

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

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- Banking is a classical principle-agent problem
- Incentives for loan officers may be very important
- What happens if these incentives are 'wrong'?

- Credit constraints are thought to be a prominent feature in emerging markets, and India
- Credit/Deposit ratio among Indian banks declined from 1990-2000
- Banks passed up profitable lending opportunities (Banerjee and Duflo, 2006)

Why?

- Bankers are lazy
- Bankers are reluctant to lend for other reasons

What Do the Bankers Say?

- “Want to lend, but...”
 - Bankers are government employees
 - Loss of government property considered as corruption
 - Thus, any loan default could trigger an investigation
 - Central Vigilance Commission is eager to find evidence of corruption
 - “Presumption of Guilt”
 - Even exoneration can delay advancement or result in an undesirable transfer
- Loan Officer: “Fear of prosecution for corruption hangs over every loan officer’s head like a sword of Damocles”

What Do the Regulators Say?

- Maybe So—Reserve Bank of India Working Group:

[We] have received representations from the managements and 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 Non Performing Assets. The group also noticed a marked reluctance at various levels to take any credit decision.

What does the Central Vigilance Commission say?

- Not So!

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... These figures reveal that a person is not damned the moment his case is referred to the Commission.

- Can fear of prosecution explain 'under-lending'?
- How does vigilance activity affect:
 - Lending
 - Risk-Taking
 - Quality of Lending
- What is the optimal level of supervision?

Event-Study Approach: What happens to lending at the bank- and branch-level following vigilance activity?

Important problem

- Understand effects of corruption on finance
- Government banks very common around the world

Opportunity

- Lending outcomes are observed
- Large database of corrupt acts

Overview of Talk

- 1 Caveat: Work in Progress
- 2 Motivation
- 3 **Institutional Setting and Related Work**
- 4 Bank-Level Analysis
- 5 Branch-Level Analysis
- 6 Future Directions

- Government Banks Dominate Banking in India
 - 80% of Market
- Incentive System for Government Bank Employees Limited
 - Promotions typically based on tenure
 - Very limited scope for pecuniary incentives
 - Strong unions, which tend to advocate equal treatment
 - Transfer to rural areas

Bankers vs. Central Vigilance Commission (CVC)

- Accusation of Corruption Hurts Career Prospects
 - Delays and limits promotion
 - Leads to transfer
 - Legal trials relatively infrequent
- Corruption is prevalent in India: Ranked 70/163 in world
- CVC Founded in 1964 to combat corruption
 - Revised CVC Banking Manual in 1999
 - April 2004, low-level loan officers removed from CVC jurisdiction

- Lending
 - Banerjee and Duflo (2005): Banks pass on profitable lending activity
 - Beck et. al. (2005): Firms report corruption as impediment to borrowing
- Information and Incentives Within the Bank
 - Stein (2002) and Berger et. al. (2005)
 - Liberti (2005) Empowering Managers Increases Effort / Profits
- Corruption and Auditing
 - Becker and Stiglitz (1974)

A more general problem

- Substantial variation in prevalence of incentive schemes
 - None at HU Credit Union
 - ...but very common in micro-credit (Cole (2007))
- Distortionary Costs of Monitoring
 - Jakarta Post: “There is a huge surplus of money in the hands of the regional governments who fear spending it lest the anti-corruption commission come after them.”
 - Prendergast (2001)

Caveat: Work in Progress

- 1 Motivation
- 2 Institutional Setting and Related Work
- 3 [Bank-Level Analysis]
- 4 **Branch-Level Analysis**
- 5 Future Directions

Branch-Level Analysis Overview

- Describe Branch Level Data
- Describe Corruption Data
- Where is corruption detected?
- What is the effect of discovery of corruption?

Quarterly

- Branch-level, 1981 to 2006, on a quarterly basis
- ca. 43,000 branches in India, 56 quarters, or 2.5 million observations
- Identifies:
 - Branch total credit
 - Credit Market / Location (city or village)
 - Bank to which branch belongs
- No other information:
 - Type of loans, size of loans, default, vintage of loans
- Difficult to work with data

Annual

- Branch-level, 1992 to 2003
- Loan Level
 - ca. 30m observations
 - Size, interest rate, industrial occupation of borrower
 - Repayment status
- Branch-level: 43,000 branches in India, 11 years, or .5 million observations
- But:
 - Not a panel
 - No information on loan vintage
 - No information on write-offs

All banks must report all acts of corruption to Reserve Bank of India

- Matched to specific bank branch
- 1378 Discoveries of Corruption over period 1980-2005
 - Of which, 354 “extension of credit for illegal gratification”
 - Balance are “other”, though most are credit related
 - Will focus only on credit-related incidents
- Additional Info:
 - Size of Fraud
 - Date of Detection
 - 82% of frauds are from public sector banks
 - Additional variables (actions taken, outcome, often missing)

Summary Statistics

Corruption Data

Types of Fraud	Total	Detection		
		1980s	1990s	2000s
Extension of Credit for Illegal Gratification	323	46	126	151
Other	1064	79	272	713
Of which, related to credit	539	45	86	408
Total	1387	125	398	864

Share of Frauds in Time Period in Government Banks

Extension of Credit for Illegal Gratification	0.90	0.89	0.87	0.92
Credit-Related Other	0.80	0.91	0.80	0.78

Where is Corruption Detected?

- Dependent variable = 100 if fraud detected at branch
- Linear probability model (effect in percentage points)

Cross-Sectional Regressions: Where are Frauds Detected?

	(1)	(2)	(3)
Public Bank	0.35 *** (0.10)		
More Urban Location		0.74 *** (0.03)	
Log Branch Size			0.88 *** (0.05)

Where is Corruption Detected?

Number of Branches in Market	-0.00 *** (0.00)		
Log Credit Market Size		0.30 *** (0.01)	
More Corrupt State			-83.42 *** (7.55)

Where is Corruption Detected?

Public Bank	-0.13 (0.10)	-0.11 (0.10)	-0.24 (0.37)
More Urban Location	0.06 (0.06)	0.25 *** (0.06)	
Log Branch Size	0.30 *** (0.07)	0.62 *** (0.08)	0.75 *** (0.14)
Number of Branches in Market			
Log Credit Market Size	-12.59 * (6.48)	-0.25 *** (0.06)	
More Corrupt State			
District FE		Yes	
Credit Market FE			Yes
R ²	0.02	0.04	0.41
N	50210	51202	51379

Identification Strategy

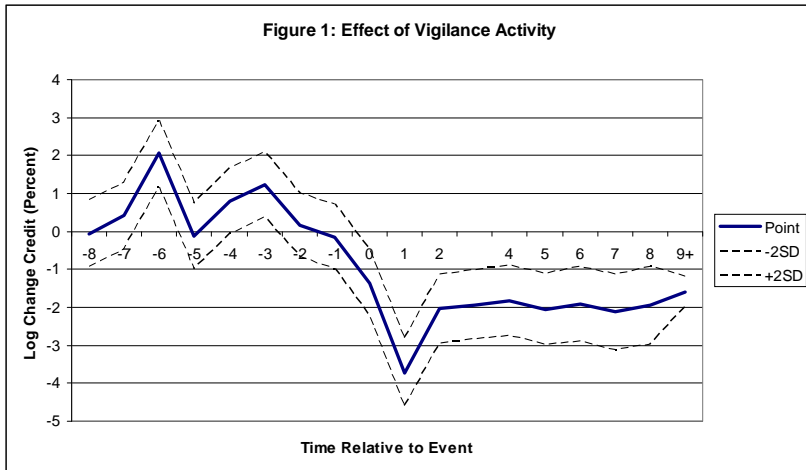
How does discovery of corruption affect lending?

Event Study Approach

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

- α_0 branch fixed-effect
- γ_t quarter fixed-effect
- θ a vector:
 $\theta_{o,t,k} : \begin{cases} k \geq 0 & \text{Corrupt act detected } k \text{ quarters ago} \\ k < 0 & \text{Corrupt act will be detected in } k \text{ quarters} \end{cases}$
- $\beta_{-8}, \beta_{-7} \dots \beta_0, \beta_1, \dots \beta_8$ coefficients of interest
- $\beta_{\geq 9}$ covers remainder of post period

Effect of Detection of Corrupt Acts on Lending: Branch Level



Effect of Detection of Corrupt Acts on Lending: Branch Level

Quarter		Quarter	
Quarter - 8	-0.06 (0.45)	Quarter + 1	-3.73 *** (0.45)
Quarter - 7	0.42 (0.45)	Quarter + 2	-2.04 *** (0.46)
Quarter - 6	2.06 *** (0.45)	Quarter + 3	-1.93 *** (0.46)
Quarter - 5	-0.12 (0.44)	Quarter + 4	-1.82 *** (0.47)
Quarter - 4	0.8 * (0.44)	Quarter + 5	-2.05 *** (0.48)
Quarter - 3	1.24 *** (0.44)	Quarter + 6	-1.9 *** (0.50)
Quarter - 2	0.17 (0.43)	Quarter + 7	-2.12 *** (0.51)
Quarter - 1	-0.14 (0.44)	Quarter + 8	-1.95 *** (0.52)
Fraud Detected	-1.36 *** (0.44)	Quarter > 8	-1.59 *** (0.21)

Fixed Effects:

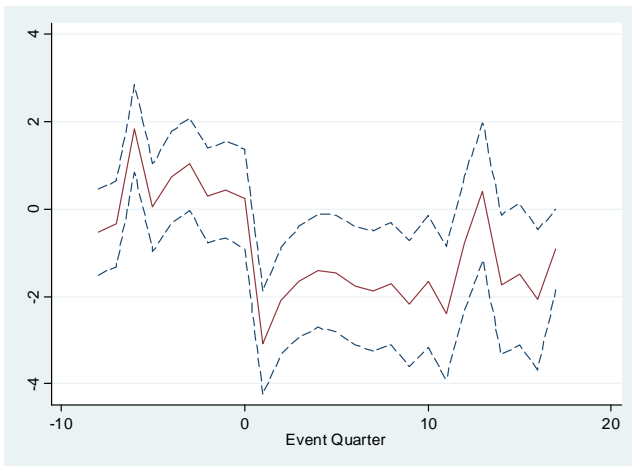
Quarter & Branch

Size of Effect:

- Average quarterly growth rate of credit approximately 3.5%
- One quarter after vigilance activity, no growth in credit
- Following two years, growth is reduced by 2/3rds, declining to 50%, relative to other branches
- Cumulative effect of 20% over two years
- Effect weakens after 11 or so quarters
- Not a mechanical effect: size of fraudulent loan small relative to size of lending in branch
- Conclusion: Vigilance activity has a sizeable effect on credit

Long-Run Effect of Vigilance Activity: Branch Level

Persistence of effect after 16 quarters



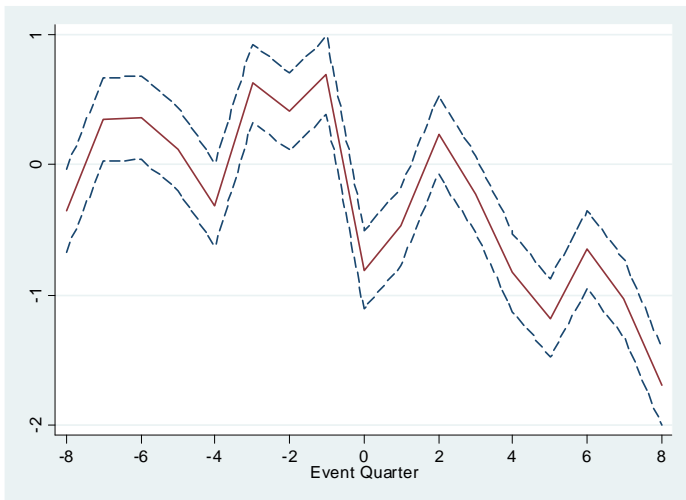
Effect of Detection of Corrupt Act on Lending

- Does other bank lending 'undo' the effect of vigilance activity?
- Reserve Bank of India "Credit Markets"
 - 20,000 of them
 - An area such that someone residing in the area could plausibly seek out a loan
 - Range in size from a small village, to all of Mumbai
- Analogous Identification Strategy

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

Credit Market Effect

Aggregate effect at credit-market



- Effect Persists
- Attenuated: 1/3-1/2 size as at branch level
- Not a simple mechanical effect of one-branch markets: average credit market in which a CVC action occurs has over 40 branches.
- Nevertheless, much is likely driven by own-branch effects, particularly in smaller markets.
- What is the effect on:
 - Other branches of the affected bank in an affected market?
 - Branches of non-affected banks in affected markets?

Effect on other Branches in Affected Market

Define a set of dummy variables prior to and following the vigilance activity:

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

So $\phi(\text{Branch})$ would be the set of dummy variables used previously to identify the effect at the branch, while $\phi(\text{banktown})$ would be a dummy set to 1 if any branch of that bank in that credit market were affected in that quarter, and finally $\phi(\text{town})$ would be set to 1 for all branches if any branch in that town in that quarter were affected.

The equation of interest is therefore:

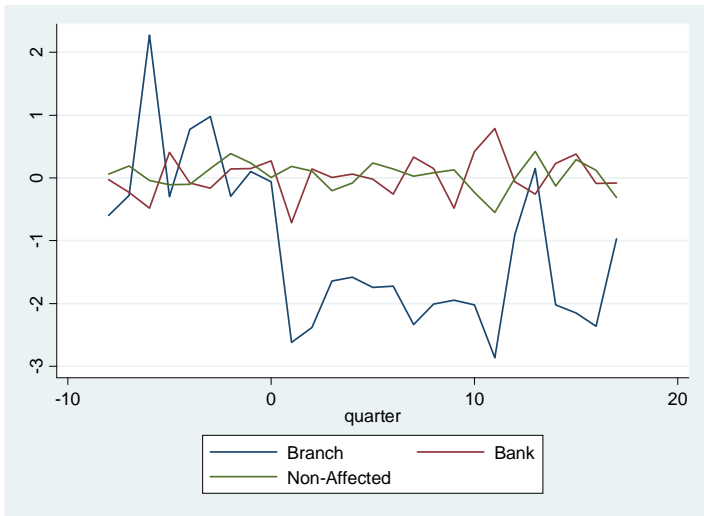
$$y_{obct} = \alpha_o + \phi(\text{branch}) + \phi(\text{banktown}) + \phi(\text{town}) + \gamma_t + \varepsilon_{obct}$$

(It identifies only off of credit markets that have more than one branch.)

Decomposing Effect of Vigilance Activity

Time Window	Affected branch	Non-affected branch of bank	Non-affected branch in same town
	(1)	(2)	(3)
Quarter - 2	(0.547)	(0.140)	(0.063)
	-0.291	0.141	0.385 ***
Quarter - 1	(0.560)	(0.142)	(0.063)
	0.097	0.147	0.237 ***
Fraud Detected	(0.571)	(0.143)	(0.063)
	-0.060	0.267 *	0.007
Quarter + 1	(0.592)	(0.148)	(0.064)
	-2.621 ***	-0.712 ***	0.180 ***
Quarter + 2	(0.605)	(0.151)	(0.063)
	-2.380 ***	0.136	0.110 *
Quarter + 3	(0.631)	(0.157)	(0.063)
	-1.642 **	0.011	-0.197 ***
	(0.650)	(0.159)	(0.064)

Decomposing Effect of Vigilance Activity



Decomposing Effect of Vigilance Activity

- Branch Effect Dominates
- Some Evidence of “Peer” Effect at other Branches of Same Bank
- Unaffected branches in same credit market appear unaffected
- No compensatory adjustment from other branches
- Will use aggregated credit, rather than branch-effect, in next version

Is this drop in lending good?

- Two Views:
- View 1: Lending was lax/corrupt, and vigilance activity caused them to avoid making bad loans, and thus cut back on lending in general
- View 2: Lending was efficient, and vigilance activity caused a reduction in lending to otherwise qualified borrowers

Two Problems

- Loan-level database is not a panel, do not know vintage of loans
- Do not understand process by which loans disappear from database

Replication with Annual Data

Two years prior to, and two years following, discovery of corrupt act

$$y_{ct} = \alpha_o + \sum_{k=-2}^2 \beta_k \theta_{o,t,k} + \beta_{\geq 2} \theta_{o,t,\geq 2} + \gamma_t + \varepsilon_{ct}$$

Replication with Annual Data

Two years prior to, and two years following, discovery of corrupt event

Time Window	Estimate
Year - 2	1.10 (1.03)
Year - 1	-0.22 (1.11)
Fraud Detected	-2.27 * (1.21)
Year + 1	-5.43 *** (1.38)
Year + 2	-6.00 *** (1.58)
Year >2	-6.67 *** (1.55)
R2	0.26
N	262401

Risk Appetite and Discovery of Corrupt Acts

Measure Riskiness of a Loan

Using data for all loans in India, identify riskiness of different industries (3 digit, approximately 300 codes).

Define the riskiness of lending to industry i as:

$$pLate_i = 100 * \frac{\text{Lending in Industry } i \text{ that is Late in 1992}}{\text{Lending in Industry } i \text{ in 1992}}$$

Define the risk appetite of the bank branch as the weighted sum of these measures:

$$branchrisk_{ot} = \sum_{i \in \text{Industries}} \frac{\text{Branch } o \text{ loans to Industry } i \text{ at time } t}{\text{Total Branch } o \text{ Lending at time } t} * pLate_i$$

Risk Appetite and Vigilance Activity

Same identification strategy. Regression is in *levels*:

Risk Appetite

Year - 2	-1.3 (2.42)
Year - 1	7.28 ** (3.43)
Fraud Detected	-2.12 (2.26)
Year + 1	-8.04 ** (3.91)
Year + 2	4.54 (3.06)
Year >2	-0.88 *** (0.12)
R2	0.48
N	398990

Risk Appetite and Vigilance Activity

- Apparent increased taste for risk prior to discovery of corruption
- Decrease in risk appetite following discovery
- May not be robust to adjusting standard errors

Vigilance Activity and Bad Loans

- Dataset gives an indicator variable indicating quality of loan
 - From 1-8 from 1992-1996
 - From 1-4 from 1997 onwards
- Quality of indicator suspect
- Code any loan whose rating is not 1 as 'bad'

Vigilance Activity and Bad Loans

How does vigilance activity affect the amount of bad credit?

$$\text{Share of Bad Credit} = \frac{\text{Amount of Bad Credit}}{\text{Amount of Total Credit}}$$

Time Window	Growth	Growth	Level
	Log Credit	Log Bad Credit	Share Bad Credit
	(1)	(2)	(3)
Year - 2	0.79 (0.92)	-0.45 (1.65)	1.74 ** (0.76)
Year - 1	-0.42 (0.97)	-0.98 (1.72)	1.96 ** (0.8)
Fraud Detected	-3.03 *** (1.03)	5.99 *** (1.88)	5.56 *** (0.87)
Year + 1	-4.66 *** (1.15)	-1.58 (2.05)	8.91 *** (0.96)
Year + 2	-5.33 *** (1.24)	4.09 * (2.18)	9.65 *** (1.06)
Year >2	-4.72 *** (1.09)	-0.75 (1.88)	9.51 *** (0.92)

Vigilance Activity and Bad Loans

How does vigilance activity affect the amount of bad credit?

- Reduces total credit lent by 13% and more
- Increase amount of bad credit by 6% in first year: no subsequent effect
- Sustained increase in level of bad credit
- Relative to other branches that expand credit, an affected branch cuts credit, but keeps close to the same level of defaulting loans

- Vigilance activity has a marked effect on lending
 - Two (three) different data sets yield same conclusion: vigilance activity leads to decreased lending
 - High-level punishments are followed by reduction in aggregate lending
 - Branch-level vigilance activity
 - Causes a drop of up to 20% in affected branch
 - Causes a decrease in lending in other branches of the same bank
 - May lead to less risk taking
- Most plausible interpretation (?) is that vigilance activity cuts down on 'good' loans
- "Contagion" effect necessary to reconcile branch- and bank-level effects

- Structural model of default
- Break down branch-level effect by:
 - Size of Fraud
 - Public vs. Private bank (but few private frauds)
 - Number of employees involved
- More refined spatial analysis
- Try to exploit term-information to get at vintage question
- Does vigilance activity affect reallocation of credit?
- Two Natural Experiments (Promising but difficult)
 - Introduction of Special Bank Vigilance Manual (ca. 2001)
 - Exemption of grade III and below loan officers from CVC purview (2004)

- Incentives for good lending decisions
- Improved enforcement:
 - Consider lending history
 - “Banking cell” to investigate corruptions by loan officers
 - Joint liability
 - Syndicated loans
- Three strikes rule?
- Alone, perhaps not sufficient:
 - Pay loan officers more
 - Privatize banks

Size of Fraud (Occurrence)	Overall	1980s	1990s	2000s
Rupees (000)	506.4	98.2	210.2	701.8
\$(000) (roughly)	14.5	2.8	6.0	20.1
Minimum	\$ 0	0	0	0
25th Percentile	\$ 94	102	112	90
Median	\$ 312	357	468	265
75th Percentile	\$ 1,314	1,247	1,748	1,104
Max	\$ 13,868,114	112,414	489,494	13,868,114