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Impact of Prudential Regulations for Unrated Exposures on the Rating Behaviour of Large Borrowers

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Unrated exposures can pose challenges in an accurate assessment of both the creditworthiness of borrowers and the capital levels in banks. The Reserve Bank modified the prudential regulatory guidelines in 2016 to plug the regulatory arbitrage in terms of risk weights between rated and unrated exposures above a specific threshold for the size of bank exposure to the borrower. Exploiting this exposure threshold in a regression discontinuity design, this study shows that the policy had a desired impact in discouraging a switch among the treated group of borrowers from the rated to the unrated category. In aggregate terms, the change in policy resulted in a 50 per cent decline in the treated borrowers' likelihood of switching from rated to unrated categories over quarters; this impact of the change in policy was significantly higher among borrowers of public sector banks than private sector banks.

1 Introduction

Credit ratings help banks in assessing the creditworthiness of their potential borrowers. Ratings are also a critical regulatory tool for estimating the capital charge against loan/investment exposures under the capital adequacy framework of the Basel Committee on Banking Supervision (BCBS). Under the Standardised Approach prescribed by the BCBS – currently followed by all Scheduled Commercial Banks (SCBs) in India – external ratings (given by accredited credit rating agencies) are used for the computation of capital for credit risk. In this context, the presence of unrated exposures can influence capital computation in banks given their opacity in providing information on the quality of such exposures.[1]

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[1] In the literature, unrated borrowers are associated with greater credit risk and less transparency, see Smith (2003) and Nini (2004).

Unrated borrowers account for about 60 per cent of the total number and 40 per cent of the total exposure of "large" borrowers (with funded and non-funded exposure in excess of Rs. 50 million) in the Central Repository of Information on Large Credits (CRILC) of the Reserve Bank (left panel, Figure 1), their share being distinctly higher in the case of private sector banks (PVBs) as compared to public sector banks (PSBs) (Figure 2). As unrated borrowers comprise a lower share in terms of the total exposure as compared to the number of borrowers, it indicates that borrowers with relatively small exposures are more likely to be unrated. The trend, however, is reversed when we examine the share of Non-Performing Assets (NPAs) within unrated borrowers. Between June 2014 (the first quarter for which CRILC data are available) and December 2015, the shares of (a) the number of NPA borrowers within the total number of unrated borrowers and (b) the amount of NPAs in the total amount of unrated exposures showed a comparable magnitude and trend (right panel, Figure 1). Post-December 2015, however, there has been a growing divergence in these two shares with the share of NPA amount in unrated exposures outpacing the share of non-performing borrowers. While the share of non-performing borrowers has stagnated in the range of 13-14 per cent, the share of NPA amount in unrated exposures has increased sharply to about 24 per cent by December 2018. Evidently, Figure 1 suggests that while the majority of unrated borrowers have small exposures, non-performing unrated borrowers are relatively large in size.

From a supervisory point of view, apart from the sheer large presence of unrated borrowers, the switch from the rated to unrated category can also be an issue of concern. For banks, there is a distinct advantage from a switch in terms of a lower capital charge if there is a regulatory arbitrage in terms of risk weights between the rated and unrated category. For borrowers too, a switch to the unrated category could be beneficial to avoid an impending downgrade.

The rated-to-unrated switch is commonly seen among large borrowers reported in CRILC. Within the subset of unrated non-performing borrowers in CRILC, about 79 per cent were unrated in the first quarter when they were reported as an NPA by their respective banks (Table 1). However, of these, about 54 per cent of the unrated non-performing borrowers were unrated throughout their period in CRILC prior to becoming an NPA, while about 25 per cent had a credit rating in at least one quarter prior to becoming an NPA but there was a switch to the unrated category in the subsequent period.

An important means to correctly assess the credit risks associated with unrated exposures and to ensure that a rated-to-unrated switch is not encouraged by banks for lower capital requirements, is to plug the regulatory arbitrage in risk weights between rated and unrated exposures, as was done by the Reserve Bank in August 2016. The prudential regulatory guidelines applicable to SCBs were modified raising the risk weight for claims on corporates, Asset Finance Companies (AFCs) and Non-Banking Financial Companies-Infrastructure Finance Companies (NBFC-IFCs) (having aggregate exposure from banking system of more than Rs. 1 billion) to 150 per cent if these exposures were rated earlier and subsequently became unrated. Furthermore, to encourage rating of banks' portfolios, the risk weight for all unrated claims on corporates, AFCs, NBFC-IFCs having aggregate exposure from banking system of more than Rs. 2 billion was also increased to 150 per cent. Thus, the weights were brought on par with those for the long-term claims on corporates having a rating of BB or below.[2]

The exposure threshold governing the policy, combined with the time dimension after which the policy became applicable, provides an appropriate research design to estimate whether the policy causally impacted the rating behaviour of borrowers, specifically, their switch from rated to unrated. The exposure threshold creates a clear counterfactual group - borrowers with systemic exposures of Rs. 1 billion and below - that remained unaffected by the policy, relative to borrowers with systemic exposures in excess of Rs. 1 billion who form the "treated" group. We exploit the presence of the exposure threshold in a regression discontinuity design (RDD) to study the impact of the policy within a narrow bandwidth around the threshold. The key assumption is that borrowers in a narrow bandwidth (taken as Rs. 100 million in this study) on either side of the Rs. 1 billion threshold are comparable in all aspects but a borrower with a systemic exposure of say, Rs. 1.03 billion is governed by this policy, while a borrower with an exposure of say, Rs. 0.98 billion is exempt from this policy. The RDD framework compares the outcomes for these two groups of borrowers. If borrowers in these two groups are comparable along most dimensions, then any change in outcomes in the aftermath of the policy intervention can be attributed solely to the policy.[3]

However, while the RDD presents a clean approach to evaluate the impact of the policy within a narrow bandwidth around the exposure threshold, its applicability reduces as one moves further away from the threshold. Thus, while a borrower with an exposure of say,

[2] See "Review of Prudential Norms Risk Weights for Exposures to Corporates, AFCs and NBFC-IFCs", dated August 25, 2016 at: https://rbi.org.in/Scripts/NotificationUser.aspx?Id=10569Mode=0 and Basel III Capital Regulations, March 31, 2016 at: https://rbidocs.rbi.org.in/rdocs/content/pdfs/58BS300685FL.pdf for a discussion on the risk weights for various rating categories.

[3] One potential concern with the Regression Discontinuity Design (RDD) in this scenario is that borrowers have private information regarding their growth in exposures and can attempt to evade the policy by switching to the unrated category prior to crossing the Rs. 1 billion threshold. If this is occurring, then we would expect a disproportionate increase in borrowers' switching from rated to unrated categories in the post-September 2016 period, for borrowers just below the Rs. 1 billion threshold. In a separate robustness check (not shown), we verify that borrowers just below the Rs. 1 billion threshold do not exhibit any differential rate of switching in the post-September 2016 period, ruling out this concern with the empirical strategy.

Rs. 0.98 billion may be arguably comparable along most dimensions with a borrower with an exposure of Rs. 1.02 billion, the same cannot be said for borrowers whose exposures are Rs. 0.7 billion and Rs. 1.4 billion. As these borrowers may differ along other dimensions, changes in outcomes may not be attributable solely to the policy. In this regard, the RDD estimates are valid only within a narrow bandwidth of the policy threshold, and uncovers a local area treatment effect (LATE), raising concerns about external validity of the research design. To address the concern of external validity, we also exploit the time variation in the policy's applicability and the presence of well-defined treatment and control groups in the spirit of a difference-in-difference (DiD) framework across all borrowers to estimate the causal impact of the policy on the rated-to-unrated switch. Under this strategy, we compare the change in outcome across the two groups of borrowers (exposures below and above Rs. 1 billion) in the aftermath of the policy, relative to the pre-intervention period.

2 Data and Empirical Strategy

The study is based on borrower-level data from CRILC covering 18 quarters (from June 2014 to September 2018). The long time horizon provides eight quarters each of pre-treatment and post-treatment data to evaluate the policy. We drop the June 2016 quarter from the pre-treatment period to preclude any concerns regarding borrowers' behaviour being affected by prior knowledge about the policy. The unit of observation in CRILC is borrower-bank. As the policy applied to borrowers' total exposures across the banking system, a given borrower's funded exposure across all banks has been aggregated (for a borrower with multi-banking relationships) to obtain his/her aggregate exposure to the banking system in a given quarter. Furthermore, exposures only of corporates, AFCs and NBFC-IFCs are considered for these calculations.

The presence of a sharp threshold for the policy's applicability permits causal identification through two distinct empirical strategies, as already noted. The first is a sharp RDD exploiting the exposure threshold of Rs. 1 billion. Under the plausible assumption that borrowers on either side of the threshold are comparable, the relative likelihood of borrowers switching from rated to unrated within a narrow bandwidth around the threshold is estimated.[4] If the policy is effective, we would expect a sharp drop in the likelihood of switching for borrowers located on the right hand side of the threshold.

To implement this approach, we first use a linear probability model to regress a binary

[4] We empirically verify this in Table 2 where we show balance on observables for borrowers located within Rs. 0.1 billion/Rs. 100 million bandwidth on each side of the policy threshold of Rs. 1 billion.

variable equaling 1 if the borrower switched from any rated category to the unrated category in a quarter on the borrower's asset category (including lags) (referring to NPA and Special Mention Account (SMA) status of the borrowers), a quadratic in exposures, and borrower-year, industry-quarter, bank and credit-rating fixed effects. We obtain the residuals from this specification, which provide the likelihood of a borrower switching from the rated to the unrated category, after partialling out observable borrower, bank and time characteristics. Subsequently, we obtain the average of this residual in each of 20 equally-spaced intervals of Rs. 0.01 billion in the range of Rs. 0.9 billion and Rs. 1.1 billion.

While the RDD exploits the exposure threshold to generate a causal treatment effect, it suffers from the disadvantage of capturing only the local average treatment effect (LATE), as noted earlier. The RDD estimate is valid only around the narrow bandwidth, calling into question the external validity of the design. To overcome the limitation, we combine the presence of clearly defined treatment and control groups in addition to the time variation in the policy's applicability in a DiD framework to identify the causal average effect of the policy, irrespective of the borrower's distance to the exposure threshold. This too is conditional on borrower-year, industry-quarter, bank and credit-rating fixed effects. Additionally, we also control for the borrowers' asset category status (including lags) and a quadratic in borrower exposures.

3 Results: Descriptive Analysis

Before discussing the results from the empirical exercise, we present some descriptive trends with respect to the likelihood of borrowers switching from rated to unrated.

1. Overall decline in the proportion of switching borrowers

Dividing borrowers based on their aggregate exposures into two categories based on the policy threshold of Rs. 1 billion, we see a decline over time in the (unconditional) likelihood of rated borrowers switching to being unrated in a given a quarter (Figure 3). There is, however, no specific differential trend discernible for borrowers with exposures above Rs. 1 billion in the immediate quarters following the policy (August 2016 - represented by the red line in Figure 3).

2. Decline in proportion of switching borrowers following the policy change

We compute the aggregate and the quarterly average likelihood of rated borrowers switching to the unrated category, across both the pre and post-treatment periods (in essence a naive unconditional DiD estimator).[5] Figure 4A presents the average likelihood of switching across quarters and shows that the quarterly unconditional DiD coefficient was 0.01, suggesting that the policy indeed reduced the switching behaviour for the treated borrowers.

3. Greater decline in proportion of switching borrowers for PSBs

As the treatment applied at the bank level, we would expect banks with lower capital to be more proactive in ensuring that the borrowers remain rated in the investment grade to avoid the additional capital requirements effected by the policy. As PSBs generally have lower capital ratios than PVBs, the likelihood of the switch was estimated separately for the two bank groups. The effect of the policy was stronger for PSBs as seen from Figure 4B. There was a decline in the likelihood for PVBs too (Figure 4C), but it occurred across both the treated and control groups of borrowers.

We compare the likelihood of borrowers' switching across the entire pre- and post-treatment period. The outcome of interest here is whether the borrower had switched at least once from the rated to unrated category across the entire pre-/post-treatment period, irrespective of the quarter of switching. The DiD estimate from this exercise was 0.04 (Figure 4D) and was again driven by PSBs (Figure 4E). Collectively, the descriptive trends indicate that the policy was effective in reducing the rated-to-unrated switch among borrowers.

4 Results: Econometric Analysis

We use a more rigorous test based on the RDD estimation to support the observations made using the naive DiD estimator discussed in the foregoing section. The residuals computed after partialling out observable borrower characteristics (including borrower-year fixed effects and credit rating fixed effects) and time-invariant factors (including bank and industry-quarter fixed effects) for 20 equally spaced exposure bins (of Rs. 0.01 billion) based on the systemic exposure of borrowers are plotted in Figure 5. Each circle represents the average conditional likelihood of borrowers switching from the rated to unrated category within that exposure interval. The line represents a linear fit and the shaded area is the 95 per cent confidence interval.

1. From Figure 5, we observe a distinct decline in the likelihood of switching in the

[5] The DiD estimate was worked out in the following manner:

$$\begin{aligned} DiD = {} & [\mathbb{E}[Switch, PostJun16|Exp > 1bil] - \mathbb{E}[Switch, PreJun16|Exp > 1bil]] \\ & - [\mathbb{E}[Switch, PostJun16|Exp < 1bil] - \mathbb{E}[Switch, PreJun16|Exp < 1bil]] \end{aligned} \tag{1}$$

where, *Switch* in (1) denotes the switching of borrowers from the rated to the unrated category.

post-treatment period. There is a sharp drop in the line depicting the linear fit suggesting that the likelihood of borrowers switching to the unrated category declined significantly in the aftermath of the policy.

2. A potential question of interest is whether the policy affected borrowers' behaviour immediately or was effective over a period of time. As seen from Figures 6 and 7, the policy had a limited impact on borrowers' switching in September 2016 – the quarter in which the policy was implemented – but had a negative impact on borrowers' switching behaviour within one year of its inception.

3. Similar to the findings based on the naive DiD estimator, the RDD estimation also showed that the policy was more effective for PSBs than PVBs (Figures 8 and 9). This result, however, needs to be interpreted in light of the descriptive statistics discussed in Figure 4 where we see that the propensity of borrowers to switch from the rated to the unrated category was higher in PSBs. Thus, while PSBs are generally capital-constrained and therefore, may be more affected by the increased capital requirements, which could serve as an incentive for them to nudge their borrowers to alter the rating behaviour, they also had a higher scope of catching up given the greater prevalence of borrowers switching to the unrated category in these banks relative to PVBs in the pre-policy period.

A DiD specification is used taking the full sample of borrowers to estimate the causal impact of the policy on the likelihood of borrowers' switching based on a well-defined counterfactual group (of borrowers with total exposure of Rs. 1 billion and below, which were unaffected by the policy) and the time variation in the policy's applicability (before and after the September 2016 quarter).

The first column in Table 3 excludes all borrower-specific covariates (but includes borrower-year, bank, industry-quarter and credit-rating fixed effects) and shows that the policy resulted in a 50 per cent decline in borrowers' likelihood of switching to the unrated category.[6] Column (2) shows that the addition of borrower-specific covariates does not affect either the coefficient size or its precision.[7] As the treatment effect is estimated across all the eight post-treatment quarters, it shows that the policy had a persistent effect in reducing borrowers' likelihood of switching over the long-term.

Column (3) estimates the specification using data only between June 2015 and September 2017 and shows that the policy had an impact within one year of its implementation. Finally, to test if the policy had a differential impact across PSBs and PVBs, a triple difference is

[6] This was calculated by comparing the coefficient relative to the mean likelihood of switching across the entire period (0.04/0.08).

[7] Borrower-specific covariates include dummies for the asset category of the borrower (including four lags) and lagged funded amount outstanding from the respective bank (including four lags).

estimated in column (4). The results show that the treatment was more effective for PSBs, consistent with Figure 8. While the direct effect of the treatment is negative, suggesting that borrowers with exposures in excess of Rs. 1 billion in PVBs also exhibited a lower likelihood of switching after the policy, the triple interaction coefficient was also negative and statistically significant, suggesting that the treatment had a larger impact on PSB borrowers.

In summary, the results show that the policy intervention had an economically and statistically significant impact on borrowers' likelihood of switching from the rated to unrated category. In economic terms, the likelihood of switching for borrowers in excess of Rs. 1 billion declined from 8 out of 100 rated borrowers, to 4 out of 100 rated borrowers, with the effects being driven by PSBs. Importantly, the effects of the policy were persistent over time and were visible even after about two years from the policy.

5 Conclusions

Given the extensive use of credit ratings in the assessment of capital adequacy in banks, the presence of unrated exposures can create information barriers for banks as well as the supervisor. Given the prevalence of large unrated exposures in the banking system, the policy measure of the Reserve Bank of raising the risk weights for such exposures was a step towards plugging the possible regulatory arbitrage and encouraging banks to have rated exposures. As shown in the study, the policy has had a desired impact in discouraging a switch from the rated to the unrated category among large borrowers. The effect was evident for both PSBs and PVBs and was distinctly higher for the former.

The Reserve Bank's decision to increase the risk weight for unrated exposures marked a deviation from the prevailing BCBS guidance.[8] The decision could even be regarded as farsighted, since the BCBS too has suggested revisions in the Standardised approach for credit risk and has recalibrated the risk weight for unrated exposures later in 2017.[9]

While the increase in risk weight has been an apt one-time regulatory measure, there is a need for continuous monitoring of unrated large exposures by banks using information

[8] The BCBS prescribes a risk weight of 100 per cent for unrated exposures (BCBS, 2017). In fact, the BCBS guidance on unrated exposures has been dubbed as "controversial" in the literature and studies have argued that they do not find any "economic or statistical" rationale for the guidance, see Altman *et al.* (2002).

[9] It has recommended a division of the unrated exposures into three grades (A, B and C) based on the repayment capacity of the borrower; Grade C signified exposures with materialised default risk for the bank with a revised risk weight of 150 per cent (equal to the risk weight for an external rating below B-). The date for implementation of the revised Standardised approach for credit risk has been specified as January 1, 2022 (BCBS, 2017).

gathered from market sources and the history of bank-borrower relationship. Also, banks cannot lose sight of the fact that external ratings cannot be a substitute for their internal due diligence on a borrower's credit quality.

6 References

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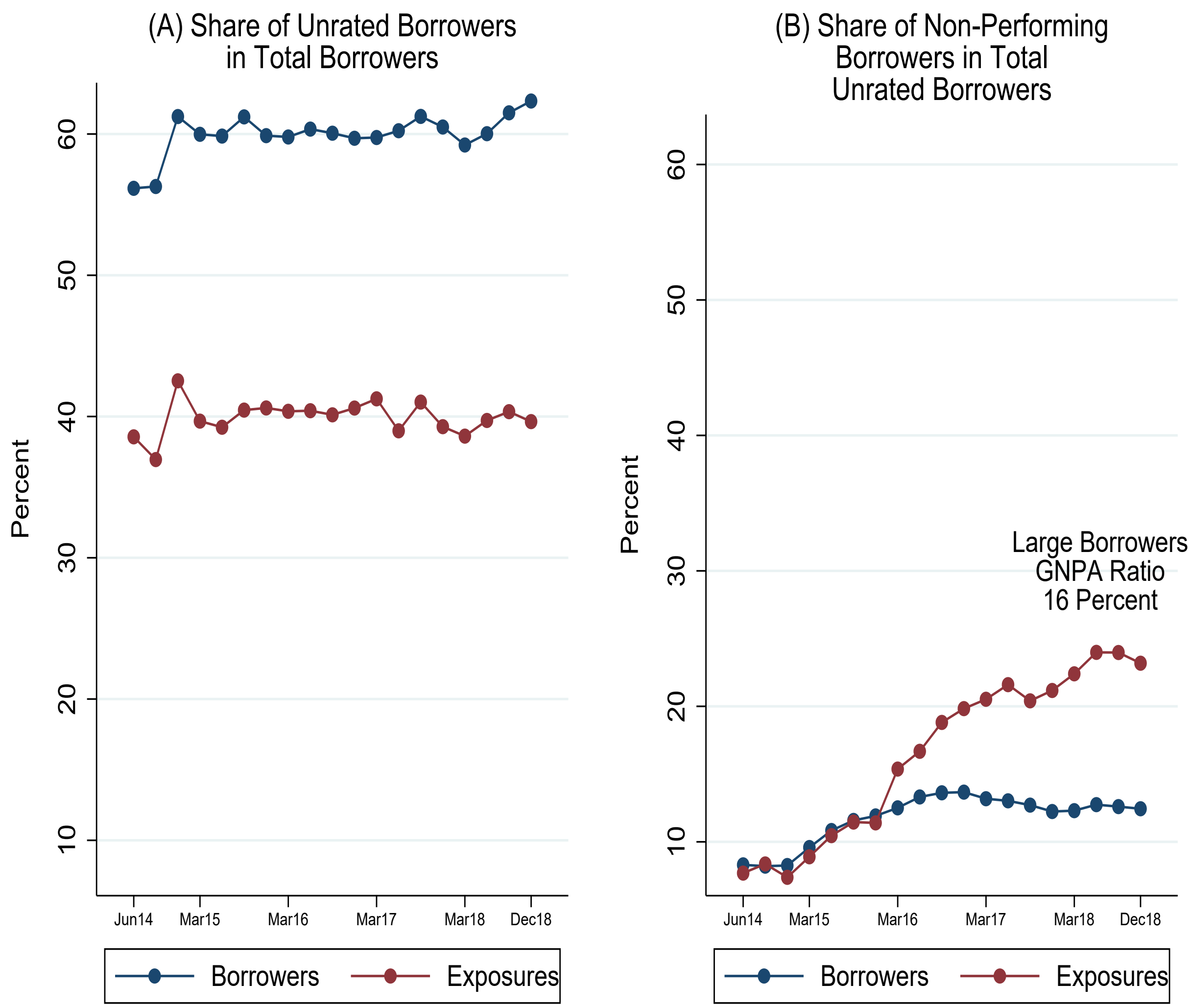
BCBS (2017). "High-level summary of Basel III Reforms." Available for download at https://www.bis.org/bcbs/publ/d424-hlsummary.pdf

Nini, G. (2004). "The Role of Local Banks in Promoting External Finance: A Study of Syndicated Lending to Emerging Market Borrowers." CGFS Working Group on Financial Sector FDI.

Smith, D. (2003). "Loans to Japanese borrowers." *Journal of Japanese and International Economics*. 17.

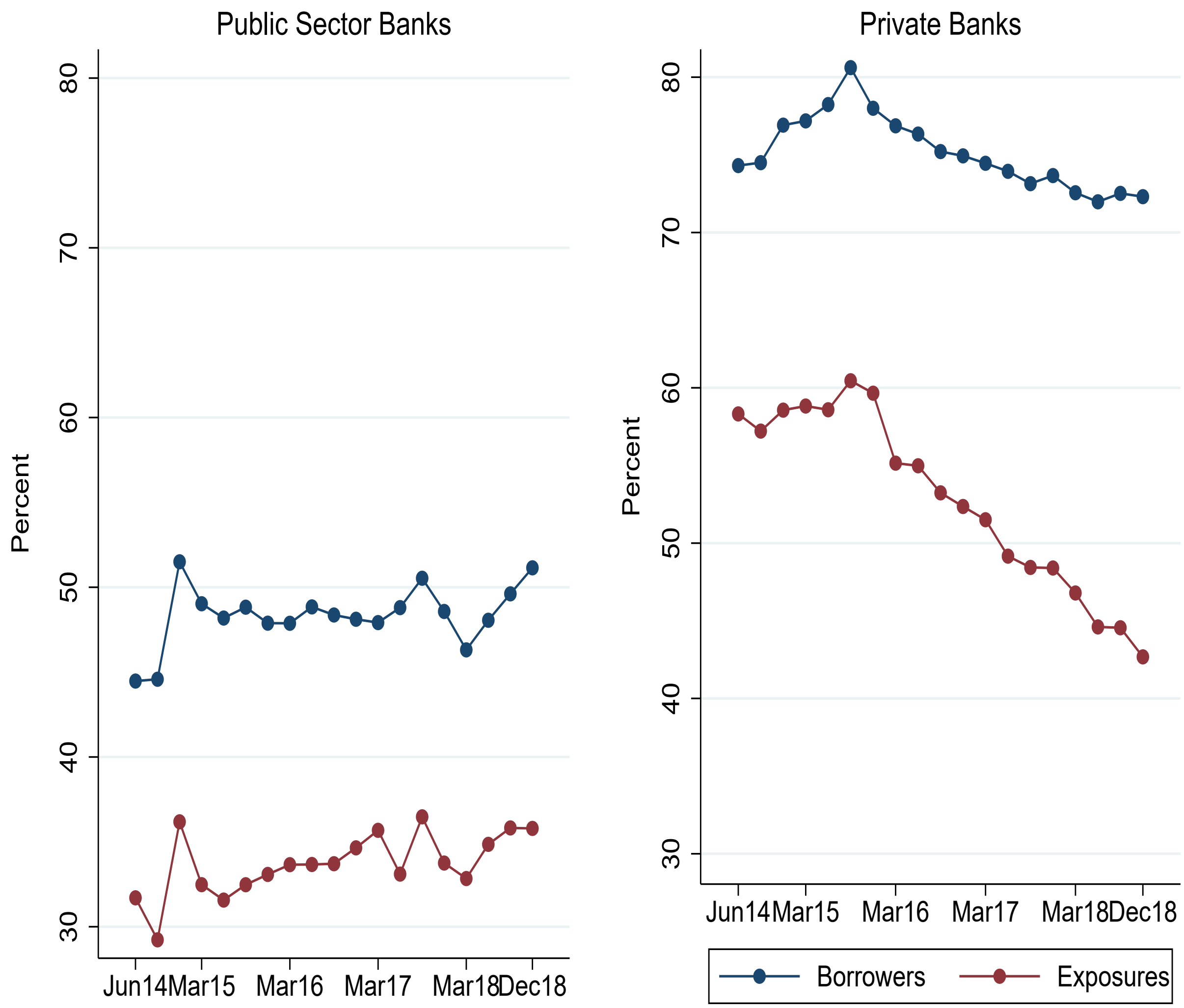
7 Figures

Figure 1: Quarterly Trends in Share of Unrated Borrowers and Gross NPA Ratio for Unrated Borrowers



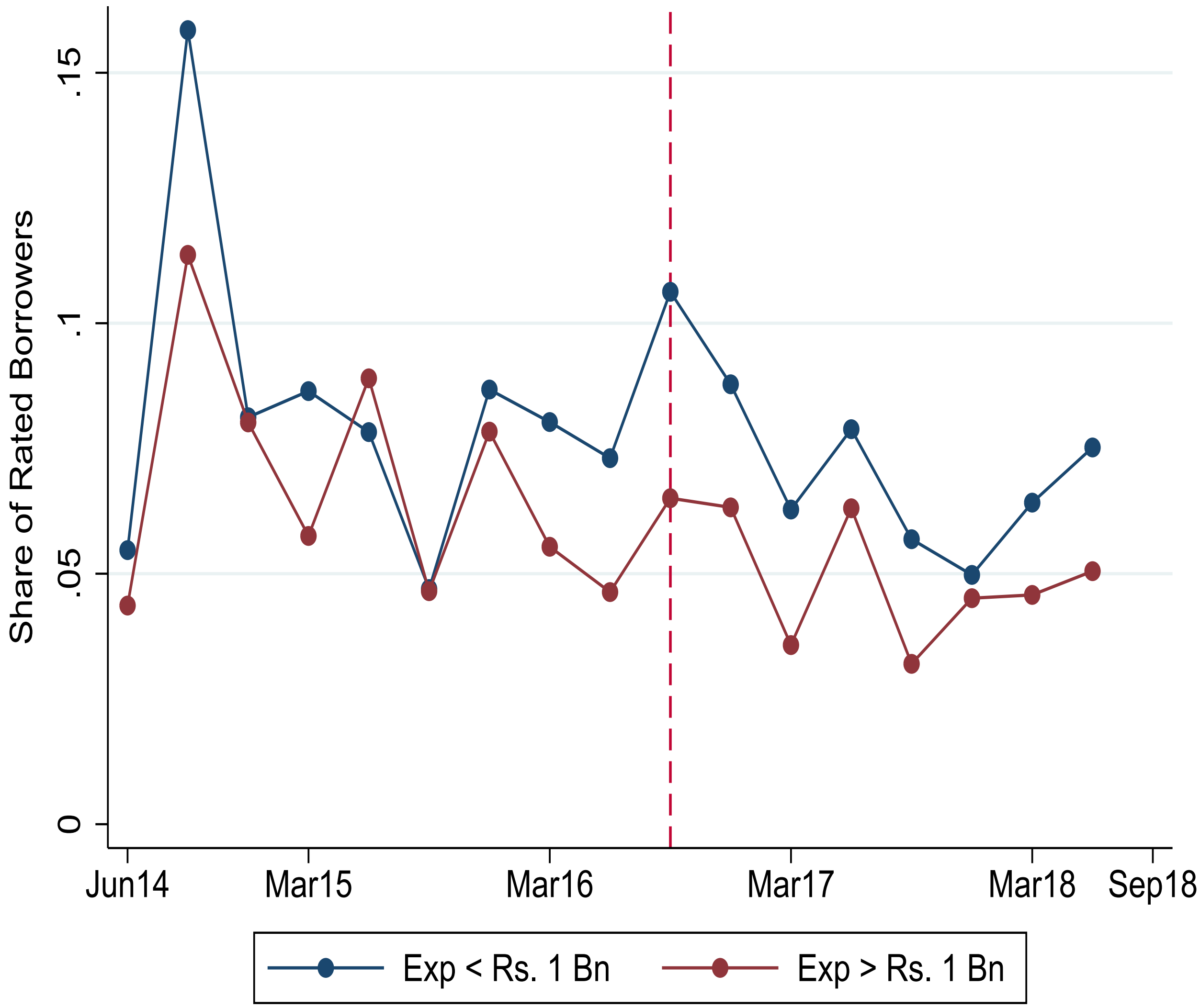
Note: This figure shows aggregate quarterly trends for unrated borrowers. The left panel shows the quarterly share of unrated borrowers in the database, both as per cent of total borrowers and total exposures. The right panel restricts the sample to unrated non-performing borrowers/exposure and computes their share in total unrated borrowers/exposure.
Source: Calculated using CRILC data.

Figure 2: Quarterly Trends in Share of Unrated Borrowers for Public and Private Sector Banks



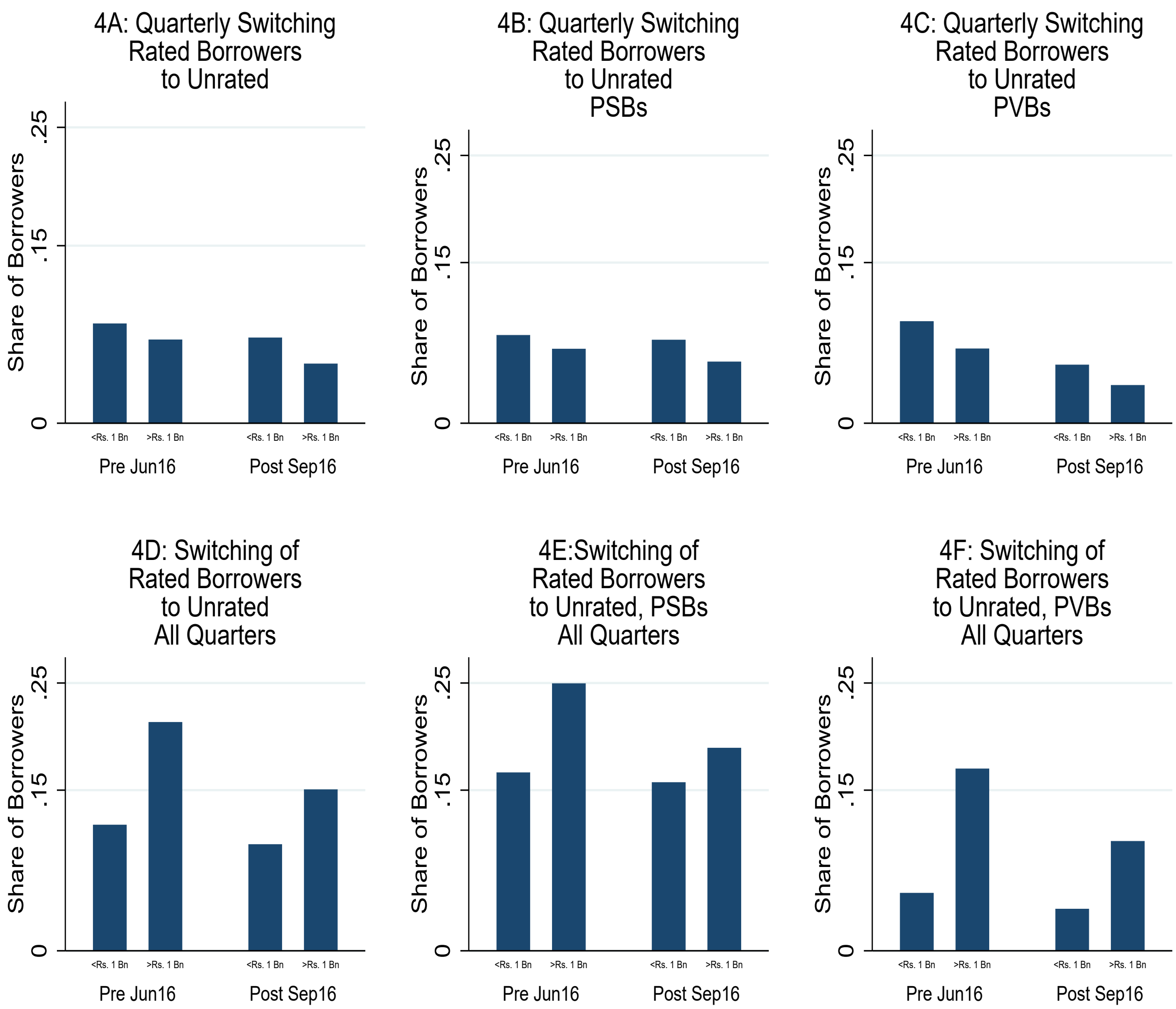
Notes: This figure plots the quarterly trends in the number and exposure of unrated borrowers across public and private sector banks.
Source: Calculated using CRILC data.

Figure 3: Quarterly trends in Rated-to-Unrated Switching Across the Policy Threshold



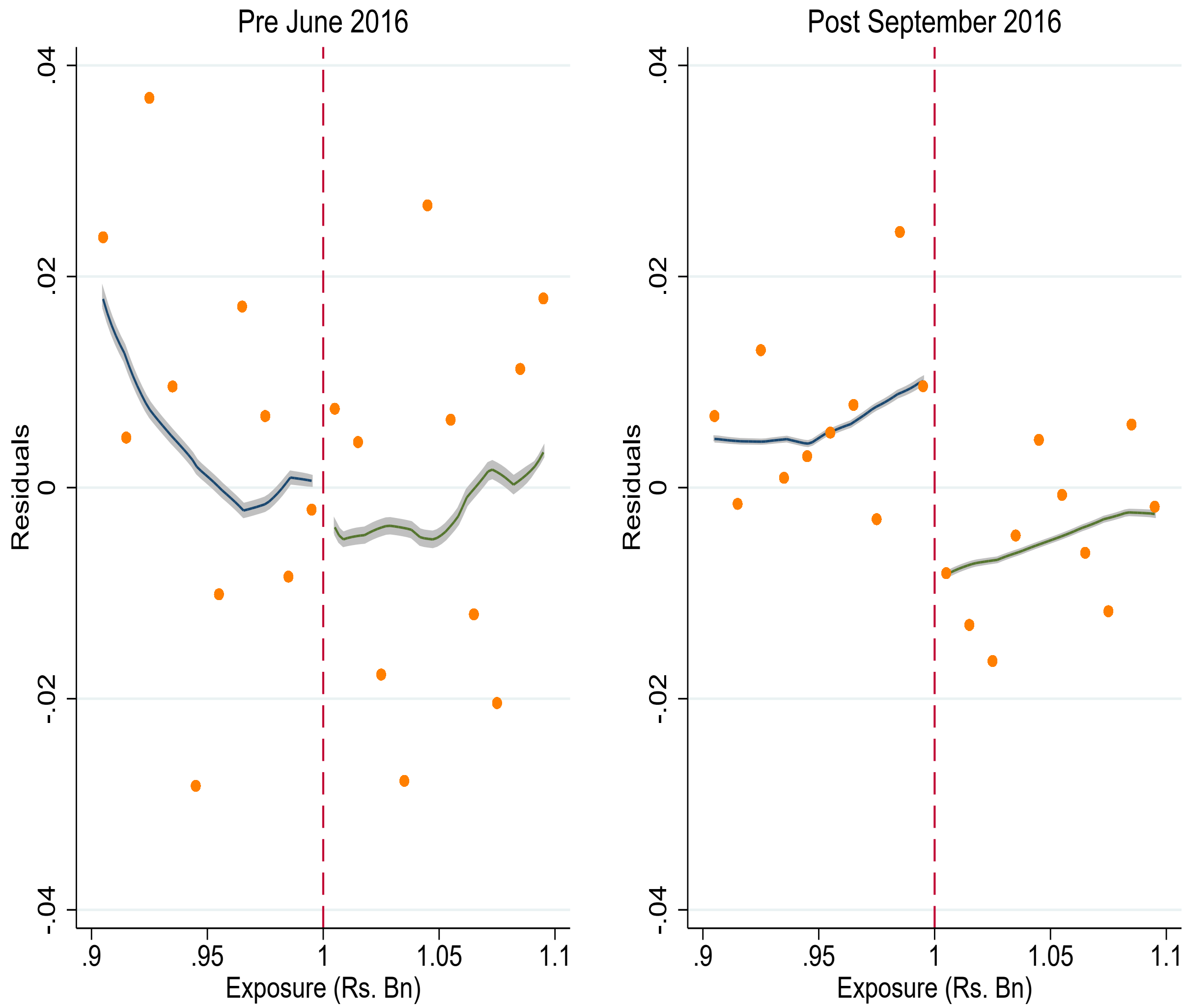
Notes: This figure plots the quarterly trends in borrowers' switching from the rated to unrated category. Each circle in the figure corresponds to the share of rated borrowers who have switched to the unrated category in that quarter. The red line depicts the onset of the policy raising the risk weight for borrowers in excess of Rs. 1 billion who switched from rated to unrated.
Source: Calculated using CRILC data.

Figure 4: Quarterly and Aggregate Difference-in-Difference Estimator across Bank Groups



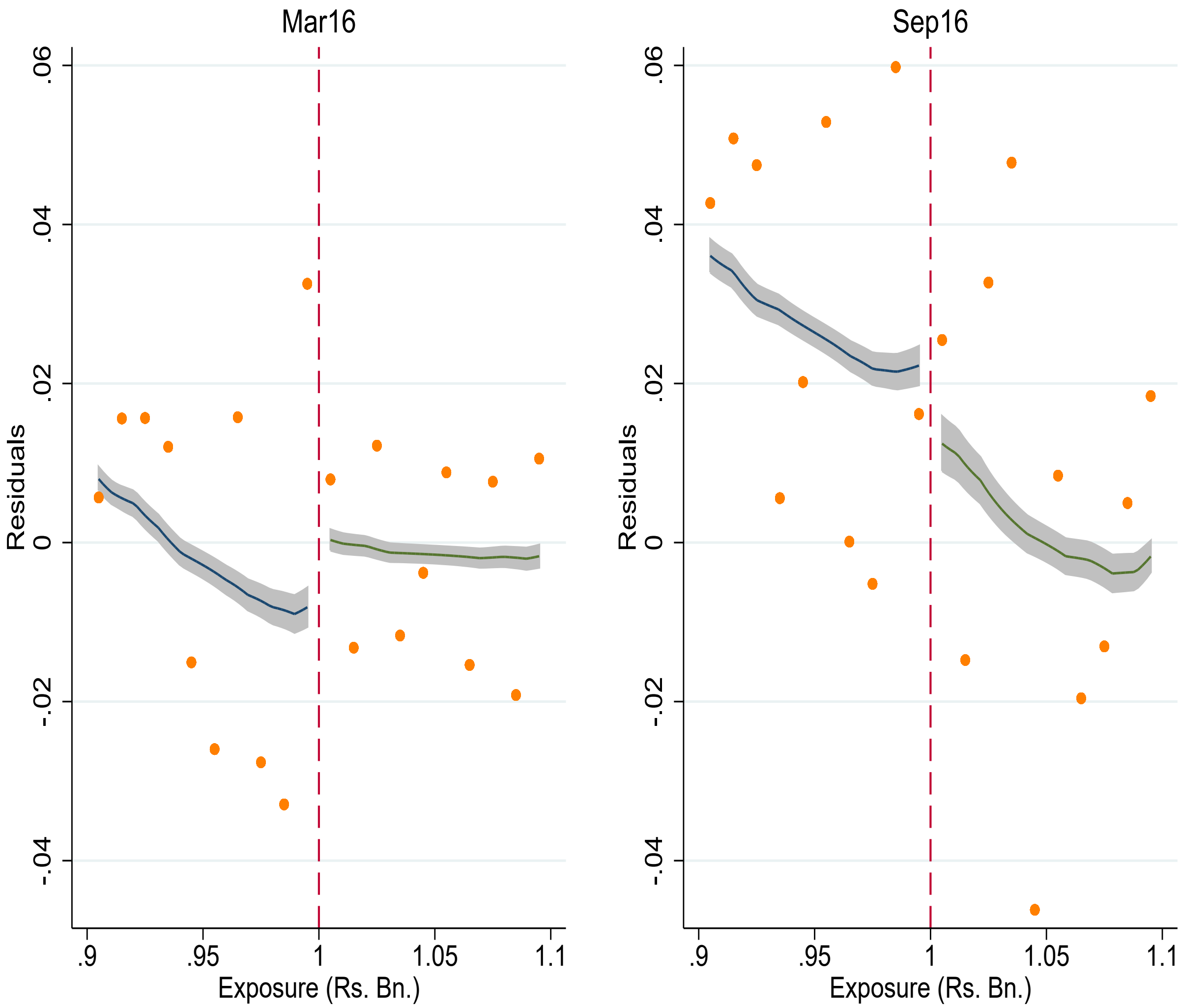
Notes: The above bar graphs compute the unconditional difference-in-difference (DiD) estimator based on the policy's timing and the treated (borrowers with exposures exceeding Rs. 1 billion) and control (borrowers with exposures of Rs. 1 billion and below) groups established by the policy. The DiD estimates are also calculated separately for bank groups. The top panel shows the average quarterly likelihood of borrowers switching from rated to unrated. The bottom panel calculates the aggregate likelihood of borrowers switching from the rated to the unrated category, irrespective of the quarter.
Source: Calculated using CRILC data.

Figure 5: Likelihood of Borrower's Switching from the Rated to Unrated Category: Aggregate RDD estimate



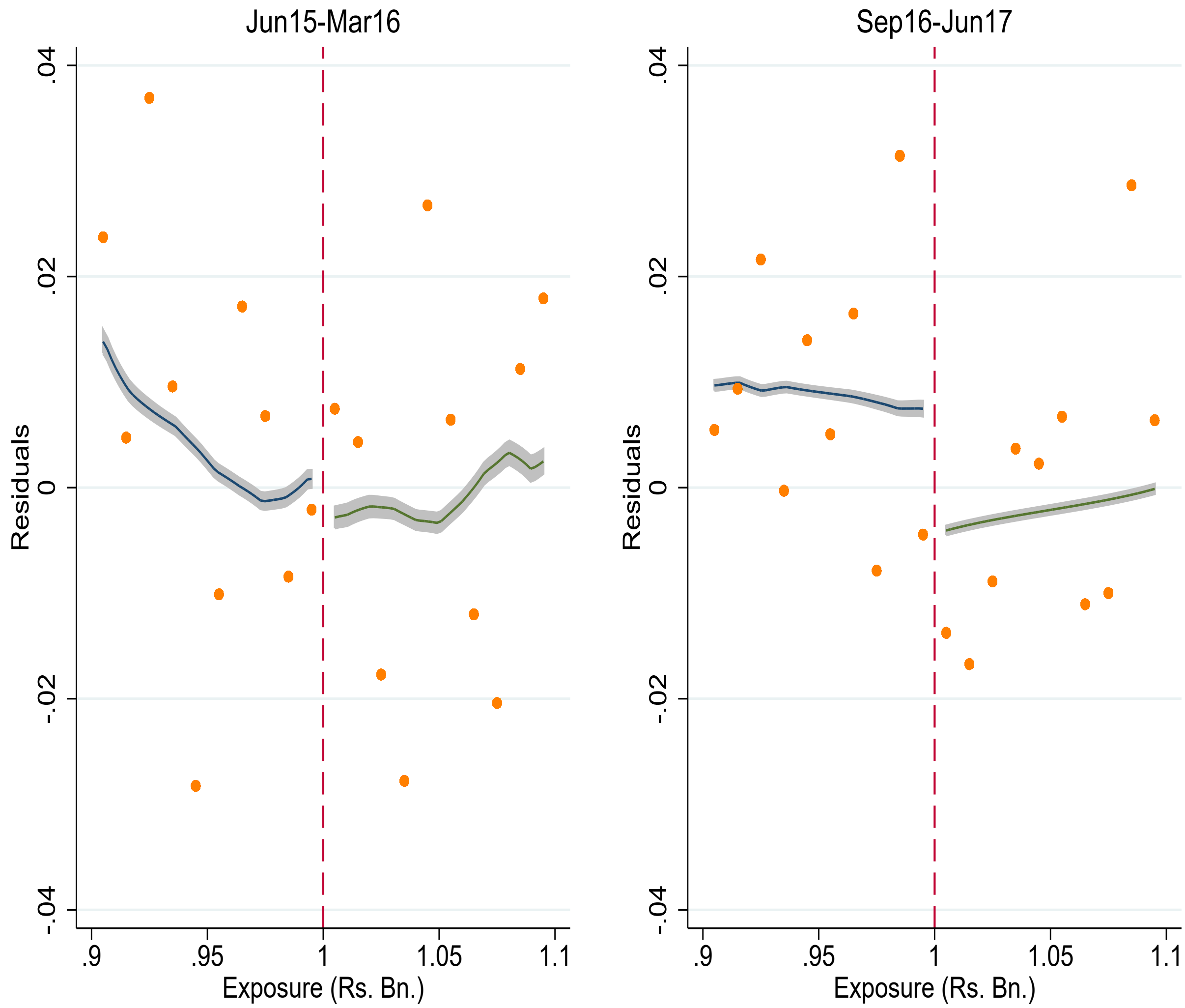
Note: This figure presents the regression discontinuity estimate of the likelihood of borrowers' switching in response to the policy within Rs. 0.1 billion bandwidth around the threshold of Rs. 1 billion. The x-axis is divided in 20 equally spaced bins of Rs. 0.01 billion based on the systemic exposure of borrowers. Each circle represents the average conditional likelihood of borrowers switching from rated to unrated, for borrowers with total exposures corresponding to that bin. The line represents a linear fit and the shaded area is the 95 per cent confidence interval. The left hand panel shows the pre-policy period; the right hand panel shows the post-policy period.
Source: Calculated using CRILC data.

Figure 6: Likelihood of Borrower's Switching from the Rated to Unrated Category - 1 Quarter Effect of the Policy: RDD Estimate



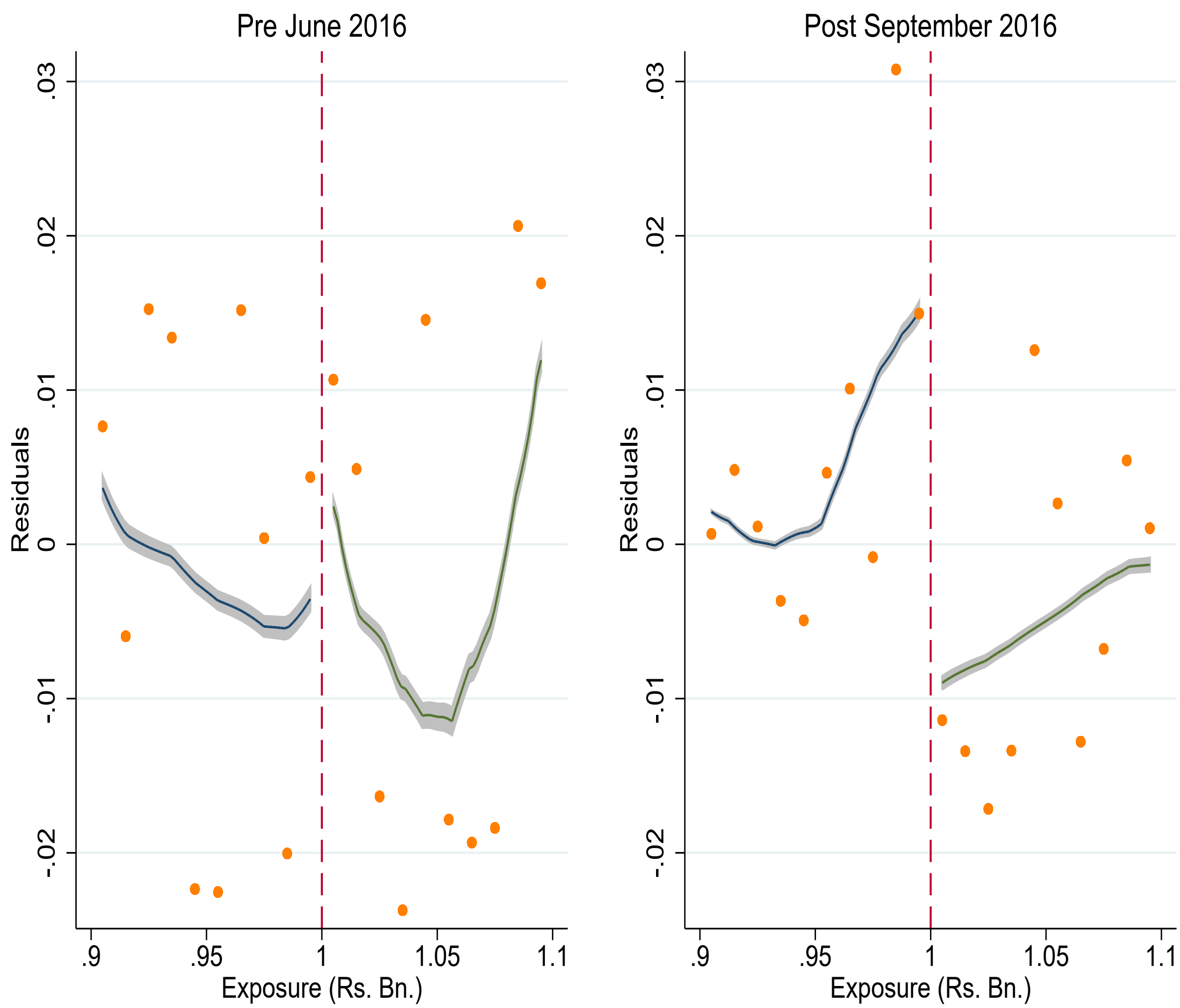
Note: This figure presents the short-run regression discontinuity estimate of the likelihood of borrowers' switching in response to the policy within Rs. 0.1 billion bandwidth around the threshold of Rs. 1 billion. The x-axis is divided in 20 equally spaced bins of Rs. 0.01 billion based on the systemic exposure of borrowers. Each circle represents the average conditional likelihood of borrowers switching from rated to unrated, for borrowers with total exposures corresponding to that bin. The line represents a linear fit and the shaded area is the 95 per cent confidence interval. The left hand panel restricts the sample to the March 2016 quarter (2 quarters before the policy); the right hand panel restricts the sample to September 2016 - the quarter the policy was implemented.
Source: Calculated using CRILC data.

Figure 7: Likelihood of Borrower's Switching from the Rated to Unrated Category - 1 Year Effect of Policy: RDD Estimate



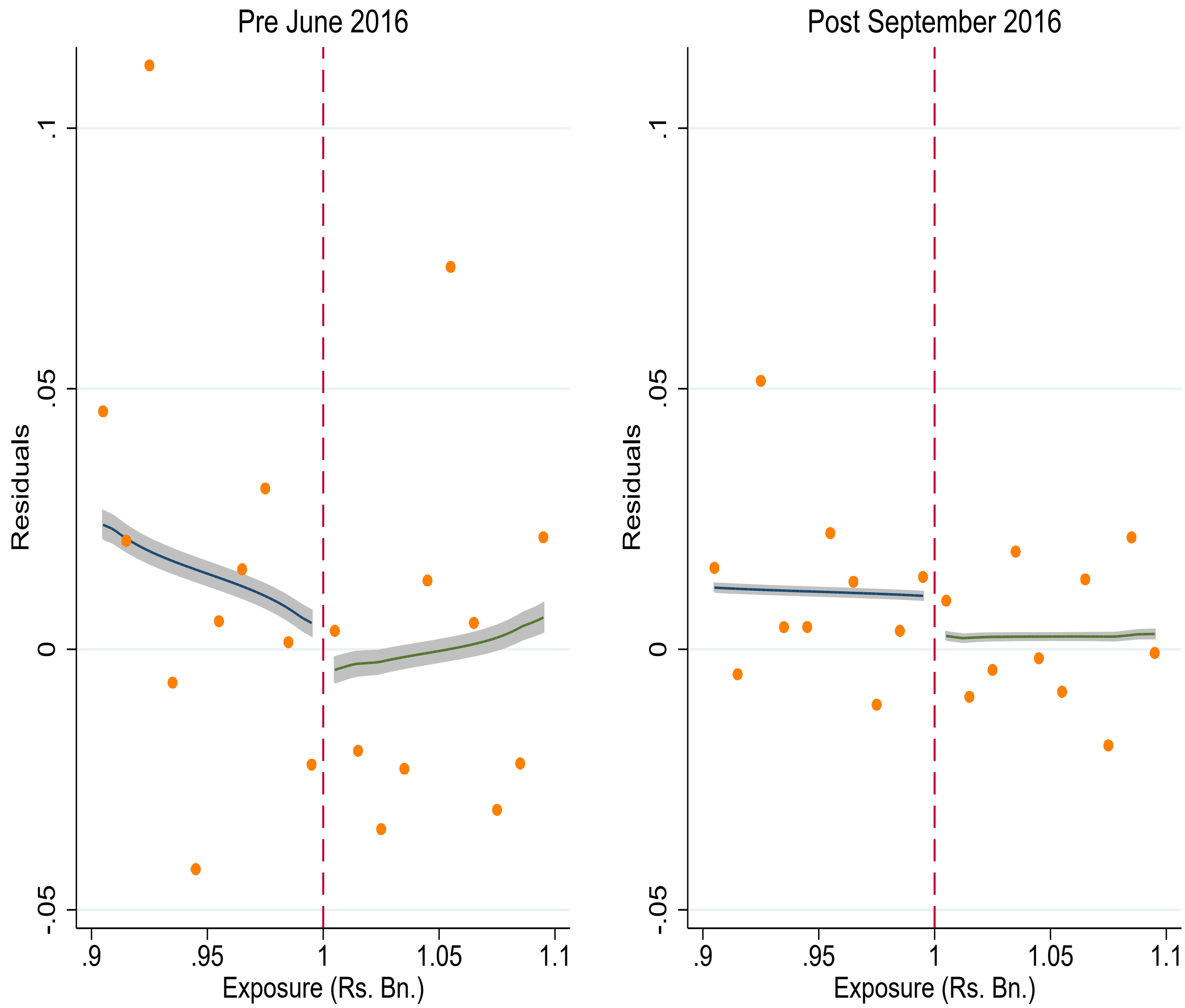
Note: This figure presents the medium-term regression discontinuity estimate of the likelihood of borrowers' switching in response to the policy within Rs. 0.1 billion bandwidth around the threshold of Rs. 1 billion. The x-axis is divided in 20 equally spaced bins of Rs. 0.01 billion based on the systemic exposure of borrowers. Each circle represents the average conditional likelihood of borrowers switching from rated to unrated, for borrowers with total exposures corresponding to that bin. The line represents a linear fit and the shaded area is the 95 per cent confidence interval. The left hand panel restricts the sample to four quarters prior to the policy; the right hand panel restricts the sample to four quarters after the policy.
Source: Calculated using CRILC data.

Figure 8: Likelihood of Borrower's Switching from the Rated to Unrated Category - Public Sector Banks: RDD Estimate



Note: This figure presents the regression discontinuity estimate of the likelihood of borrowers' switching in response to the policy within Rs. 0.1 billion bandwidth around the threshold of Rs. 1 billion. The x-axis is divided in 20 equally spaced bins of Rs. 0.01 billion based on the systemic exposure of borrowers. Each circle represents the average conditional likelihood of borrowers switching from rated to unrated, for borrowers with total exposures corresponding to that bin. The line represents a linear fit and the shaded area is the 95 per cent confidence interval. The left hand panel shows the pre-policy period; the right hand panel shows the post-policy period. The sample is restricted to borrowers in public sector banks.
Source: Calculated using CRILC data.

Figure 9: Likelihood of Borrower's Switching from the Rated to Unrated Category - Private Sector Banks: RDD Estimate



Note: This figure presents the regression discontinuity estimate of the likelihood of borrowers' switching in response to the policy within Rs. 0.1 billion bandwidth around the threshold of Rs. 1 billion. The x-axis is divided in 20 equally spaced bins of Rs. 0.01 billion based on the systemic exposure of borrowers. Each circle represents the average conditional likelihood of borrowers switching from rated to unrated, for borrowers with total exposures corresponding to that bin. The line represents a linear fit and the shaded area is the 95 per cent confidence interval. The left hand panel shows the pre-policy period; the right hand panel shows the post-policy period. The sample is restricted to borrowers in private sector banks.
Source: Calculated using CRILC data.

8 Tables

Table 1: Unrated Borrower's Rating at the time they were first reported as NPA and Best Rating Pre-NPA

	Investment Grade	**Sub-Investment Grade**	**Unrated**
Rating when first reported as NPA	3.88	17.03	79.09
Best Rating Prior to Becoming NPA	16.00	30.09	53.91

Note: This table presents the share of unrated borrowers by rating categories in the quarter in which they were first reported as an NPA by the bank, and the best rating of the borrowers in the bank, prior to being reported as NPA. The sample is restricted to borrowers who are unrated and NPAs.

Table 2: Borrower-Level Covariate Balance Across Rs. 1 billion Threshold

	< Rs. 1 Bn	**> Rs. 1 Bn**	**Significance**
Likelihood of Borrowing from Public Sector Bank	0.545	0.547	No
Likelihood of Being NPA	0.112	0.106	No
Likelihood of Being SMA0	0.035	0.035	No
Likelihood of Being SMA1	0.026	0.023	No
Likelihood of Being SMA2	0.046	0.042	No
Likelihood that Borrower is in Agriculture	0.014	0.014	No
Likelihood that Borrower is in Industries	0.562	0.548	No
Likelihood that Borrower is in Services	0.331	0.321	No

Note: This table presents a test of covariate balance for borrowers within Rs. 0.1 billion bandwidth on either side of the Rs. 1 billion exposure threshold.

Table 3: Borrower Switching Across Rating Categories - Differential Effects by Public Sector Banks

	(1) Pr(Switch) Unrated	(2) Pr(Switch) Unrated	(3) Pr(Switch) Unrated	(4) Pr(Switch) Unrated
Post*Exp > 1	-.040***	-.045***	-.047***	-.032***
	(.003)	(.003)	(.004)	(.005)
PSB*Exp > 1				.011**
				(.005)
Post*PSB				.034***
				(.005)
Post*PSB*Exp > 1				-.014**
				(.006)
Post	.048***	.065***	.060***	.038***
	(.002)	(.003)	(.003)	(.004)
Exp > 1	.012***	.021***	.015***	.011**
	(.003)	(.004)	(.005)	(.006)
PSB				-.237
				(.157)
Observations	585462	385169	284427	385169
R^2	.37	.38	.43	.38
Dep Var Mean	.08	.08	.07	.09

This table presents the results estimating whether the policy affected the quarterly switching of borrowers from the rated to the unrated category. The unit of observation is borrower-bank. *Post* is a dummy equaling 1 for all quarters after June 2016. *Exp > 1* is a dummy equaling 1 for borrowers with total systemic exposures in excess of Rs. 1 billion. *PSB* is a dummy equaling 1 if the borrowers is banking with a public sector bank. All specifications include borrower-year, industry-quarter, bank and credit rating fixed effects and a quadratic in total systemic exposure of the borrower. Column (2)-(4) include four lags of the borrower's asset category and four lags of funded exposures. Column (3) restricts the sample to June 2015 to September 2017. Standard errors are clustered at the level of the borrower. The sample is restricted to rated borrowers.