1)	(2)	(3)
		0.774	-0.085	-0.103
		(0.535)	(0.137)	(0.063)
Quarter - 3		0.979 *	-0.161	0.148 **
		(0.547)	(0.140)	(0.063)
Quarter - 2		-0.291	0.141	0.385 ***
		(0.560)	(0.142)	(0.063)
Quarter - 1		0.097	0.147	0.237 ***
		(0.571)	(0.143)	(0.063)
Fraud Detected		-0.060	0.267 *	0.007
		(0.592)	(0.148)	(0.064)
Quarter + 1		-2.621 ***	-0.712 ***	0.180 ***
		(0.605)	(0.151)	(0.063)
Quarter + 2		-2.380 ***	0.136	0.110 *
		(0.631)	(0.157)	(0.063)
Quarter + 3		-1.642 **	0.011	-0.197 ***
		(0.650)	(0.159)	(0.064)
Quarter + 4		-1.585 **	0.056	-0.080
		(0.670)	(0.163)	(0.065)
Quarter + 5		-1.740 **	-0.021	0.240 ***
		(0.690)	(0.168)	(0.064)
Quarter + 6		-1.720 **	-0.264	0.141 **
		(0.710)	(0.174)	(0.064)
Quarter + 7		-2.330 ***	0.326 *	0.034
		(0.710)	(0.179)	(0.064)
Quarter + 8		-2.010 ***	0.149	0.077
		(0.730)	(0.186)	(0.064)
Quarter + 9		-1.950 ***	-0.480 **	0.135 **
		(0.750)	(0.192)	(0.064)
Quarter + 10		-2.020 ***	0.418 **	-0.226 ***
		(0.770)	(0.197)	(0.064)
Quarter + 11		-2.860 ***	0.794 ***	-0.548 ***
		(0.790)	(0.197)	(0.066)
Quarter + 12		-0.900	-0.056	-0.014
		(0.790)	(0.194)	(0.065)
Quarter + 13		0.150	-0.256	0.415 ***
		(0.800)	(0.193)	(0.065)
Quarter + 14		-2.020 **	0.226	-0.134 **
		(0.830)	(0.200)	(0.066)
Quarter + 15		-2.150 **	0.382 *	0.293 ***
		(0.840)	(0.205)	(0.066)
Quarter + 16		-2.360 ***	-0.087	0.118 *
		(0.870)	(0.208)	(0.067)
Quarter > 16		-0.970 **	-0.080	-0.311 ***
		(0.480)	(0.130)	(0.071)
Fixed Effects	Quarter & Branch			
R^2	0.080			
N	1,421,538			

Table VII
Credit Using Annual Data

This table reports coefficients from a regression of log annual credit growth at the branch level on event-time indicators for vigilance activity. "Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific year. The "Year + (-) N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-(+)N. Each column represents a separate regression. Column (1) includes year fixed effects and column (2) includes year and branch fixed effects. The time period covered is1992-2005.

Time Window	(1)	(2)
Year - 2	0.97	1.1
	(0.87)	(1.03)
Year - 1	-0.01	-0.22
	(0.89)	(1.11)
Fraud Detected	-1.87 **	-2.27 *
	(0.94)	(1.21)
Year + 1	-4.18 ***	-5.43 ***
	(1.04)	(1.38)
Year + 2	-3.89 ***	-6 ***
	(1.17)	(1.58)
Year >2	-3.01 ***	-6.67 ***
	(0.43)	(1.55)
R2	0.04	0.26
N	262,401	262,401
Fixed Effects	Year	Year & Branch

Table VII
Risk Appetite and Discovery of Fraud

This table reports coefficients from a panel regression at the bank branch level. The dependent variable is the riskiness of the loan portfolio at the branch level., while the right hand side variables are event time indicators around the year in which fraud is detected. "Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific year. The "Year + (-) N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-(+)N. Each column represents a separate regression. Column (1) includes branch fixed effects and column (2) includes year and branch fixed effects.

Time Window	**All Credit Definition**	
	(1)	(2)
Year - 2	-1.16	-1.3
	(2.44)	(2.42)
Year - 1	7.15 **	7.28 **
	(3.46)	(3.43)
Fraud Detected	-2.14	-2.12
	(2.28)	(2.26)
Year + 1	-7.76 **	-8.04 **
	(3.94)	(3.91)
Year + 2	4.61	4.54
	(3.08)	(3.06)
Year >2	-1.27 ***	-0.88 ***
	(0.04)	(0.12)
R2	0.47	0.48
N	408,555	398,990
Fixed Effects	Branch	Year & Branch

Table IX
Bad Credit and Discovery of Fraud

This table reports coefficients from regressions measuring the effect of discovery of fraud on lending at the branch level. The dependent variable is change in log credit at the branch level (column (1) and (2), and change in log bad credit (column (3) and (4). The right hand side variables are event time indicators around the year in which fraud is detected. "Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific year. The "Year + (-) N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-(+)N. Each column represents a separate regression. Columns (1) and (3) include branch fixed effects, while columns (2) and (4) includes year and branch fixed effects.

	Change in Log Credit		Change in Log Bad Credit	
	(1)	(2)	(3)	(4)
Year - 2	0.85	0.79	-0.64	-0.45
	(0.82)	(0.92)	(1.36)	(1.65)
Year - 1	0.08	-0.42	-0.54	-0.98
	(0.85)	(0.97)	(1.39)	(1.72)
Fraud Detected	-2.42 ***	-3.03 ***	4.39 ***	5.99 ***
	(0.89)	(1.03)	(1.53)	(1.88)
Year + 1	-4.03 ***	-4.66 ***	-2.01	-1.58
	(0.97)	(1.15)	(1.59)	(2.05)
	-4.52 ***	-5.33 ***	4.37 ***	4.09 *
	(1.03)	(1.24)	(1.66)	(2.18)
Year >2	-3.48 ***	-4.72 ***	-0.81	-0.75
	(0.39)	(1.09)	(0.57)	(1.88)
R2	0.04	0.2	0.01	0.29
N	357,266	357,266	154,139	154,139
Fixed Effects	Year	Year & Branch	Year	Year & Branch

Table X

Effect Prior to and Following the Introduction of Special Vigilance Manual

This table reports coefficients from regressions measuring the effect of discovery of fraud on lending at the branch level before and after the introduction of a special vigilance manual. The dependent variable is quarterly log credit growth, while the right hand side variables are event time indicators around the year in which fraud is detected. "Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific year. The "Year + (-) N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-(+)N. Each column represents a separate regression. Column (1) includes branch fixed-effects and column (2) includes branch and quarter fixed-effects.
Panel (B) gives the cumulative effect, the summation of Fraud Detected, Year +1, Year +2, and Year >=3.

Panel A: Regression Results		All	Public
		(1)	**(2)**
PRE-REFORM	Year -2	0.15	0.16
		0.4	0.41
	Year -1	0.1	0.47
		0.44	0.46
	Fraud Detected	-1.06	-0.68
		0.85	0.89
	Year + 1	-3.03 ***	-2.95 ***
		0.49	0.51
	Year + 2	-1.86 ***	-2.15 ***
		0.55	0.57
	Year >=3	-2.2 ***	-2.05 ***
		0.32	0.33
POST-REFORM	Year -2	0.67 **	0.8 ***
		0.29	0.3
	Year -1	0.61 **	0.48
		0.27	0.28
	Fraud Detected	-1.51 ***	-0.88
		0.52	0.54
	Year + 1	-2.28 ***	-2.34 ***
		0.28	0.29
	Year + 2	-2.18 ***	-2.24 ***
		0.3	0.31
	Year >=3	-1.67 ***	-1.55 ***
		0.23	0.24
	R^2	0.42	0.43
	N	2,493,609	2,260,733

Panel B: Cumulative Effect			
PRE	Cumulative Effect	-8.15	-7.83
POST	Cumulative Effect	-7.64	-7.01

APPENDIX: Main Results with Flexible Error Structure

This table presents regressions relating quarterly credit growth to vigilance activity, at the bank branch level, for all bank branches in India over the period 1990-2005. The dependent variable is log change in credit, while the right hand side variables are event time indicators around the quarter in which vigilance activity occurs. "Vigilance Activity" is a dummy variable taking the value of 1 if a vigilance activity occurs at a specific branch in a specific quarter. The "Quarter + (-) N" dummy is equal to 1 at time t if vigilance activity occurs at that branch at time t-(+)N, for example Quarter-1 indicates the quarter one month prior to vigilance activity. In Column 2, standard errors are adjusted for correlation over time in each particular bank branch, using the SAS GENMOD command.

	Unadjusted Errors	**Clustered by Branch**
	(1)	**(2)**
Quarter - 8	-0.060	0.195
	(0.450)	(0.584)
Quarter - 7	0.420	0.425
	(0.450)	(0.571)
Quarter - 6	2.060 ***	2.412 ***
	(0.450)	(0.570)
Quarter - 5	-0.120	1.124 *
	(0.440)	(0.608)
Quarter - 4	0.800 *	1.116 *
	(0.440)	(0.675)
Quarter - 3	1.240 ***	0.964
	(0.440)	(0.662)
Quarter - 2	0.170	1.052
	(0.430)	(0.661)
Quarter - 1	-0.140	-0.401
	(0.440)	(0.675)
Fraud Detected	-1.360 ***	-0.639
	(0.440)	(0.694)
Quarter + 1	-3.730 ***	-3.785 ***
	(0.450)	(0.684)
Quarter + 2	-2.040 ***	-1.093
	(0.460)	(0.698)
Quarter + 3	-1.930 ***	-2.583 ***
	(0.460)	(0.737)
Quarter + 4	-1.820 ***	-0.913
	(0.470)	(0.746)
Quarter + 5	-2.050 ***	-2.641 ***
	(0.480)	(0.760)
Quarter + 6	-1.900 ***	0.049
	(0.500)	(0.829)
Quarter + 7	-2.120 ***	-3.123 ***
	(0.510)	(0.850)
Quarter + 8	-1.950 ***	-1.956 **
	(0.520)	(0.852)
Quarter > 8	-1.590 ***	-1.338 ***
	(0.210)	(0.252)
Fixed Effects	Quarter & Branch	Quarter & Branch
Clusters		55,390
N	2,493,542	2,493,542