Are the Monitors Over-Monitored? Evidence from Corruption and Lending in Indian Banks

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Abstract

Most credit in India is provided by public-sector banks. Previous research has found that loan officers in public banks decline profitable lending opportunities, and are strikingly reluctant to enhance loans of growing and profitable firms. Loan officers in government owned banks often cite fear of prosecution for corruption as a reason for their rigid and conservative lending decisions. Using data from all commercial banks, from 1981 to 2003, we test this claim, using an event-study methodology to examine how lending decisions react to vigilance activity. We find evidence that vigilance activities result in reduced lending: the amount of credit declines sharply at the affected bank branch, as well as neighboring branches. This effect is economically and statistically significant, persisting up to two years. Bank risk-taking also declines following a vigilence event.

1 Introduction

Macro and microeconomic theorists have demonstrated the importance of credit and credit constraints to economic growth and development. Theoretical models argue that credit constraints

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can prevent investment in human capital (Galor and Zeira, 1993) or create poverty traps (Banerjee and Newman (1993)). Evidence suggests that returns to capital can be high. A recent paper by de Mel, McKenzie, and Woodruff (2006) used randomized evaluation to measure the returns of small capital grants ($100-$200) to small firms. They find that the *average* marginal return of that grant is close to 40%.

Banerjee and Duflo (2003) study firms that already have a banking relationship, and demonstrate that even those firms face binding credit constraints. Using an Indian public bank's lending policy change, generated by a government mandate, they find that an increase in credit causes an increase in firm profits that is much larger than the cost of the additional capital. Banerjee and Duflo also examine the decisions taken by loan officers using data from the loan officers' files as well as bank policy. The official bank lending policy dictates that banks loan as much as possible, as long as the credit limit does not exceed a certain multiple of projected turnover. In a majority of cases, predicted sales increase from one year to the next, but the sanctioned credit limit remains the same in nominal terms, meaning that firm's real credit actually shrinks over time. Banerjee and Duflo speculate that bank managers are responding to incentives that provide little reward for repaid loans but potentially serious punishment for defaulting loans. In particular, officers who authorize loans that go bad may be charged with corruption.

If this were indeed true, it would be important for several reasons. First, it would provide a striking example of the deleterious effects of corruption: not only do corrupt agents misallocate goods, but their behavior causes honest agents to under allocate credit, potentially significantly slowing economic growth. Second, one would be able to estimate reasonably precisely the costs due to corruption, which is often quite hard to do. Finally, if the sources of credit frictions are well understood, policy remedies may be devised to address them.

In this paper, we seek to test this hypothesis: using detailed, high-frequency credit data, we study the effect of anti-corruption actions on lending at the bank branch level. We adopt an event-study methodology to measure how credit evolves in a branch before and after a fraud is discovered. The richness of our data set allow us to include branch- and time- fixed effects. We find that vigilance activity leads to substantial reduction in credit. Relative to an unaffected branch, a branch in which an officer is accused of corruption experiences a 20% decline in credit over a period of two years. These estimates are very precise and robust to alternative specifications. Vigilance action has important economic effects: credit drops in nearby branches (in which no fraud was discovered); the share of non-performing loans change; and loan officers lend to less risky industries after the discovery of a fraud.

This paper is motivated by the findings in Banerjee and Duflo (2003), discussed above. Banerjee, Cole, and Duflo (2004) provide evidence that aggregate public sector banks tend to invest in government bonds, rather than lend to firms, when state growth opportunities are poor. Cole (2006) focuses on political aspects of lending decisions, and demonstrates that public sector banks in India lend more in election years than in non-election years.

This paper is also closely related to at least two other literatures. States have traditionally found it difficult to provide incentives to public employees, and, as in firms, incentive schemes can have perverse effects. Prendergast (2001), for example, finds that increased oversight of Los Angeles police officers may have caused the officers to reduce crime-fighting activity.

Second, this paper contributes to the literature on the effects of corruption. Beck, Demirguc-Kunt, and Levine (2006) look at corruption and lending in an international context. Their goal is to determine how the type of bank regulatory systems (e.g., strong central monitor, etc.) affect corruption as a barrier to obtaining a loan. They find that supervision systems with less central control, and more outside monitoring, are more common in countries where corruption is not reported to be major barrier in obtaining a loan.

Economists have found very few opportunities to study corruption in large sample datasets, and have instead had to rely on indirect measures, such as individuals' or firms' perceptions of corruption, to measure its impact. This study makes use of a dataset that includes almost two thousand corrupt acts. Moreover, because output is directly observed (both quantity (amount of credit) and quality (repayment rates)), we are able to measure the exact effects of corruption on branch performance.

Finally, this paper is of policy interest: these results should inform the Indian government's decision on how to optimally regulate bank employees, and whether (and to what extent) to privatize government owned banks.

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. Section gives a brief literature review. Section 3 introduces the data, while section 4 describes the methodology and presents the baseline results. Sections 5 measures how the effect of discovering credit may spill over to other branches, and 6 examines how the nature of lending decisions change after a vigilance inquiry, including the quality of loans, and the risks taken by bank employees. Finally, section 7 concludes.

2 Context & 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. Nevertheless, public sector banks had 92% of all bank accounts in 1996, and issued 83% of all credit.

There is no doubt that fraud is an important problem faced by public sector banks. Indeed, in a theoretical model of credit provision in rural India, Gupta and Chadhuri (1997) model three players: a borrower, a bank officer, and an informal money lender. The only choice variable for the bank officer is the amount of bribe she will demand.

Frauds are regularly discovered by banks or the government, and range from illegal overdrafts of 5000 Rs. ($100 US) to major frauds such as loans to politicians or fictitious corporations. In addition to the direct costs (misallocation of resources, and increased taxes, as the government acts as an insurer of public sector banks), corruption also produces additional distortions.

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. Bankers have expressed concern that it is very easy to be charged with corruption. Some felt 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.

Bankers feel strongly that One loan officer described his fear of being charged with corruption as follows: "Fear of prosecution for corruption hangs over every loan officer's head like a sword of Damocles." Fear of prosecution for fraud has also prevented banks from settling NPAs (RBI 2000, p. 29), as bank managers are reluctant to settle bad debts 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 (p. 30). To address this concern, in 1999 the government introduced Special Advisory Committees to make recommendations on the settling of non-performing assets.

The Economic Times of India has attributed slowdowns in lending directly to vigilance activity (1999). 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. Their 2000 report states "Out of every 100 cases coming before it, the Commission would advice 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)

In April 2004, apparently in response to this criticism, lower-level loan officers were removed from the jurisdiction of the Central Vigilance Commission.

3 Data

This study uses two sources of credit data, both collected by the Reserve Bank of India from scheduled banks in India. The first, at a quarterly frequency, gives the aggregate amount of lending and deposits of each bank branch, in India, from June 1991 to May 2006. In this work, we include all scheduled commercial banks (public, private, and foreign), but exclude Rural Regional Banks[1]. The dataset is an unbalanced panel, and a regression in changes includes about 56 quarters and 2.5 million observations, which includes approximately 43,000 bank branches.

The second set of data are loan-level 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,

[1] Rural Regional Banks are not scheduled commercial banks, and thus not subject to the same set of regulations.

etc.[2] Analysis was performed on aggregated data only (the aggregations are described below). At the branch level, annual credit growth is available for 11 years, totaling 408,555 observations.

The quarterly dataset has two advantages. The higher frequency 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. Second, these data are available for a longer time series (15 years) than the loan-level data.

The quarterly data include only aggregate credit and deposits. To understand how the nature of the loan portfolio is affected by vigilance activity, we use information on the repayment status of loans and the industries to which banks lend.

Both sets 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.

Vigilance data is also from the Reserve Bank of India. Banks in India are required to report any frauds discovered to the central bank within one quarter of their discovery, and update the Reserve Bank of additional developments.

4 Effect of Vigilance Activity on Lending

4.1 Baseline Specification

4.1.1 Branch-Level Effects

We adopt 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:

$$y_{obct} = \alpha_o + \sum_{k=-8}^{8} \beta_k \theta_{o,t,k} + \beta_{\geq 9} \theta_{o,t,\geq 9} + \gamma_t + \varepsilon_{obct}, \tag{1}$$

[2] 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.

where α_0 is a branch-specific fixed effect, γ_t is a quarter fixed effect, and $\theta_{o,t,k}$ is a dummy variable indicating the timing of a fraud. $\theta_{o,t,0}$ is set to one if a fraud is detected in branch o in quarter t, and zero otherwise. Similarly, $\theta_{o,t,1}$is set to 1 if a fraud was detected in branch o one period prior (e.g., at time t-1). When k is negative, the dummy serves as a 'leading indicator:' $\theta_{o,t,-3}$ is set to 1 at time t if a fraud will occur in branch o at time t+3. Finally, $\theta_{o,t,\geq 9}$ is a dummy that is set to 1 if a fraud was detected at any point more than 8 quarters ago prior to time t.

Table 2 reports results from the baseline specification, for the sample of frauds coded as "extension of credit for illegal gratification" or "other." Under the null hypothesis that vigilance activity does not affect lending, these θ coefficients should be zero.[3] Columns (1)-(4) build to the preferred specification. Column (1) estimates equation 1 in levels, with log credit from branch office o at time t as the dependent variable, and without any year or branch office fixed effects. Because credit is highly serially correlated, and because credit growth may be more relevant than the stock of credit, the remaining equations are estimated using log change in credit, $\log(credit_{obc,t}/credit_{obc,t-1})$. Column (2) reports results from Equation (2) without branch or time fixed effects. Column (3) adds quarter fixed effects (γ_t); column (4) adds branch fixed effects (a_0); and column (5) presents the results with quarter and branch office fixed effects. Column (5) 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 of "six months prior" and "three months prior," when the growth rate is above average. Following the

[3] The average size of a fraudulent loan is a tiny fraction of the branch portfolio, so there is no mechanical relationship between discovery of fraud and the amount of lending.

discovery of fraud, credit drops precipitously: by 1.4 percent relative to branches in which a fraud is not discovered in the quarter of discovery. 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, $\theta_{o,t\geq 9}$, is negative and significant, suggesting that credit continues to decline (relative to other branches) even two years after the discovery of the fraud. The duration of the effect is not surprising, given both the stickiness of lending decisions, the lethargy of the legal process in India, and the fact that the accused may remain in their position until either acquitted or found guilty.

Even though our dependent variable is change in log credit, specification 1 is likely to suffer from serial correlation. Running a regression with branch and quarter fixed effects, and 2.5 million observations, correcting for clustering in SAS taxes the available computer facility, so the majority of the regressions presented in this paper are currently presented with unadjusted standard errors.[4] However, in table 3 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.

We next examine the two types of frauds separately. We expect "extension of credit for illegal gratification" to have a larger effect on credit growth than frauds in the "other" category. These results are presented in table 4. Columns (1) and (2) present results for "extension of credit for illegal gratification."Credit growth prior to discovery of a fraud is high more often (seven, six, and four through one quarters prior to discovery of the fraud). Credit growth in the quarter in which the fraud is discovered is negative but indistinguishable from zero, while in the following quarter it drops by over four percent relative to branches in which no fraud was discovered. The point estimates for the post-event time windows are again negative and statistically significant. Columns (3) and (4) present the same set of regressions for frauds categorized as "other." The "other" category may include crimes such as "negligent extension of credit." The results are broadly similar: in the preferred specification (column 5), all but one of the pre-event

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

coefficients is statistically indistinguishable from zero. The post-event dummies are all negative and significant. The point estimates are slightly smaller in magnitude than table 4, thought not statistically distinguishable. In both instances, the cumulative effect from the negative coefficients after the detection of fraud is much larger than the sum of the positive coefficients prior to discovery of fraud, suggesting that this is not simply mean-reversion.

4.1.2 Credit-Market Effects

Whether the discovery that fraud has an effect on credit at the branch level has important implications for bank operations, the finding does not necessarily mean that discovery of fraud has an effect on aggregate credit: perhaps other branches, not affected by fraud, increased credit allocation to make up for the drop in lending by the branch in which the fraud was discovered. Credit markets are defined by the Reserve Bank of India, as the geographical area in which an individual in that area could reasonably be expected to go for a loan. The Reserve Bank of India defines approximately 35,000 credit markets, which range in size from a small village, to the entire city of Mumbai (Bombay).

The average effect of a fraud being discovered in a particular branch office in a town may be measured using an equation similar to 1, where the indicator variables $\theta_{c,t,0}$ are set to 1 if a fraud was discovered in any bank branch within a given credit market c experienced at time t (and $\theta_{c,t,k}$ defined analogously):

$$y_{ct} = \alpha_o + \sum_{k=-8}^{8} \beta_k \theta_{o,t,k} + \beta_{\geq 9}\theta_{o,t,\geq 9} + \gamma_t + \varepsilon_{ct}$$

Table 5 presents these results. The results show that discovery of fraud has a substantial and lasting effect on credit within a town. The immediate effect is an average decline of approximately .4 percentage points: substantially smaller than the effect on an individual bank branch, but significant nonetheless. If anything, the average trend in credit is slightly negative prior to the discovery of the fraud. The sum of coefficients in column (2) suggest an aggregate effect of a 3.4 percentage points relative decline following the discovery of a fraud. Columns (3)-(6) show this effect holds for frauds related to "extension of credit for illegal gratification" (where there is no uniform pre-trend) as well as frauds classified as "other."

5 Spillover Effects of Vigilance Activity

There are two reasons one may expect a decline in credit at the credit market level following discovery of fraud: as shown above, credit in the branch in which fraud is detected drops precipitously. Second, there could be spillover effects: news of the accusations against an employee may cause employees in other bank branches to lend more cautiously. This effect may be stronger for employees of other branches of the affected bank.

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

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

Thus, $\phi\left(\text{branch}\right)$ indicates a series of 26 dummy variables, in the same fashion as the dummy variables introduced above in equation 1. (Here we extend the window from 8 quarters before through sixteen quarters after, along with a dummy for more than 16 quarters following the discovery of a fraud.) Similarly, $\phi\left(\text{Town}\right)$ is a set of 26 dummy variables comprising an event window around a fraud being discovered in a particular town: the indicator $\theta_{c,t,0}$ is 1 for all branches within a town if a fraud was discovered that quarter at any branch within that town. Finally, $\phi\left(\text{TownBank}\right)$ 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:

$$y_{obct} = \alpha_o + \phi\left(branch\right) + \phi\left(banktown\right) + \phi\left(town\right) + \gamma_t + \varepsilon_{obct} \tag{2}$$

Table 6 estimates equation 2 without $\phi\left(banktown\right)$ or $\phi\left(town\right)$. This replicates the main specification presented above, but includes a longer series of post-event dummies. Including sixteen post dummies reduces the sample size by two years, 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.

Table 7 presents regression 2 with $\phi\,(banktown)$ but without $\phi\,(branch)$ or $\phi\,(town)$. The seventy-eight coefficients of interest (26 for each set of dummies) are presented in columns (1), (2), and (3). The most important effect is clearly at the affected branch: these coefficients are all negative and significant following the discovery of fraud. There is an immediate decline in other branches of the same bank as the bank in which the fraud was discovered (column (2)): credit declines by almost 1 percent. This effect is short-lived, however. There does not appear to be an effect on the other bank branches in the town: the sum of the post-event coefficients is very close to zero: this suggests that other branches do not increase credit to "undo" the decline observed in the "treated" branch.

6 Vigilance Activity and Repayment Rates

Section 4 clearly established that credit in a branch (and indeed, a town) declines following the discovery of a fraud. In this section, we examine more closely the compositional effects of this reaction: do banks react by reducing risky lending?

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 8. 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.

6.1 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:

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

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

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

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 9 reports how $branchrisk_{ot}$ varies following the discovery of an alleged fraud. Column (2) presents equation 1 with branch and year fixed effects. 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. Following the discovery of fraud, however, the riskiness of the loan portfolio drops substantially, with $branchrisk_{ot}$ falling approximately six points.

6.2 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 construct two measures: first, the share of loans repaid late. This is simply:

$$sharelate_{o,t} = \frac{\text{Value of Loans from Branch O late at time t}}{\text{Total lending at time t}}.$$

Because this number will increase mechanically if branches reduce new credit in response to vigilance activity, we also calculate the log change of the *amount* of bad loans, $d \ln latevol_{o,t}$.

The effect on aggregate credit is presented in columns (1) and (2) of Table 10. Columns (2), (4), and (6) 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 slightly in the following year, but is again slightly above the steady state amount for that branch in year 3. In contrast, the share of loans marked as late increase substantially in the event year, climbing by 9 percent. This increased level remains steady for at least two years following the discovery of the fraud

7 Conclusion and Future Research

This paper presents compelling evidence that the detection of fraud leads to a decrease in overall lending. I present evidence that the bankers are right: increases in vigilance activity result in significant reductions in credit. 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. 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." First, the effect is found in other branches belonging to the same bank in the same town. Second, 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.

The results described above suggest numerous promising directions in which to continue this investigation: a more careful accounting of non-performing loans may allow us to "unpack" which NPL are from loans made prior to discovery of the fraud, and which are from loans made after discovery of the fraud. A rich set of variables about the fraud (size, are of operations, number of individuals involved, etc.) will allow us to better understand *how* corruption occurs, as well as whether historical credit data is useful in predicting the probability of a corrupt act occurring. The removal of certain officers from the purview of the Central Vigilance Commission, in 2004, may provide a useful natural experiment.

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Table 1: Summary Statistics

Panel A: Fraud

General Frauds Data Overview

Number of Observations

Fraud Type	**Frequency**
"Extension of Credit for Illegal Gratification"	354
"Other"	1378
Total	1732

Panel B: Areas of Bank Operation in Which Frauds Occur

			Classification	
			Credit	Other
1	Cash		0	36
2	Deposits	(i) Savings	6	77
3	Deposits	(ii) Current	21	42
4	Deposits	(iii) Term	4	13
5	Non-Resident Accounts		0	4
6	Advances	(i) Cash Credit	75	140
7	Advances	(ii) Term Loans	94	214
8	Advances	(iii) Bills	42	49
9	Advances	(iv) Others	70	198
10	Foreign Exchange Transactions		7	11
11	Inter-branch Accounts		1	21
12	Cheques/Demand drafts		3	51
13	Clearing, etc., accounts		1	23
14	Off-balance sheet	(i) Letters of credit	8	13
15	Off-balance sheet	(ii) Guarantees	2	4
16	Off-balance sheet	(iii) Co-acceptance	0	1
17	Off-balance sheet	(iv) Others	0	6
18	Others		16	479
	Total		350	1382

Panel C: Staff Involvement in Frauds

	Classification	
Fraud Type	Credit	Other
"Extension of Credit for Illegal Gratification"	250	100
"Other"	1058	324
Total	1308	424

Notes: This table provides a basic overview of the data on frauds available for the study. All frauds involve loan officers at the local (branch) level.

Table 2: Effect of Discovery of Fraud on Lending
All Frauds, Regressions at Branch Office Level

Time Window	**Log Credit**	**Dlog Credit**	**Dlog Credit**	**Dlog Credit**	**Dlog Credit**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Quarter - 8	1.08 ***	0.66	0.47	0.19	-0.06
	(0.06)	(0.58)	(0.45)	(0.59)	(0.45)
Quarter - 7	1.13 ***	0.97 *	1 **	0.42	0.42
	(0.06)	(0.57)	(0.44)	(0.58)	(0.45)
Quarter - 6	1.17 ***	2.95 ***	2.61 ***	2.41 ***	2.06
	(0.06)	(0.57)	(0.44)	(0.58)	(0.45)
Quarter - 5	1.39 ***	1.73 ***	0.48	1.12 **	-0.12
	(0.06)	(0.56)	(0.43)	(0.57)	(0.44)
Quarter - 4	1.48 ***	1.72 ***	1.38 ***	1.11 *	0.8
	(0.06)	(0.56)	(0.43)	(0.57)	(0.44)
Quarter - 3	1.48 ***	1.61 ***	1.83 ***	0.96	1.24
	(0.06)	(0.55)	(0.43)	(0.57)	(0.44)
Quarter - 2	1.59 ***	1.69 ***	0.74 *	1.05 *	0.17
	(0.06)	(0.55)	(0.43)	(0.56)	(0.43)
Quarter - 1	1.57 ***	0.21	0.41	-0.41	-0.14
	(0.06)	(0.55)	(0.43)	(0.57)	(0.44)
Fraud Detected	1.71 ***	0.04	-0.75 *	-0.65	-1.36
	(0.06)	(0.56)	(0.44)	(0.58)	(0.44)
Quarter + 1	1.66 ***	-3.11 ***	-3.13 ***	-3.8 ***	-3.73
	(0.06)	(0.57)	(0.44)	(0.58)	(0.45)
Quarter + 2	1.72 ***	-0.47	-1.48 ***	-1.11 *	-2.04
	(0.06)	(0.58)	(0.45)	(0.59)	(0.46)
Quarter + 3	1.64 ***	-1.96 ***	-1.39 ***	-2.6 ***	-1.93
	(0.06)	(0.59)	(0.45)	(0.60)	(0.46)
Quarter + 4	1.74 ***	-0.31	-1.29 ***	-0.93	-1.82
	(0.06)	(0.60)	(0.47)	(0.62)	(0.47)
Quarter + 5	1.61 ***	-2.05 ***	-1.54 ***	-2.65 ***	-2.05
	(0.06)	(0.61)	(0.48)	(0.63)	(0.48)
Quarter + 6	1.83 ***	0.55	-1.47 ***	0.04	-1.9
	(0.06)	(0.63)	(0.49)	(0.65)	(0.50)
Quarter + 7	1.71 ***	-2.66 ***	-1.73 ***	-3.14 ***	-2.12
	(0.07)	(0.64)	(0.50)	(0.66)	(0.51)
Quarter + 8	1.68 ***	-1.49 **	-1.55 ***	-1.97 ***	-1.95
	(0.07)	(0.66)	(0.51)	(0.68)	(0.52)
Quarter > 8	1.49 ***	-1.17 ***	-1.36 ***	-1.36 ***	-1.59
	(0.01)	(0.13)	(0.10)	(0.27)	(0.21)
N	2632614	2493542	2493542	2493542	2493542
Fixed Effects	None	None	Quarter	Branch	Quarter & Branch
Time Period	1990-2005	1990-2005	1990-2005	1990-2005	1990-2005

Notes:

Each column represents a separate regression. The dependent variable, a measure of credit at the branch level, is indicated above the regression.

Column (2)-(5) use change in log credit as the dependent variable.

The regressions measure the effect of discovery of fraud on lending at the branch level.

The approach is a difference-in-difference or "event study" methodology.

"Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific quarter.

The "Quarter + N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-N.

The "Quarter - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

Columns 3 includes quarter fixed effects; Column 4 includes branch level fixed effects, and Column 5 includes branch and quarter fixed effects.

Column 5 is the preferred specification.

Table 3: Effect of Adjusting for Clustering at Branch Level

	Unadjusted Errors (1)	Clustered by Branch (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		55390
N	2493542	2493542

Notes:

"Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific quarter.
The approach is a difference-in-difference or "event study" methodology.
"Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific quarter.
The "Quarter + N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-N.
The "Quarter - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.
In Column 2, standard errors are adjusted for correlation over time in each particular bank branch.

Table 4: Effect of Discovery of Fraud by Fraud Type

Time Window	"Credit for Illegal Gratification"		"Other Fraud (Related to Credit)"	
	Dlog Credit	Dlog Credit	Dlog Credit	Dlog Credit
	(1)	(2)	(3)	(4)
Quarter - 8	1.62	1.6	-0.31	-0.66
	(1.15)	(0.89)	(0.68)	(0.52)
Quarter - 7	2.27	1.96	-0.13	-0.03
	(1.14)	(0.88)	(0.67)	(0.52)
Quarter - 6	3.78	3.45	1.95	1.6
	(1.13)	(0.87)	(0.67)	(0.52)
Quarter - 5	2.27	0.57	0.87	-0.27
	(1.13)	(0.87)	(0.66)	(0.51)
Quarter - 4	0.92	2.96	1.12	0.07
	(1.12)	(0.86)	(0.66)	(0.51)
Quarter - 3	3.26	2.43	0.22	0.87
	(1.11)	(0.86)	(0.65)	(0.50)
Quarter - 2	4.34	3.2	-0.08	-0.83
	(1.11)	(0.85)	(0.65)	(0.50)
Quarter - 1	0.64	1.71	-0.7	-0.72
	(1.12)	(0.86)	(0.66)	(0.51)
Fraud Detected	-1.05	-1.39	-0.28	-1.25
	(1.11)	(0.86)	(0.67)	(0.52)
Quarter + 1	-3.52	-4.11	-3.86	-3.46
	(1.12)	(0.86)	(0.68)	(0.52)
Quarter + 2	-1.65	-2.53	-0.97	-1.82
	(1.13)	(0.87)	(0.69)	(0.53)
Quarter + 3	-2.35	-2.35	-2.77	-1.88
	(1.14)	(0.88)	(0.70)	(0.54)
Quarter + 4	-1.29	-2.06	-0.76	-1.69
	(1.14)	(0.88)	(0.73)	(0.56)
Quarter + 5	-1.55	-2.08	-3.04	-1.96
	(1.14)	(0.88)	(0.75)	(0.58)
Quarter + 6	0.02	-1	0.03	-2.25
	(1.16)	(0.89)	(0.77)	(0.60)
Quarter + 7	-3.7	-2.63	-2.84	-1.86
	(1.17)	(0.90)	(0.79)	(0.61)
Quarter + 8	-2.3	-2.58	-1.75	-1.59
	(1.20)	(0.93)	(0.82)	(0.63)
Quarter > 8	-1.13	-1.36	-1.35	-1.57
	(0.49)	(0.38)	(0.33)	(0.25)
R2	0.03	0.42	0.03	0.42
N	2493537	2493537	2493542	2493542
Fixed Effects	Branch	Quarter & Branch	Branch	Quarter & Branch
Time Period	1990-2005	1990-2005	1990-2005	1990-2005

Notes:

This table breaks down the analysis into a) Credit extended for illegal gratification (bribes), Columns (1) and (2), and b) Other Frauds (related to credit), columns (3) and (4)

Each column represents a separate regression.

All columns use change in log credit as the dependent variable.

The regressions measure the effect of discovery of fraud on lending at the branch level.

The approach is a difference-in-difference or "event study" methodology.

"Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific quarter.

The "Quarter - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

Columns 1 and 3 include branch level fixed effects; Columns 2 and 4 include branch and quarter fixed effects.

Table 5: Average Effect at Town (Credit-Market) Level

	All Fraud Types		Credit for Bribe		Other Credit Fraud	
Time Window	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Quarter - 8	-0.44	-0.51	-1.35	-0.35	-0.37	-0.53
	(0.15)	(0.11)	0.2	0.16	0.15	0.12
Quarter - 7	0.27	-0.13	0.69	0.35	0.26	-0.14
	(0.14)	(0.11)	0.2	0.16	0.15	0.12
Quarter - 6	1.66	0.38	0.69	0.36	1.63	0.35
	(0.14)	(0.11)	0.2	0.16	0.15	0.11
Quarter - 5	3	-0.53	1	0.12	3.22	-0.61
	(0.14)	(0.11)	0.2	0.16	0.15	0.11
Quarter - 4	-2.75	-0.09	-2.21	-0.31	-2.87	-0.04
	(0.14)	(0.11)	0.2	0.16	0.14	0.11
Quarter - 3	-0.05	-0.12	2.11	0.63	0.36	-0.19
	(0.14)	(0.11)	0.2	0.15	0.14	0.11
Quarter - 2	6.2	-0.36	0.33	0.41	6.01	-0.35
	(0.14)	(0.11)	0.2	0.15	0.14	0.11
Quarter - 1	-7.84	-0.64	3.08	0.69	-8.43	-0.72
	(0.15)	(0.11)	0.2	0.15	0.15	0.12
Fraud Detected	-0.4	-0.42	-3.49	-0.81	-0.27	-0.47
	(0.15)	(0.12)	0.2	0.15	0.15	0.12
Quarter + 1	0.14	-0.3	0.52	-0.47	0.04	-0.35
	(0.15)	(0.12)	0.2	0.15	0.16	0.12
Quarter + 2	1.82	-0.41	1.01	0.23	1.93	-0.41
	(0.17)	(0.13)	0.19	0.15	0.18	0.14
Quarter + 3	-2.29	-0.57	3.36	-0.23	-1.52	-0.46
	(0.17)	(0.13)	0.19	0.15	0.18	0.14
Quarter + 4	0.89	-0.61	-4.3	-0.83	0.05	-0.62
	(0.17)	(0.14)	0.19	0.15	0.18	0.14
Quarter + 5	-1.28	-0.25	0.54	-1.18	-1.92	-0.33
	(0.17)	(0.14)	0.19	0.15	0.19	0.14
Quarter + 6	2.07	-0.25	1.32	-0.65	2.94	-0.3
	(0.18)	(0.14)	0.19	0.15	0.19	0.15
Quarter + 7	4.63	-0.29	-1.8	-1.03	3.36	-0.21
	(0.18)	(0.14)	0.2	0.15	0.19	0.15
Quarter + 8	-8.07	-0.74	-3.24	-1.7	-7.14	-0.69
	(0.18)	(0.14)	0.19	0.15	0.2	0.15
Quarter > 8	-0.26	-0.83	-0.29	-0.6	-0.28	-0.83
	(0.07)	(0.06)	0.08	0.07	0.08	0.07
N	2493537	2493537	2493537	2493537	2493537	2493537
Fixed Effects	Branch	Quarter & Branch	Branch	Quarter & Branch	Branch	Quarter & Branch
Time Period	1990-2005	1990-2005	1990-2005	1990-2005	1990-2005	1990-2005

Notes:

Each column represents a separate regression. The dependent variable, a measure of credit at the town level, is indicated above the regression.

The regressions measure the effect of discovery of fraud on lending at the town level.

The approach is a difference-in-difference or "event study" methodology.

"Fraud Detected in Town" is a dummy variable taking the value of 1for all branches in a town if a fraud was detected in any branch in the town in a specific quarter.

The "Quarter + N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-N.

The "Quarter - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

Columns 1, 3 and 5 include branch level fixed effects, and Column 2, 4 and 6 include branch and quarter fixed effects.

Table 6: Longer-Term Effect of Fraud Discovery

Time Window	Branch Level Effect	Bank-Town Level Effect
	(1)	**(2)**
Quarter - 8	-0.533	0.021
	(0.487)	(0.124)
Quarter - 7	-0.337	-0.126
	(0.489)	(0.125)
Quarter - 6	1.841 ***	-0.339 ***
	(0.500)	(0.128)
Quarter - 5	0.033	0.468 ***
	(0.503)	(0.128)
Quarter - 4	0.727	0.014
	(0.517)	(0.131)
Quarter - 3	1.022 *	0.042
	(0.530)	(0.133)
Quarter - 2	0.300	0.352 ***
	(0.543)	(0.135)
Quarter - 1	0.444	0.230 *
	(0.555)	(0.136)
Fraud Detected	0.226	0.306 **
	(0.574)	(0.141)
Quarter + 1	-3.074 ***	-0.705 ***
	(0.586)	(0.143)
Quarter + 2	-2.102 ***	0.085
	(0.613)	(0.149)
Quarter + 3	-1.655 ***	0.007
	(0.630)	(0.151)
Quarter + 4	-1.412 **	0.097
	(0.650)	(0.154)
Quarter + 5	-1.470 **	0.092
	(0.670)	(0.159)
Quarter + 6	-1.750 ***	-0.187
	(0.680)	(0.165)
Quarter + 7	-1.870 ***	0.292 *
	(0.690)	(0.169)
Quarter + 8	-1.710 **	0.139
	(0.700)	(0.176)
Quarter + 9	-2.170 ***	-0.383 **
	(0.720)	(0.182)
Quarter + 10	-1.660 **	0.286
	(0.750)	(0.186)
Quarter + 11	-2.380 ***	0.335 *
	(0.760)	(0.186)
Quarter + 12	-0.790	-0.061
	(0.770)	(0.184)
Quarter + 13	0.390	0.085
	(0.780)	(0.183)
Quarter + 14	-1.730 **	0.050
	(0.800)	(0.190)
Quarter + 15	-1.490 *	0.452 **
	(0.810)	(0.195)
Quarter + 16	-2.070 ***	-0.095
	(0.800)	(0.198)
Quarter > 16	-0.920 **	-0.006
	(0.460)	(0.121)
Fixed Effects	Quarter & Branch	Quarter & Branch
N	1421749	1421538

Notes:

Each column represents a separate regression. The dependent variable is change in log credit at the branch level.

The regressions measure the effect of discovery of fraud on lending at the branch level.

The approach is a difference-in-difference or "event study" methodology.

"Fraud Detected" is a dummy variable taking the value of 1 if a fraud was detected at a specific branch in a specific qu
The "Quarter + N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t-N.
The "Quarter - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.
Column (1) gives the branch level effect.
Column (2) gives the effect on all branches in a town that belong to the bank in which the fraud was discovered in tha

Table 7: Effect of Fraud on Lending

Time Window	Affected branch	Non-affected branch of bank	Non-affected ranch in same town
	(1)	(2)	(3)
Quarter - 8	-0.600	-0.035	0.056
	(0.501)	(0.130)	(0.062)
Quarter - 7	-0.278	-0.231 *	0.188 ***
	(0.505)	(0.131)	(0.062)
Quarter - 6	2.274 ***	-0.477 ***	-0.041
	(0.517)	(0.134)	(0.062)
Quarter - 5	-0.305	0.409 ***	-0.115 *
	(0.520)	(0.134)	(0.062)
Quarter - 4	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	1421538		

Note: All three columns present coefficients from **one** regression. The coefficients are estimates from the event window, as defined by the ϕ function in the text.

The dependent variable in column 1 is changes in log credit from affected branches.

The dependent variable in column 2 is changes in log credit from non-affected branches of same bank in same town.

The dependent variable in column 3 is changes in log credit from non-affected branches of non-affected bank in town.

Table 8: Credit Using Annual Data

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	262401	262401
Fixed Effects	Year	Year & Branch

Notes:
Each column represents a separate regression.
The dependent variable is change in log credit at the branch level.
The regressions measure the effect of discovery of fraud on lending at the branch level.
The approach is a difference-in-difference or "event study" methodology.
"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.
The "Year - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

Table 9: Risk Appetite and Discovery of Fraud

Time Window	Using All Banks		Private Banks Only	
	(1)	(2)	(3)	(4)
Year - 2	-1.16	-1.3	-0.53	-0.64
	(2.44)	(2.42)	(1.31)	(1.3)
Year - 1	7.15	7.28	2.2	2.29
	(3.46)	(3.43)	(1.86)	(1.84)
Fraud Detected	-2.14	-2.12	-0.18	-0.28
	(2.28)	(2.26)	(1.22)	(1.21)
Year + 1	-7.76	-8.04	-2.91	-3.02
	(3.94)	(3.91)	(2.12)	(2.1)
Year + 2	4.61	4.54	1.69	1.79
	(3.08)	(3.06)	(1.66)	(1.64)
Year >2	-1.27	-0.88	-0.01	-0.17
	(0.04)	(0.12)	(0.02)	(0.06)
R2	0.47	0.48	0.46	0.47
N	408555	398990	408555	398990
Fixed Effects	Branch	Year & Branch	Branch	Year & Branch

Notes:

Each column represents a separate regression.
The dependent variable is the riskiness of the loan portfolio at the branch level.
The regressions measure the effect of discovery of fraud on the risk appetite at the branch level.
The approach is a difference-in-difference or "event study" methodology.
"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.
The "Year - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

Table 10: Bad Credit and Discovery of Fraud

Time Window	Log Credit		Log Bad Credit		Share Bad Loans	
	(1)	(2)	(3)	(4)	(5)	(6)
Year - 2	0.85	0.79	-0.64	-0.45	-0.39	1.74
	(0.82)	(0.92)	(1.36)	(1.65)	(0.85)	(0.76)
Year - 1	0.08	-0.42	-0.54	-0.98	-0.8	1.96
	(0.85)	(0.97)	(1.39)	(1.72)	(0.89)	(0.8)
Fraud Detected	-2.42	-3.03	4.39	5.99	2.9	5.56
	(0.89)	(1.03)	(1.53)	(1.88)	(0.95)	(0.87)
Year + 1	-4.03	-4.66	-2.01	-1.58	5.89	8.91
	(0.97)	(1.15)	(1.59)	(2.05)	(1.03)	(0.96)
Year + 2	-4.52	-5.33	4.37	4.09	6.83	9.65
	(1.03)	(1.24)	(1.66)	(2.18)	(1.13)	(1.06)
Year >2	-3.48	-4.72	-0.81	-0.75	7.39	9.51
	(0.39)	(1.09)	(0.57)	(1.88)	(0.43)	(0.92)
R2	0.04	0.2	0.01	0.29	0.08	0.49
N	357266	357266	154139	154139	417314	417314
Fixed Effects	Year	Year & Branch	Year	Year & Branch	Year	Year & Branch

Notes:

Each column represents a separate regression.
The dependent variable is change in log credit at the branch level, change in log bad credit or share of bad loans.
The regressions measure the effect of discovery of fraud on lending at the branch level.
The approach is a difference-in-difference or "event study" methodology.

"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.
The "Year - N" dummy is equal to 1 at time t if a fraud was detected at that branch at time t+N.

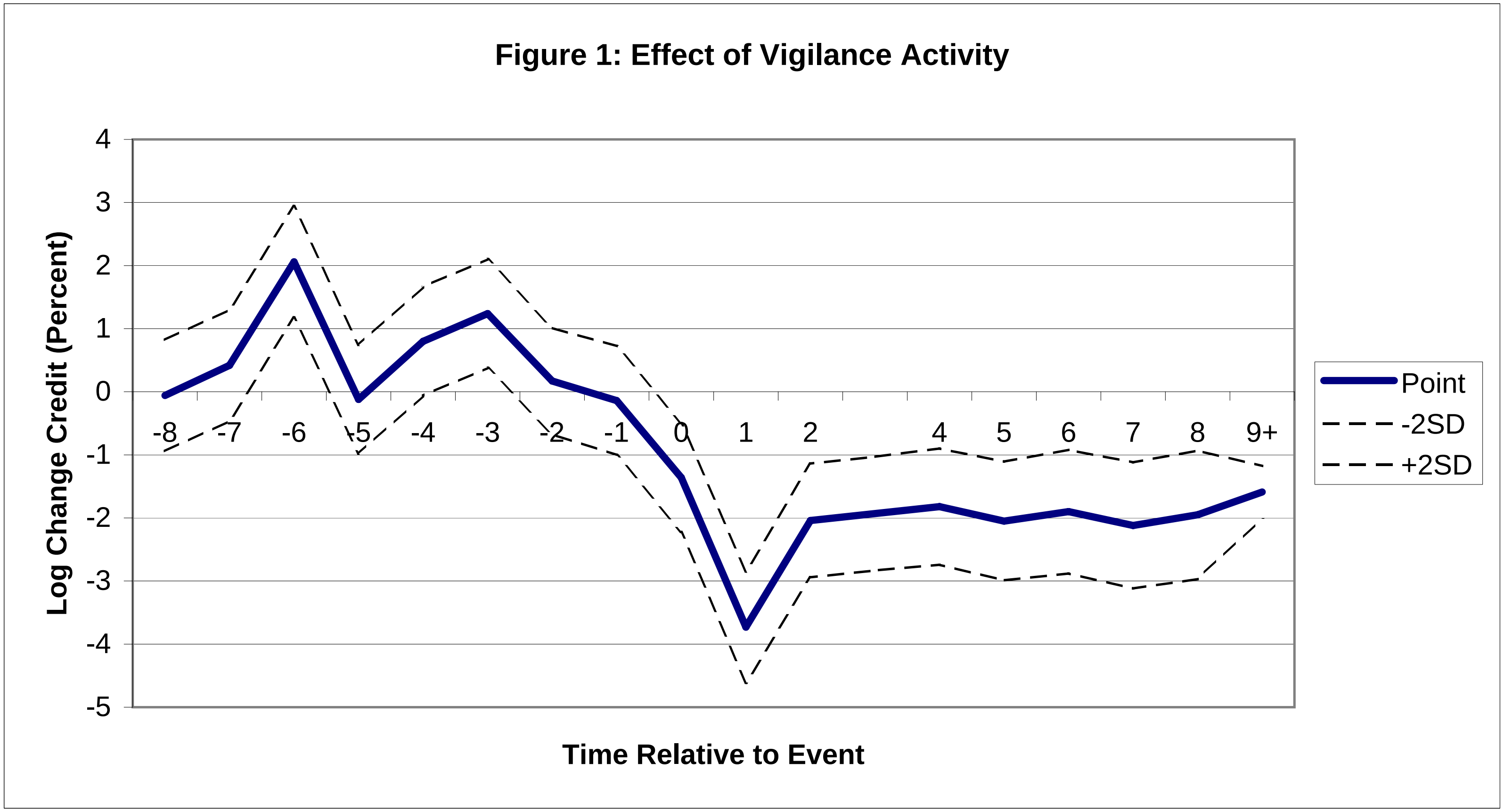

Figure 1: Effect of Vigilance Activity
4
3
2
1
0
-1
-2
-3
-4
-5
Log Change Credit (Percent)
-8 -7 -6 -5 -4 -3 -2 -1 0 1 2 4 5 6 7 8 9+
Time Relative to Event
Point
-2SD
+2SD