# Do Firms Have A Preference Order While Repaying Lenders? Relationship vs Transaction Banking

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**Abstract**

Do firms prefer repaying a relationship lender over a transaction lender or vice versa? It is unclear whether a shock to aggregate default in the economy would show a higher default rate towards the informed relationship lenders or the uninformed arm's length lenders? A difference in differences analysis shows that firms are more likely to default on relationship lenders compared to arm's length lenders. Firms default even more on relationship lenders that have helped the firm in the past, indicating that relationship banking may create a soft budget constraint. This effect is observed for under-capitalized and well-capitalized banks, and also for both public and private lenders. The findings are robust to alternate definitions of relationship banking and controlling for the outstanding loan amount.

Keywords: Information Asymmetry, Zombie Lending, Regulatory Forbearance, Lender Pecking Order

**JEL Codes: D22, G21, G33**

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# 1 Introduction

The financial economics literature has extensively examined the pros and cons of relationship banking. The bright side of relationship banking is that it reduces information asymmetry between the bank and the borrowing firm (Boot (2000)), which helps the bank mitigate risk and increase lending (Petersen and Rajan (1994), Bharath, Dahiya, Saunders, and Srinivasan (2011)). The dark side of relationship banking is that it can lead to the continuation of credit flow towards undeserving firms (Dewatripont and Maskin (1995), Hu and Varas (2021), Acharya, Borchert, Jager, and Steffen (2020), Caballero, Hoshi, and Kashyap (2008)).

An understudied aspect of firm-bank relationships is the preference of a firm in repaying a relationship bank *vis-à-vis* a transaction bank. A firm can simultaneously borrow from a relationship bank as well as a transaction bank. In such a setting, the firm's strategic behavior towards these two types of banking arrangements becomes important. This paper examines how a firm's repayment behavior differs towards these two types of lenders. Whether a firm that finds itself in a position to repay only one out of the two running loans will repay the relationship lender or the transaction lender?

As the relationship lender knows the true quality of a borrower, it will roll over a loan only if the struggling firm's chances of recovery are genuine. A strong banking relationship signals low default rate (Bolton, Freixas, Gambacorta, and Mistrulli (2016), Herpfer (2020)). On the other hand, theory (Dewatripont and Maskin (1995), Hu and Varas (2021)) suggests that sometimes relationship banks have incentives to roll over bad loans, or in other words, perform zombie lending.[1] Suppose a firm with two loans, one from a transaction bank and the other from a relationship bank, is in distress and has to default on one of the two loans. It is unclear whether the firm will default on the transaction lender or the relationship lender?

An apt empirical setting to answer this question would be a period of a forbearing banking regulator, followed by a period when the regulator turns vigilant. The first period would allow banks greater discretion in choosing whether to roll over a loan. Relationship lenders

[1] Acharya, Borchert, Jager, and Steffen (2020), Caballero, Hoshi, and Kashyap (2008)

can utilize their information advantage to liquidate bad loans and extend lending to firms with a genuine chance of recovery. In the following period, the strict regulator would force the banks to disclose the true quality of their loan books (Agarwal, Lucca, Seru, and Trebbi (2014)). Then we can observe whether firms have different preferences towards repaying the two types of lenders.

For identification, I use the credit market in India, which saw a drastic change in the regulator's stance from forbearing to vigilant around 2015. Starting in 2008, India's banking regulator, the Reserve Bank of India (RBI), provided regulatory forbearance on asset classification of restructured loan accounts to cushion the economy against the global financial crisis. Banks were allowed to retain asset classification upon loan restructuring, which would have led to a downgrade of such loan accounts in the absence of the forbearance scheme. Thus, the banks could show a healthy loan book and be saved from providing additional risk capital. Regulatory forbearance was withdrawn in the year 2015 as the economy had stabilized by then. It was followed by an Asset Quality Review (AQR) of unprecedented scale, which continued in the following years.[2] I consider 2008-14 as the period of the forbearing regulator, and 2015-19 as the period of the vigilant regulator.

I use secured corporate loans data collected from the website of the Ministry of Corporate Affairs, Government of India, for approximately 25,000 firms and 376 lenders between 2008 and 2019. The loans dataset is merged with defaults data obtained from a credit bureau (TransUnion CIBIL). Next, I run a difference-in-differences analysis with Firm x Time and Lender fixed effects while considering 2015 as the year of intervention. I find that firms have a 1.76 percentage points higher increase in default rate for relationship lenders from the pre-period to the post-period, compared to the increase for transaction lenders. This rise in default rate is 72 percent of the pre-period default rate on transaction lenders, making it economically meaningful.

The measure of relationship used in this paper combines the relationship measures based

[2] https://indianexpress.com/article/business/business-others/rbis-asset-quality-review-deep-surgery-starting-to-show-results-2838340/

on the frequency of interaction between the firm and the bank (Boot (2000)), the amount of loan lent by the bank to the firm (Bharath, Dahiya, Saunders, and Srinivasan (2011)) and physical proximity between the headquarters of the firm and the bank (Agarwal and Hauswald (2010), Beck, Ongena, and Şendeniz yüncü (2019)). Among several banks that a firm borrows from, the bank which lies above the median for all the above three criteria, is classified as a relationship bank for that firm. The results are robust to classification based on seventy-fifth percentile instead of median. To alleviate the concern that forbearance itself plays a role in forming these relationships, I restrict the sample to firm-bank pairs that existed at the beginning of the forbearance period and define a relationship as it was in the year 2007. Additionally, I use the standalone definition of relationship measure based only on physical proximity, and in both cases, the results go through.

An alternate explanation for higher defaults on relationship lenders could be that relationship pairs have larger outstanding loan amounts, and firms prefer to pay off the smaller loans first (Amar, Ariely, Ayal, Cryder, and Rick (2011)). I introduce the total unpaid loan amount lent by a bank to the borrowing firm as control and find that despite partialling out the effect of outstanding loan amount, relationship lenders still see higher default rates. Furthermore, I do not find evidence to support the conjecture that the results might be driven by idiosyncratic decline in overall lending by a bank.

It is also possible that the observed results are restricted to bank types: classified either by ownership (government or private) or by capital adequacy ratio (under-capitalized or well-capitalized). Public sector banks might form stronger relationships with poorly performing firms (Kornai, Maskin, and Roland (2003)), and thus the results can be driven by government-owned banks only. Though the regressions have lender fixed effects, I run additional tests by segregating the dataset into two subsamples: government-owned banks and privately owned banks. Relationship lenders see a larger increase in defaults in both subsamples. In line with the findings of Acharya, Eisert, Eufinger, and Hirsch (2019) who show that under-capitalized banks have incentives to keep funding bad firms, relationship lenders face a higher rise in defaults in the subsample of under-capitalized banks, but not for well-capitalized banks. I repeat a similar exercise for subsamples of distressed firms and healthy firms. Here, firms are classified as distressed firms if they cannot repay their interest expenses from the earnings; other firms are classified as healthy. In this case, the results hold for both kinds of firms.

One possible reason for the observed firm behavior could be the 'soft budget constraint.' If a lender helps a borrowing firm once, the firm might expect this lender to extend help in the future as well. Hu and Varas (2021) argue that relationship lenders sometimes hide negative information about a firm. A relationship bank can hide negative information by lending a new loan or restructuring an existing one while the firm pays off a loan due to a transaction lender. In this way, the relationship lender can possibly prevent the negative information from reaching uninformed lenders. I find that the relationship lenders that lent to a firm or restructured its loan account while it repaid a transaction lender's loan, face even higher default rates compared to other relationship lenders. This lender-specific 'softness' of the budget constraint could be possible reason firms defer payments towards relationship lenders. Under-capitalized banks, as well as well-capitalized banks tend to hide negative firm information in this manner.

Other robustness tests rule out alternate explanations, like the results might differ by categorization of default. RBI defines two types of loan defaults: Wilful Defaults and Non-wilful Defaults, and the results for both these types are similar to that for the combined default measure. Additionally, I run two placebo tests. The first one checks what if the intervention's year was 2011 instead of 2015, and the second one randomly assigns firm-lender pairs to relationship status. Both these settings do not reproduce the paper's primary results, indicating that the results are not obtained by chance. Another concern could be that the strict regulator is biased against relationship lenders, i.e., it pays disproportionate attention towards relationship lending during the clean-up process. I define relationships at the lender level (instead of firm-level) and find that this new definition of relationship does not reproduce the primary result.

This paper fits in the relationship banking literature (Donker, Ng, and Shao (2020), Berger, Miller, Petersen, Rajan, and Stein (2005), Schenone (2009), Bharath (2009), Schwert (2018), Bolton, Freixas, Gambacorta, and Mistrulli (2016), Agarwal and Hauswald (2010), Bhue and Prabhala (2015)) and contributes towards understanding the role of relationships in repayment behavior of firms. It documents the evidence that firms prefer repaying transaction lenders over relationship lenders, showing that relationship banking can be associated with higher strategic defaults despite private information about firms. 'Soft budget constraint' problem seems to trump the information advantage of relationship banks in terms of loan repayments by firms, which adds to our understanding of zombie lending by banks (Chopra, Subramanian, and Tantri (2020), Acharya, Borchert, Jager, and Steffen (2020), Caballero, Hoshi, and Kashyap (2008), Kulkarni, Ritadhi, Vij, and Waldock (2019)). The paper finds evidence in line with the theory that zombie lending is inevitable in relationship banking (Hu and Varas (2021)).

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting, and Section 3 describes the data source and sample construction. Section 4 outlines the empirical strategy used in this paper. Section 5 documents the results on the difference in default rates on relationship vs. transaction banking, rules out alternate explanations, and presents a potential mechanism. Section 6 concludes the paper.

# 2 Institutional Setting

The question about the difference in loan performance between relationship and transaction banking can be answered in a setting where the relationship banker has more discretion to lend and refinance for a limited period, without repercussions in the short-term; followed by a period where the regulator becomes strict and conducts an audit of lenders' loan books. Such audit could lead to the revelation of the actual position of the loan book quality.

In 2008, to preserve the Indian economy from being negatively impacted by the global financial crisis, India's banking regulator, the Reserve Bank of India (RBI), provided regulatory forbearance on asset classification of restructured loan accounts. Loan restructuring is the renegotiation of loan terms after the loan's disbursement and before the due date. The renegotiation is aimed at helping the borrower repay. Under this scheme, loan accounts were allowed to retain their asset classification upon loan restructuring. This regulation gave the banks a breather in terms of providing additional risk capital for distressed loan accounts. Think of a firm whose loan repayment is due for over 30 days, and the bank has provided some risk capital for this bad loan. If the firm further does not repay after 60 days, more risk capital has to be provided in the absence of forbearance. However, during the forbearance period, the bank has the option not to do the additional provisioning.

Regulatory forbearance was withdrawn in the year 2015 as the Indian economy had stabilized by then,[3] and was growing over 7 percent annually.[4] 2015 was the beginning of a period of the strict and vigilant regulator. Soon after withdrawing the relaxed provisioning norms, RBI conducted a massive cleanup exercise. This audit - broadly similar to stress tests conducted by the US and European authorities after the global financial crisis - was called Asset Quality Review (AQR) and was larger and stricter compared to the annual audits RBI conducted earlier (Chopra, Subramanian, and Tantri (2020)). I believe that these actions from the central bank forced the banks to recognize the bad loans they had been rolling forward by providing new debt or renegotiating the repayment duration of the loan.

Secured loans require regular repayments to the lender by the borrowing firm. If the repayment remains overdue for more than 90 days, the loan account is classified as a default or Non-performing Asset (NPA) by the bank. Then the bank asks the firm to repay the entire overdue amount within the next 60 days. If the firm does not comply, the bank can then take possession of the collateral and auction it, or initiate proceedings to change firm management (For a detailed discussion, see Vig (2013)).[5] There are two kinds of defaults that banks disclose in India. One is the usual default which occurs if the firm is unable to repay for 90 days. The second category of defaults is called 'Willful Defaults,' which means

[3]https://home.kpmg/content/dam/kpmg/in/pdf/2017/01/KPMG-Flash-News-India-Economic-Survey-2015-16%E2%80%93Key-Highlights-3.pdf

[4]https://economictimes.indiatimes.com/news/economy/indicators/indias-growth-at-7-6-in-2015-16-fastest-in-five-years/articleshow/52522153.cms

[5]The Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest Act (SARFAESI Act), 2002

that the firm has either defaulted despite being capable of repayment or not utilized the funds as they were intended. [6] In case of wilful defaults, the firm's directors are prohibited from getting any further financial services from the lender, debarred from starting any new venture for the next 5 years, and the lender can initiate criminal proceedings which can land the accused in jail for up to 10 years.[7] In this paper, I do not treat the two categories of default differently (other than in a robustness test), and the value of default used in the rest of the analysis indicates a non-repayment of dues within the stipulated time frame (regardless of the bank categorizing it as wilful or non-wilful).

# 3 Data

Lending data is obtained from the Ministry of Corporate Affairs (MCA), Government of India.[8] Their website keeps a repository of data relating to all secured loans borrowed by firms on which a charge has been registered under the Companies Act, 2013. First, a list of firms is obtained from the Prowess database of the Centre for Monitoring Indian Economy (CMIE), which has records of over 50,000 firms. Then a manual search for Company Identification Number (CIN) was performed on the MCA website for each of the firms in Prowess. Secured lending information of 24,930 listed and unlisted firms was collected for a period between 2008 and 2019. Lenders are required to register a charge on secured loans, as in case of going concerns, an unregistered secured lender is treated on par with unsecured lenders. So I assume that banks register charges in most cases.

I create a Firm-Lender-Year level data set where each observation represents a firm-lender pair for all years when they had at least one active or unpaid loan running. From the MCA website, I obtain the names of the firms, names of the lenders, corresponding loan amount, the transaction date, the type of record (new loan, repayment, or modification). If a lender has not made any loan in a year, then the loan amount will be zero for the firm-

[6] https://www.rbi.org.in/scripts/BS_ViewMasCirculardetails.aspx?id=9907
[7] Companies Act, 2013
[8] http://www.mca.gov.in/mcafoportal/showIndexOfCharges.do

year-lender observation. I downloaded data on defaults and wilful defaults of a firm-lender pair from the website of TransUnion CIBIL and matched it with the MCA firm-lender-year dataset to indicate a default or willful default. Lenders are mandated to report defaults (wilful) publicly if the outstanding loan amount is larger than 10 million (2.5 million) Indian Rupees (INR).[9] Other firm-level information like Interest Expense, Earnings Before Interest and Taxes, Total Assets Size, Industry, Address is obtained from the Prowess database of the Center For Monitoring Indian Economy (CMIE). Hence, I got a matched dataset of a large sample of secured corporate loans in India for approximately 24,930 firms across 157 industries and 376 lenders between 2008 and 2019, as documented in Table 1. These lenders can be of different types as mentioned in Table A2.

From Table 2, one can note that the average loan amount is INR 377 million with an outstanding loan amount of INR 2.28 billion. We see a total default rate of 1.91 percentage points. Non-wilful default is 1.41 percentage, and wilful default is 78 basis points. In any given year, the average firm borrows from 6 lenders. 32 percent of the firms in the dataset have been listed on the National Stock Exchange or the Bombay Stock Exchange in India. There are a total of 569975 firm-lender-year observations, 13 percent of which are classified as relationship pairs.

# 4 Empirical Strategy

The first step in carrying out a study about relationship banking is defining whether a firm and lender are in a relationship or the pair is following transactional lending. Transaction or "arm's length" lending, as opposed to, relationship lending does not depend on soft information. Soft-information collection is the specialty of relationship banking. Relationship banks can cater to small and unlisted firms, unlike transaction lenders, who rely on hard information from traditional sources like financial statements.

[9] https://suit.cibil.com/

## 4.1 Measure of Relationship

This paper calculates the strength of relationship using the following three criteria: frequency of interaction (Boot (2000)), depth of relationship (Agarwal, Chomsisengphet, Liu, Song, and Souleles (2018)), and physical proximity (Agarwal and Hauswald (2010), Beck, Ongena, and Şendeniz yüncü (2019)), and then combine the three of them to come up with a single classification of relationship.

The first criterion is the frequency of interaction between a firm-lender pair, and it is proxied by the number of loans between the firm-lender pair. I divide the number of loans lent in previous years by the time elapsed until the current period and sum them up.

$$RelationshipStrength_{Num,flt} = \sum_{y=0}^{t-1} \frac{NumberOfNewLoans_{y+1}}{t-y} \tag{1}$$

where $f$ stands for firm, $l$ represents lender, and $t$ represents year of observation. The division by elapsed time accounts for the depreciation of information over time. You can also think about this measure as the weighted sum of all the information collected in the past, where the weights are inverse of time elapsed since the information was collected. One way to do this weighting is by using the loans in the last few years. Bharath, Dahiya, Saunders, and Srinivasan (2011) use 5 years, which is effectively equivalent to having the weight of one for the last five years and zero before that.

The second criterion is the 'depth' of relationship, that is proxied by the loan amount between the firm-lender pair, and I repeat the calculation in equation (1) with loan amount instead of number of loans:

$$RelationshipStrength_{Amt,flt} = \sum_{y=0}^{t-1} \frac{AmountOfLoans_{y+1}}{t-y} \tag{2}$$

Third criterion is the physical proximity, and is measured by the reciprocal of distance (kilometers) between headquarters of the firm and the bank. The closer a firm-bank pair is, stronger is the strength of relationship between them.

$$RelationshipStrength_{Dist,flt} = \frac{1}{Distance_{fl}} \tag{3}$$

where $f$ stands for firm, $l$ represents lender, and $t$ represents year of observation.

For each firm with multiple borrowing channels in a year, I calculate the median of relationship strength for all three measures, based on the number of loans, amount of loans, and distance. Finally, a firm-bank pair is classified as a relationship if the lender has above median relationship strength based on all three criteria (median values calculated within-firm-year). Thus, *Relationship* is an indicator variable that takes the value of one for a firm-lender pair if all the three relationship strengths (number, amount, and distance) of that pair for a given year lie above their respective (within-firm-year) median values, and zero otherwise. This combination of different criteria allows me to incorporate the definition of relationship banking used in two strands of literature: one that uses number or amount of loans, and the other that uses distance.

## 4.2 Regression Analysis

To estimate the differential change in default from the period of the forbearing regulator to the period of the vigilant regulator for relationship lenders compared to arm's length lenders, I use difference-in-differences analysis. I follow Bertrand, Duflo, and Mullainathan (2004) to collapse the yearly observations for firm-lender pairs into pre-period and post-period, which helps in reducing auto-correlation among the dependent variable. A firm-lender pair which is classified as a relationship pair for at least one year during the forbearance period as per the definition in section 4.1, is classified as the treatment group (relationship banking) for the diff-in-diff analysis. A firm-lender pair that is not classified as a relationship pair for all the years during the forbearance period is classified as the control group (transaction banking). If a firm defaults in any year during the pre-period or the post-period, I call it a default for the entire period after collapsing. To compare the defaults within-firm - across banks, I introduce Firm x Period fixed effects along with Lender fixed effects. These fixed effects absorb time-variant and invariant firm-level properties, which can influence the results. Standard errors are clustered at the lender level. After collapsing the data set into pre-period (2008-14) and post-period (2015-19), I run the following regression:

$$Default_{flt} = \beta_0 + \beta_1 Relationship_{fl} + \beta_2 Relationhsip_{fl} * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \tag{4}$$

In the above equation, the subscript $f$ stands for a firm, $l$ stands for a lender, and $t$ stands for the period of observation: pre-period ($t = 0$) or post-period ($t = 1$). The independent variable $Default_{flt}$ is an indicator variable that takes the value of one if the firm $f$ is unable to repay its dues for 90 days towards the lender $l$ in the period $t$, at least once, and zero if the firm paid all its dues towards the lender on time during this period. The value of $Relationship_{fl}$ is also an indicator variable as defined in section 4.1. The value used in this regression is from the period of forbearance.

In equation (4), $\beta_0$ absorbs the economy wide changes, $\gamma_{ft}$ is the Firm x Time fixed effects which absorbs firm-level properties unique to the period, and $\delta_l$ absorbs lender specific fixed effects. The coefficient of interest here is $\beta_2$ which represents the difference in increase of defaults from pre-period to post-period for relationship lenders compared to transaction lenders. In some regressions, I replace $Default_{flt}$ with $log(1 + DefaultedLoanAmount_{flt})$ as the dependent variable, in which case $\beta_2$ estimates the difference between percentage change in defaulted loan amounts from pre-period to post-period for the relationship lenders compared to that of transaction lenders.

# 5 Results

## 5.1 Main Result

The question I ask in the paper is: Do firms prefer to repay relationship lenders or transaction lenders in a time of distress? The idea is to check if the information advantage of relationship lenders dominates or does the soft-budget-constraint inherent to a relationship leads to a higher default rate? Theoretically, either of the two effects can dominate, which makes this an empirical question. To answer this question, I use the change in the stance of the Indian banking regulator, the RBI, from forbearance to that of scrutiny. As explained in section 2, this shift happened in 2015. Around this year, I divide the dataset into two periods: the pre-period (2008-14) and the post-period (2015-19), and aggregate them.

Default for a firm-lender pair takes the value of one if the firm defaults on this lender during the period at least once, and zero otherwise. The independent variable is an indicator variable *Relationship* which takes the value of one if the firm and the lender are in a relationship (as defined in section 4.1) for at least one year during the forbearance period, and zero otherwise. $Post_t$ equals one for the post-period and zero for the pre-period. The regression is run as per equation (4), and result is documented in column (1) of Table 3.

The difference-in-differences coefficient estimates that the increase in default rate from the pre- to post-period is 1.76 percentage points higher for relationship lenders compared to transaction lenders. Defaulted amount is aggregated by taking a mean of yearly values over the respective pre and post-periods. In column (3) of Table 3, I document the result of using log(1+defaulted loan amount) as the dependent variable in equation (4). Defaulted loan amount increases 6.76 percent more for relationship lenders than transaction lenders, from the pre to the post-period.

I also show the regression results for the following equation, which does not collapse the data into pre and post-periods:

$$Default_{flt} = \beta_0 + \beta_1 Relationship_{fl,t-1} + \beta_2 Relationhsip_{fl,t-1} * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \tag{5}$$

Here, the data is arranged at firm($f$)-lender($l$)-year($t$) level, and default takes the value one if the firm did not repay the lender's dues on time at least once in that year, and zero otherwise. The independent variable $Relationship_{t-1}$ is the value of *Relationship* from the previous year based on the definition in section 4.1. $Post_t$ takes the value one for all years starting 2015, and zero before that. Column 2 (4) of Table 3 shows an increase of 1.25 percentage points (10 percent) in default rate (defaulted loan amount) for relationship lenders compared to transaction lenders from the pre-period to the post-period.

The coefficients of *Relationship* and $Relationship_{t-1}$ in Table 3 are statistically indistinguishable from zero, indicating an absence of pre-trends. To verify this diagrammatically, I regress $Default$ on $Relationship_{t-1}$ for each year between 2008 and 2019 with firm and lender fixed effects, and plot the coefficients of $Relationship_{t-1}$ along with their confidence intervals in Figure 1. I repeat the same exercise with $log(1+DefaultAmount)$ on the y-axis, and show the plot in Figure 2. In both the figures, I don't find any significant pre-trends. For pre and post-trends in overall default, see Figures A1 and A2.

## 5.2 Alternate Relationship Measures

There can be some concerns about the method of classification of a firm-lender pair into a relationship. One possible concern could be that regulatory forbearance itself can influence a lender to extend the relationship to a bad firm. Even if that is the case, the question about a firm's strategic decision regarding non-repayment towards a relationship vs. a transaction bank is not *ex-ante* clear. Regardless, to verify that forbearance is not causing the results described in the previous section, I restrict the definition of relationship to the one before forbearance, i.e., to the year 2007. I run the regression defined in equation (4) by collapsing the observations into a pre and post-period. The sample is restricted to the firm-lender pairs which existed in 2007. A firm-lender pair is said to have a default in a period if the firm did not repay its dues towards the lender within the stipulated time frame. The loan amount is aggregated by taking a mean of yearly defaulted loan amounts and then taking a log. The results are presented in columns (1) and (3) of Table 4, and I find them to be similar to the main result.

To further alleviate concerns about the endogeneity of the relationship measure, I use the relationship measure defined by using distance only and repeat the main regression. Note that distance can be used as an instrument for relationship banking (Li, Lu, and Srinivasan (2017)). A firm-lender pair is called a $Relationship_{Dist}$ if the relationship strength (as defined by equation (3)) of the firm with a lender is above the median strength of the relationship among all the lenders of the firm. This is the third criterion defined in section 4.1. The results are documented in columns (2) and (4) of Table 4. In both cases, the coefficient of $Relationship * Post$ remains positive and significant and similar to the main results. To check the robustness of results concerning the measure of relationship, I modify the definition of relationship in section 4.1 by using the 75th percentile of relationship strength instead of median and replicate Table 3. The results are presented in Table A3 and are similar to the main results.

## 5.3 Role of Loan Amount in Default on Relationship Banks

### 5.3.1 Outstanding Loan Amount

Relationship lenders often lend more to a borrowing firm compared to an arm's length lender, and if firms prefer to repay smaller loans first, then we should see higher defaults on relationship lenders. First, I verify if firms default more on lenders with higher outstanding loan amounts by running the regression:

$$\begin{aligned} Default_{flt} &= \beta_0 + \beta_1 log(1 + OutstandingLoanAmount_{flt}) \\ &\quad + \beta_2 log(1 + OutstandingLoanAmount_{flt}) * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \end{aligned} \tag{6}$$

This difference in differences regression is run after collapsing the firm-lender-year dataset into pre and post-periods. Default is defined the same way as done in the previous section, and outstanding loan amount is aggregated by taking the mean outstanding loan amount in each period and then taking a logarithm.[10] Firm x Period and Lender fixed effects absorb period-specific firm properties and time-invariant lender properties; standard errors are clustered at lender level. The results are shown in column (1) of Table 5.

To control for outstanding loan amount while estimating the differential rise in default rates of relationship and transaction lenders, I run the following regression and show the result in column (2) of Table 5.

$$\begin{aligned} Default_{flt} &= \beta_0 + \beta_1 log(1 + OutstandingLoanAmount_{flt}) \\ &\quad + \beta_2 log(1 + OutstandingLoanAmount_{flt}) * Post_t \\ &\quad + \beta_3 Relationship_{fl} + \beta_4 Relationhsip_{fl} * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \end{aligned} \tag{7}$$

In column (3) of this table, I present the result of the regression equation (4) after replacing Firm x Period fixed effects with Firm x Outstanding Loan Amount Quintiles x Period fixed effects. This regression allows for the comparison of default rates among lenders of a firm

[10] I do not have data on amortization of loans, but I know when a loan is completely paid-off, or if some part is still outstanding. So I assume the total sanctioned amount of all currently unpaid loans between a firm-lender pair as the total outstanding loan amount.

that have comparable outstanding loan amounts to each other. Column (4) shows the result of equation (7) after replacing Firm x Period fixed effects with Firm x Outstanding Loan Amount Quintiles x Period fixed effects. The results indicate that though the magnitude of repayable amount matters in determining default rates, relationship banking sees more defaults even after controlling for the outstanding loan amount.

#### 5.3.2 Decline in Bank Lending

Chopra, Subramanian, and Tantri (2020) show that Indian banks reduced lending after the AQR of 2016. Some banks were affected more than others. One concern could be that banks that reduced lending more faced higher defaults. To address this concern, I calculated bank-specific year-wise idiosyncratic change in lending by following Amiti and Weinstein (2011) and regressed default on $NegativeLendingShock_{lt}$ which is an indicator variable that takes the value of one if in a given year a lender sees an idiosyncratic decline in lending, and zero otherwise. I run the regression:

$$Default_{flt} = \beta_0 + \beta_1 NegativeLendingShock_{lt} + \beta_2 NegativeLendingShock_{lt} * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \quad (8)$$

Data is arranged at the firm-lender-year level, and other variables are as defined for regression 5. Results are shown in Column (2) of Table 6, while column (1) shows the first-stage test to validate the shock variable. One way to control for time-varying lender properties like the idiosyncratic decline in bank lending could be absorbing Lender x Time fixed effects. So, I run regression (5) with firm-lender-year level data after including Lender x Year fixed effects instead of Lender fixed-effects, and regression (4) with data collapsed into pre and post-periods including Lender x Period fixed effects instead of Lender fixed-effects. The results are shown in columns (3) and (4) of Table 6, respectively.

An idiosyncratic decline in bank lending does not seem to be correlated with higher defaults on relationship lenders, probably because the same lender can be a relationship lender for some firms and a transaction lender for others. Controlling for such shocks does not seem to take away the average effect on firm preference in repaying transaction lenders over relationship lenders.

### 5.4 Distressed Firms

A firm that repeatedly fails to repay its interests from its profits is often called a zombie firm (Banerjee and Hofmann (2018), Hu and Varas (2021)). Do relationship lenders face higher default rates only from zombie firms? As it is difficult to define a zombie firm, I define an indicator variable $DistressedFirm$ which equals one if Interest Coverage Ratio is less than one at least for one year during the forbearance period, and zero otherwise. I divide the sample into two parts: Distressed firms vs Non-distressed (or Healthy) firms, and run the regression (4). You can find the results in columns (1) and (2) respectively of Table 7. For completion, after collapsing data of firm-lender-year into firm-lender-period (there are two periods: during forbearance and after forbearance ends) level, I run another regression to check for rise in default for distressed firms from pre to post-period:

$$Default_{flt} = \beta_0 + \beta_1 DistressedFirm_{fl} + \beta_2 DistressedFirm_{fl} * Post_t + \gamma_{isat} + \delta_l + \varepsilon_{flt} \tag{9}$$

As $DistressedFirm$ is a firm-level variable, Firm x Period fixed effects were replaced by Firm Cluster x Period fixed effects, where Firm Cluster is defined by combining Industry, Location (State), and Size (industry-wise tertile of asset size) in line with Degryse, De Jonghe, Jakovljević, Mulier, and Schepens (2019), and Acharya, Eisert, Eufinger, and Hirsch (2019, 2018). $\gamma_{isat}$ stands for Industry (i) x Location (s) x Asset Size Tertile (a) x Time (t) fixed effects, where Asset Size Tertile is calculated for each industry separately. Though Industry x Location x Size (ILS) fixed-effects do not absorb all firm-level time-variant and invariant characteristics, they allow for comparison between firms of a similar kind. The rest of the variables are defined in the same way as regression 4, and the result is shown in column (3) of Table 7. Column (4) has the following regression results, which separates relationship lenders of distressed firms from the transaction lenders.

$$\begin{aligned} Default_{flt} = {} & \beta_0 + \beta_1 DistressedFirm_{fl} + \beta_2 DistressedFirm_{fl} * Post_t + \beta_3 Relationship_{fl} \\ & + \beta_4 Relationhsip_{fl} * Post_t + \beta_5 DistressedFirm_{fl} * Relationship_{fl} \\ & + \beta_6 DistressedFirm_{fl} * Relationhsip_{fl} * Post_t + \gamma_{isat} + \delta_l + \varepsilon_{flt} \end{aligned} \tag{10}$$

$\beta_4$ and $\beta_6$ are the coefficients of interest, and both are positive and statistically significant. The results show that relationship lenders face higher default rates not only from distressed firms but also from the seemingly healthier firms.

## 5.5 Lender Heterogeneity: Ownership and Capital Adequacy

Public sector banks are known to be less efficient, especially in emerging economies. The higher default rate on relationship lenders may be restricted only to public sector banks.[11] I divide the sample into two parts: government-owned banks and privately owned banks, and run regression (4) after aggregating the data into pre and post-periods. The results are respectively documented in columns (1) and (2) of Table 8. Furthermore, struggling banks are more likely to engage in zombie lending (Peek and Rosengren (2005)). To check if the main result is confined only to under-capitalized banks, I divide the sample into two parts: well-capitalized and under-capitalized. I calculated the median of minimum Capital Adequacy Ratio (CAR) reported by banks during 2008-19. Banks whose minimum capital adequacy ratio was below the median were called under-capitalized, and the rest were classified as well-capitalized. I repeat the above regression and report the results in columns (3) and (4) of Table 8.[12] I find that relationship lenders are more likely to face defaults for both public or privately owned lenders. Similar results exist for the sub-sample of under-capitalized lenders. However, the well-capitalized do not show such results.

I also check if the results are restricted to government owned firms. I take four subsamples: (i) government owned firm borrowing from government lender, (ii) private firm borrowing from government lender, (iii) government owned firm borrowing from non-government lender, and (iv) private firm borrowing from non-government lender. I run the main regression and document results in Table A8. The results are restricted to privately owned firms, irrespective of the ownership status of the bank.

[11]Different bank types are listed in Table A2.

[12]Median of lender-wise minimum CAR was found to be 11.08 percent. The results are robust to increasing the CAR threshold to 11.5 percent.

## 5.6 Potential Mechanism

Firms rely on relationship lenders during times of distress (Bolton, Freixas, Gambacorta, and Mistrulli (2016)), and they might expect this service irrespective of the regulatory environment. So, when the regulator goes after banks to become more transparent, the banks might find it challenging to extend help to bad firms. However, a firm is likely to expect service from a lender who has helped it in the past, and this expectation might lead firms to lower relationship lenders in repayment preference. A relationship lender can help a firm by issuing a new loan when the firm needs liquidity to repay elsewhere. The firm can use this new loan from an informed lender to repay an uninformed lender. Through such a practice, the relationship lenders help the firm hide its true type (bad) from the uninformed lenders.

I define a variable $Help$ which equals one in a given year for a firm-lender pair if the relationship lender makes a new loan to the firm or restructures an existing one in the same year, while the firm pays off a running loan from a transaction lender, and zero otherwise.[13] I run the following regression, which is similar to regression (4) in terms of data arrangement, but instead of *Relationship*, the main independent variable is $Help$.

$$Default_{flt} = \beta_0 + \beta_1 Help_{fl} + \beta_2 Help_{fl} * Post_t + \gamma_{ft} + \delta_l + \varepsilon_{flt} \tag{11}$$

Column (1) of Table 9 shows the result for the above regression. You can see that relationship lenders that help firms in hiding negative information from transaction lenders during the forbearance period face more defaults in the post-period. This result is true even after controlling for *Relationship* in column (4). Additionally, I run the same analysis on subsamples of well-capitalized and under-capitalized banks and show the results in columns (2) and (3) of Table 9, respectively. Firms default more on relationship lenders not only for the subsample of the under-capitalized banks but also for the well-capitalized ones. The finding is in line with Hu and Varas (2021), who show that relationship bankers (irrespective of their capital adequacy ratio) hide negative information about the borrower from the uninformed lenders. The results presented in this section show that firms are more likely to delay re-

[13] https://www.livemint.com/Opinion/MrHUkHobcTRc389OKVk62N/Finally-RBI-cracks-the-Da-Vinci-code-of-Indian-banking.html

payments towards a lender who has helped them in the past. Thus, soft-budget-constraint seems to dominate over the information advantage of relationship lending.

To further examine the kind of firms that indulge in rotating debt funds across lenders, run the following regression:

$$DistressedFirm_{ft} = \beta_0 + \beta_1 HelpReceivingFirm_{ft} + \gamma_{isat} + \varepsilon_{ft} \tag{12}$$

Here the data is arranged at Firm-Year level, and the variable $HelpReceivingFirm$ equals one in a given year if a firm received $Help$ from a relationship lender in that year, and zero otherwise. $\gamma_{isat}$ stands for Industry (i) x Location (s) x Asset Size Tertile (a) x Time (t) fixed effects. The regression results documented in column (1) of Table 10 show the firms are not observably zombie firms. To investigate the kind of investment these firms make, I replace the dependent variable with $NewProject_t$ ($StalledProject_{t+1}$), an indicator variable that takes the value one if the firm announces a new project in a given year (announces that an existing project gets stalled in the following year), and zero otherwise. Investment data is obtained from CapexDx database maintained by the Center for Monitoring Indian Economy (CMIE). Column (2) shows that a $HelpReceivingFirm$ is more likely to announce new investment projects compared to other firms in that industry, state, and size category. Column (3) shows that projects of these firms often get stalled, and column (4) shows the same result, given that the firm announced a new project in the previous year. These findings imply that a $HelpReceivingFirm$ is either risk-seeking or inefficient, or both.

## 5.7 Other Robustness Tests

I run several other robustness tests. The first one is to check if the results differ by categorization of default. RBI defines two types of loan defaults: Wilful Defaults and Non-wilful Defaults. Lenders categorize a loan as a default if the borrower fails to repay for over 90 days. The default is categorized as wilful if the lender believes that the firm had the resources to repay but still chose not to, or used the funds for purposes not disclosed at the time of disbursal. A non-wilful default can lead to a credit downgrade, discontinuation of further lending, change in management, and liquidation of collateral, whereas in case of wilful default, all these sanctions are applicable and the lender can also take the firm to court for fraud where the punishment can include imprisonment or banning the directors from starting new businesses. I run regression (4) with dependent variables: non-wilful default, wilful-default, outstanding loan amount of non-willful default, and that of wilful-default, and document the results in columns (1) to (4) of Table A4, respectively. Firms default more on relationship lenders whether the default was categorized as willful or not.

The second set of robustness tests I performed was around the date of intervention, 2015, the year when forbearance was withdrawn. RBI announced the withdrawal of forbearance in 2013. So, I check for announcement effect by separating the years 2013 and 2014 using a dummy variable $Announcement$, which takes the value one if year equals 2013 or 2014 and zero otherwise. I run regression 4 after restricting the sample to 2008 to 2014, and show the result in column (1) of Table A5. In column (2), I include the post-period as well. Next, I check if the changes to bankruptcy laws (Insolvency and Bankruptcy Code or IBC) which took effect in 2017, were driving the results. I divide the data into two periods, 2008-2012 as the pre-period, and 2013-2016 as the pre-IBC period, collapse the data into these periods, run a regression similar to equation (4) with $PreIBC$ dummy, which equals one for years 2013-16 and zero otherwise, instead of $Post$ dummy. The results are shown in column (3) of Table A5. If the rise in defaults were not a result of conducting AQR after ending forbearance, we should observe an insignificant coefficient for $Relationship * PreIBC$ in the regression run for period 2008-2016. I also include the post-IBC (2017-19) period in column (4). Relationship lenders started facing more defaults even before IBC took effect, but not before AQR was conducted.

Third, I conduct falsification tests to rule out that the observed results can occur randomly. I run two placebo tests as documented in Table A6 that demonstrate the absence of the primary results if the year of the intervention (AQR and withdrawal of forbearance) was 2011 (instead of 2015) in Columns (1) and (2). Columns (3) and (4) randomly assign firm-lender pairs into a relationship and show that this random assignment does not reproduce the main results.

Finally, one concern could be that the AQR is biased against relationship banking. If this caveat is true, the auditor pays disproportionate attention to the relationships of a bank. As AQR occurs at the lender level, I define $Relationship_{bank}$ at the level of the lender using the similar method as described in section 4.1, but instead of classifying lenders of a firm into a relationship, I classify borrowing firms of a lender into relationship or transaction. Then I replicate Table 3 using this new measure of relationship. Table A7 shows that this new definition of relationship does not reproduce my primary result, which would have been true had AQR disproportionately uncovered defaults from relationship lenders.

# 6 Conclusion

The lender collects soft information about the firm due to frequent interactions and physical proximity with its borrowing firms. This soft information is not available with transaction banks. A relationship lender can use this information to lend more efficiently compared to a transaction lender. Firms expect help from relationship banks during times of distress, creating a soft-budget constraint on the part of the borrowing firm. When a firm simultaneously borrows from a relationship bank and a transaction bank, the firm's strategic behavior towards these two types of banking arrangements becomes important. Whether a firm that finds itself in a position to repay only one out of the two running loans will repay the relationship lender or the transaction lender?

As the relationship lender knows the true quality of a borrower, it will roll over a loan only if the firm's chances of recovery are genuine. On the other hand, relationship banks have incentives to roll over bad loans, and doing so would become even easier during the period of regulatory forbearance. Regulatory forbearance was practiced in India from 2008 to 2014 and was withdrawn in 2015. It was followed by an Asset Quality Review of the banks' loan books. I use this shift in regulator's stance and exploit within-firm across banks variation in firm-lender relationship to quantify the differential change in defaults for the two types of lenders. A difference-in-differences analysis shows that increase in defaults for relationship lenders is 1.76 percentage points higher than that of arm's length lenders. This rise in default rate is 72 percent of the pre-period default rate of transaction lenders, making it economically meaningful. The evidence implies that firms have an implicit repayment preference towards different types of lenders, and transaction lenders stand higher in that preference order *vis-à-vis* relationship lenders.

As additional support of this finding, I find that firms that borrow from relationship lenders and repay transaction lenders in the same year are more likely to strategically default on relationship lenders later. I rule out several alternative explanations, like the results are restricted to public sector lenders, under-capitalized banks, or zombie firms only. The results also hold after controlling for other potential factors like outstanding loan amount or bank lending shock.

Giver this evidence, bank management can keep a closer watch on risk analysis while helping out firms, as the helpful relationship lenders fall lower in the repayment preference of a distressed firm. The regulator can also keep a tab on firms that simultaneously borrow and repay, not only from one lender but also from multiple channels.

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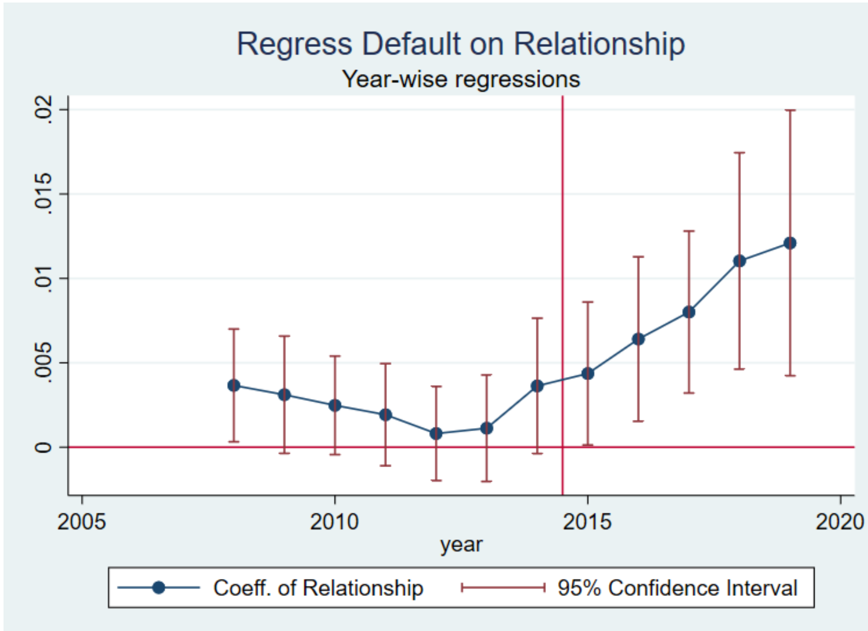


Figure 1: Default and Relationship Banking: Co-efficient plot for *Default* on *Relationship* year-wise regressions with firm and lender fixed effects.

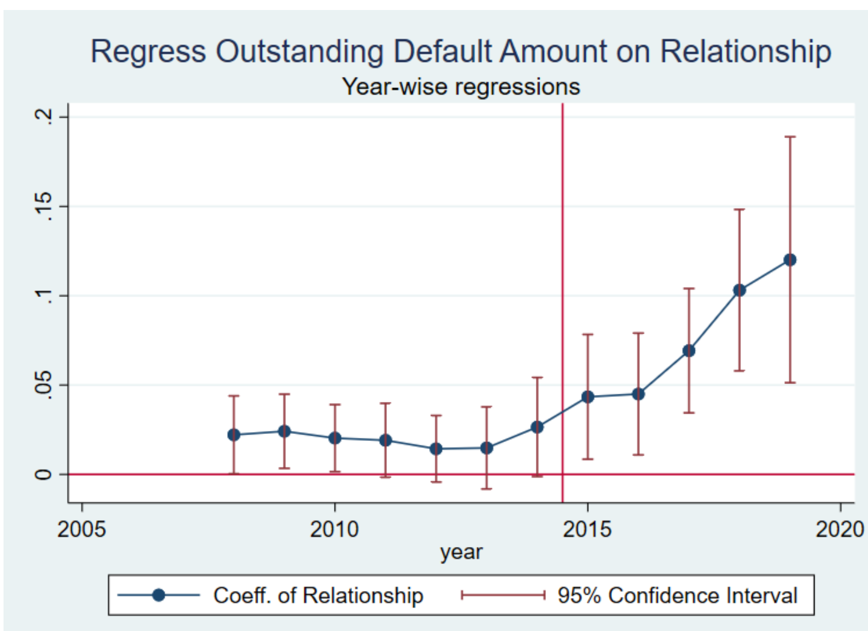


Figure 2: Default Amount and Relationship Banking: Co-efficient plot for $log(1+DefaultAmount)$ on *Relationship* year-wise regressions with firm and lender fixed effects.

## TABLE 1: Data Description

The table describes the data used in this study, including the time-period, number of firms, number of lenders, etc.

| Variable | Value |
|---|---|
| Time Period | 2008-19 |
| Number of Firms | 24930 |
| Listed Firms (At least once) | 4839 |
| Never Listed Firms | 20091 |
| Number of Lenders | 376 |
| Number of Active Firm-Lender Relationships | 86718 |
| Average Number of Lenders/Firm/Year | 6.57 |
| Number of Firm-Lender-Year Observations | 569975 |
| Average Outstanding Loan/Firm/Year (Million INR) | 5497.18 |
| Average New Loan/Firm/Year (Million INR) | 910.65 |
| Average Outstanding Loan/Firm/Lender/Year (Million INR) | 2277.53 |
| Average New Loan/Firm/Lender/Year (Million INR) | 377.29 |
| Number of Defaulting Firms | 2140 |
| - Wilful Default | 729 |
| - Non-Wilful Default | 1982 |
| Number of Lenders with Defaults | 71 |
| Number of Firm-Lender Pairs with Defaults | 3098 |
| Number of Firms for which ICR is available | 20091 |

## TABLE 2: Summary Statistics

The table presents the distribution of key variables in terms of their mean, standard deviation, and values at several percentiles (5, 25, 50, 75 , 95). The table also shows the total number of observations.

| | Mean | Std Dev | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|
| New Loan Amt(INR 10mn) | 37.72 | 538.44 | 0.00 | 0.00 | 0.00 | 0.00 | 89.00 |
| Outstanding Loan Amt (INR 10mn) | 227.75 | 2733.63 | 0.00 | 2.60 | 19.40 | 76.00 | 620.00 |
| Num of New Loans | 0.28 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Total Default | 0.0191 | 0.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Non-wilful Default | 0.0142 | 0.12 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Wilful Default | 0.0078 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Num Lenders/Firm/Year | 6.56 | 8.26 | 1.00 | 2.00 | 3.00 | 8.00 | 24.00 |
| Relationship | 0.13 | 0.34 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Listed Firm | 0.32 | 0.47 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| Interest Coverage Ratio | 4.01 | 6.70 | -2.00 | 1.02 | 1.74 | 3.76 | 26.21 |
| Distressed Firm | 0.14 | 0.35 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| Default Amount (INR 10mn) | 0.96 | 28.39 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Non_wilful Default Amount (INR 10mn) | 0.47 | 18.95 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Outstanding Loan on Willful Default (10mn INR) | 0.49 | 14.83 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Observations | 569975 | | | | | | |

## TABLE 3: MAIN RESULT: DEFAULT IN RELATIONSHIP VS TRANSACTION BANKING

The table documents the difference in differences estimates of regressing $Default$ (or default amount) on *Relationship*. Columns (1) and (3) show results for equation (4) where the observations are collapsed into pre- and post-periods. Columns (2) and (4) show results for equation (5) where the data is arranged in firm-lender-year level observations. Default for a firm-lender pair takes the value of one if the firm defaults on this lender during the period, and zero otherwise. $log$(1+Default Amount) is the logarithmic value of the outstanding loan amount on which the firm defaulted in that year (Column (4)). For column (3), yearly values of defaulted loan amount are aggregated (mean) over the pre- and post-periods, before applying the log function. *Relationship* takes the value of one if the firm and the lender are in a relationship (as defined in section 4.1) for at least one year during the forbearance period, and zero otherwise. $Relationship_{t-1}$ is the value of *Relationship* from the previous year based on the definition in section 4.1. $Post_t$ equals one starting 2015 and zero for all years before that. All regressions have Firm x Time and Lender fixed-effects. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | $log$(1+Default Amount) | |
| *Relationship* | -0.00121 | | -0.00566 | |
| | (-0.89) | | (-0.70) | |
| $Relationship * Post$ | 0.0176*** | | 0.0676*** | |
| | (5.75) | | (4.22) | |
| $Relationship_{t-1}$ | | -0.000404 | | 0.00111 |
| | | (-0.27) | | (0.11) |
| $Relationship_{t-1} * Post$ | | 0.0125*** | | 0.101*** |
| | | (4.79) | | (5.17) |
| Constant | 0.0244*** | 0.0205*** | 0.0988*** | 0.133*** |
| Observations | 112939 | 385668 | 112939 | 385668 |
| Adjusted $R^2$ | 0.256 | 0.218 | 0.134 | 0.187 |
| Firm x Period FE | Yes | | Yes | |
| Firm x Year FE | | Yes | | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | ———Lender——— | | | |

# TABLE 4: Regulatory Forbearance and Relationship Measure

The table documents the difference in differences estimates of regressing $Default$ (or default amount) on $Relationship$. The objective is to check if the effects seen in the previous table are observed because regulatory forbearance aids the formation of bad relationships. All columns show results of the regression equation (4), which is run after collapsing the observations into pre- and post-periods. The relationship measure in Columns (1) and (3) are the relationship status as defined by section 4.1 before regulatory forbearance started (the year 2007). Columns (2) and (4) use $Relationship_{Dist}$ which takes the value one if relationship measure for a firm-lender pair (as defined in equation (3)) is above the median relationship strength for the lenders of that firm, and zero otherwise. Default for a firm-lender pair takes the value of one if the firm defaults on this lender during the period and zero otherwise. $log$(1+Default Amount) is the logarithmic value of the mean of the year-wise outstanding loan amount on which the firm defaulted during the period. $Post_t$ equals one starting 2015 and zero for all years before that. Subsample in columns (1) and (3) are restricted to firm-lender pairs which exited in 2007, i.e., before regulatory forbearance started. All regressions have Firm x Time and Lender fixed-effects. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | $log$(1+Default Amount) | |
| $Relationship_{2007}$ | 0.00381 | | 0.0154 | |
| | (1.30) | | (1.14) | |
| $Relationship_{2007} * Post$ | 0.0127** | | 0.0715** | |
| | (2.54) | | (2.04) | |
| $Relationship_{Dist}$ | | -0.00234* | | -0.0152** |
| | | (-1.90) | | (-1.99) |
| $Relationship_{Dist} * Post$ | | 0.0109*** | | 0.0489*** |
| | | (4.20) | | (3.15) |
| Observations | 37428 | 112939 | 37428 | 112939 |
| Adjusted $R^2$ | 0.246 | 0.256 | 0.149 | 0.133 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | Lender | | | |

## TABLE 5: Outstanding Loan Amount

If relationship lenders lend more compared to arm's length lenders, and firms prefer to repay smaller loans first, then we should see higher defaults on relationship lenders. I verify if firms default more on lenders with higher outstanding loan amounts by running the regression in equation (6). This difference in differences regression is run after collapsing the firm-lender-year dataset into pre- and post-periods. $Default$ for a firm-lender pair takes the value of one if the firm defaults on this lender during the period and zero otherwise. The outstanding loan amount is aggregated by taking the mean outstanding loan amount in each period and then taking a logarithm. *Post* equals one starting 2015 and zero for all the previous years. The results are shown in column (1). *Relationship* takes the value of one if the firm and the lender are in a relationship (as defined in section 4.1) for at least one year during the forbearance period, and zero otherwise. Column (2) shows the result of regression (7). Column (3) presents the result of regression equation (4) after replacing Firm x Period fixed effects with Firm x Outstanding Loan Amount Quintiles x Period fixed effects, and column (4) does the same for equation (7). T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Default | | |
| $log(1 + LoanAmount)$ | 0.000187 | 0.000233* | | -0.0000301 |
| | (1.30) | (1.67) | | (-0.06) |
| $log(1 + LoanAmount) * Post$ | 0.000868*** | 0.000703*** | | 0.0000299 |
| | (4.58) | (3.99) | | (0.07) |
| *Relationship* | | -0.00175 | -0.00147 | -0.00146 |
| | | (-1.35) | (-0.83) | (-0.84) |
| $Relationship * Post$ | | 0.0168*** | 0.00912** | 0.00911** |
| | | (5.75) | (2.24) | (2.24) |
| Observations | 112939 | 112939 | 79959 | 79959 |
| Adjusted $R^2$ | 0.256 | 0.256 | 0.269 | 0.269 |
| Firm x Period FE | Yes | Yes | | |
| Firm x Loan Amt Quintile x Period FE | | | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | | Lender | | |

## TABLE 6: Idiosyncratic Decline in Bank Lending

This table checks for concerns regarding negative bank lending shocks causing higher defaults. Bank-specific year-wise idiosyncratic change in lending is calculated by following Amiti and Weinstein (2011). Default is regressed on $NegativeLendingShock_{lt}$ which is an indicator variable that takes the value of one if in a given year a lender sees an idiosyncratic decline in lending, and zero otherwise. I run regression (8) with data arranged at firm-lender-year level, and other variables are as defined in regression 5. Results are shown in Column (2), while column (1) shows the first-stage test to validate the shock variable. To control for time-varying lender properties like the idiosyncratic decline in bank lending, I run regression (5) with firm-lender-year level data after including Lender x Year fixed effects instead of Lender fixed-effects, and regression (4) with data collapsed into pre- and post-periods including Lender x Period fixed effects instead of Lender fixed-effects. The results are shown in columns (3) and (4), respectively. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $log(1 + LoanAmt)$ | | Default | |
| $NegativeLendingShock$ | -1.031*** | -0.0000345 | | |
| | (-7.83) | (-0.02) | | |
| $NegativeLendingShock * Post$ | | -0.00460 | | |
| | | (-1.11) | | |
| $Relationship_{t-1}$ | | | 0.00232* | |
| | | | (1.79) | |
| $Relationship_{t-1} * Post$ | | | 0.00609*** | |
| | | | (2.61) | |
| $Relationship$ | | | | 0.00192 |
| | | | | (1.62) |
| $Relationship * Post$ | | | | 0.0101*** |
| | | | | (3.49) |
| Observations | 439122 | 439122 | 385156 | 112879 |
| Adjusted $R^2$ | 0.189 | 0.222 | 0.226 | 0.262 |
| Firm x Year FE | Yes | Yes | Yes | |
| Lender FE | Yes | Yes | | |
| Lender x Year FE | | | Yes | |
| Firm x Period FE | | | | Yes |
| Lender x Period FE | | | | Yes |
| Std Error Cluster | Lender | | | |

## TABLE 7: Distressed Firms

This table documents results of tests that verify if relationship lenders face more defaults only for zombie firms. I define an indicator variable $DistressedFirm$ which equals one if Interest Coverage Ratio is less than one at least for one year during forbearance and zero otherwise. I divide the sample into two parts: Distressed firms vs. Non-distressed (or Healthy) firms. I run regression (4), and document the result in column (1) and (2) respectively. Columns (3) and (4) show results of regressions (9) and (10) respectively. As $DistressedFirm$ is a firm-level variable, Firm x Period fixed effects were replaced by Firm Cluster x Period fixed effects, where Firm Cluster is defined by combining Industry, Location (State), and Size (industry-wise tertile of asset size). T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | | |
| $Relationship$ | -0.00247 | -0.000129 | | -0.00206*** |
| | (-1.04) | (-0.17) | | (-2.61) |
| $Relationship * Post$ | 0.0174*** | 0.00630*** | | 0.00523** |
| | (3.46) | (2.69) | | (2.49) |
| $DistressedFirm$ | | | 0.0173*** | 0.0164*** |
| | | | (7.18) | (7.69) |
| $DistressedFirm * Post$ | | | 0.0188*** | 0.0152*** |
| | | | (3.86) | (3.52) |
| $DistressedFirm * Relationship$ | | | | 0.00386 |
| | | | | (1.26) |
| $DistressedFirm * Relationship * Post$ | | | | 0.0160*** |
| | | | | (3.27) |
| Observations | 37202 | 52062 | 102983 | 102983 |
| Adjusted $R^2$ | 0.207 | 0.144 | 0.073 | 0.074 |
| Firm x Period FE | Yes | Yes | | |
| Firm Cluster x Period | | | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Subsample | Distressed Firms | Healthy Firms | | |
| Std Error Cluster | Lender | | | |

## TABLE 8: Heterogeneous Effects: Bank Ownership and Capital Adequacy

This table examines if the main result varies across different types of lenders based on ownership and capital adequacy. First, the sample is divided into two parts: government-owned banks and privately owned banks, and regression (4) is run after collapsing data into pre- and post-period. The results are respectively documented in columns (1) and (2). Second, the same regression is run after dividing the sample into well-capitalized and under-capitalized banks, and results are documented in columns (3) and (4), respectively. I calculated the median of minimum Capital Adequacy Ratio reported by banks during 2008-19. Banks whose minimum capital adequacy ratio was below the median were called Under-capitalized, and the rest were classified as well-capitalized. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | | |
| *Relationship* | -0.00202 | -0.00129 | 0.000467 | 0.00105 |
| | (-1.08) | (-0.79) | (0.22) | (0.50) |
| $Relationship * Post$ | 0.0190*** | 0.00995*** | 0.00268 | 0.0178*** |
| | (3.63) | (3.36) | (0.82) | (3.39) |
| Observations | 39937 | 57463 | 34961 | 33615 |
| Adjusted $R^2$ | 0.336 | 0.179 | 0.304 | 0.347 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Sub-sample | Govt Lender | Non-Govt Lender | Well-capitalized | Under-capitalized |
| Std Error Cluster | Lender | | | |

## TABLE 9: Helping Firms Repay Other Loans

This table shows if relationship lenders that help a firm by issuing a new loan when the firm needs liquidity to repay elsewhere face even more defaults. I define a variable $Help_t$ which equals one in a given year for a firm-lender pair if the relationship lender makes a new loan to the firm or restructures an existing one in the same year, while the firm pays off a running loan from a transaction lender, and zero otherwise. *Help* is an indicator variable that equals one if $Help_t$ is one for at least one of the years during the pre-period and zero otherwise. I run the regression (11), and document the result in column (1). This result is true even after controlling for *Relationship* in column (4). Additionally, I run the same analysis on subsamples of well-capitalized and under-capitalized banks and show the results in columns (2) and (3), respectively. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | | |
| *Help* | -0.00393** | -0.0000765 | 0.000250 | -0.00479* |
| | (-2.59) | (-0.03) | (0.13) | (-1.81) |
| $Help * Post$ | 0.0217*** | 0.0127** | 0.0177** | 0.00982** |
| | (5.57) | (2.25) | (2.71) | (2.15) |
| *Relationship* | | | | 0.00117 |
| | | | | (0.52) |
| $Relationship * Post$ | | | | 0.0128*** |
| | | | | (3.48) |
| Observations | 112939 | 34961 | 33615 | 112939 |
| Adjusted $R^2$ | 0.256 | 0.304 | 0.346 | 0.256 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Sub-sample | | Well-capitalized | Under-capitalized | |
| Std Error Cluster | Lender | | | |

## TABLE 10: Risky Investment

This table shows the investment status of firms that borrow from relationship lenders and simultaneously repay transaction lenders. Data is arranged at the Firm-Year level, and the variable *HelpReceivingFirm* equals one in a given year if a firm received *Help* from a relationship lender in that year and zero otherwise. I run regression 12 and document the result in column (1), which shows that the firms are not observably zombies. Furthermore, I replace the dependent variable with $NewProject_t$ ($StalledProject_{t+1}$), an indicator variable that takes the value one if the firm announces a new project in a given year (announces that an existing project gets stalled in the following year), and zero otherwise. Column (2) shows that *HelpReceivingFirm* are more likely to announce new investment projects compared to other firms in that industry, state, and size category. Column (3) shows that projects of these firms often get stalled, and column (4) shows the same result, conditional on the firm announcing a new project in the previous year. T-statistics are reported in parentheses, and standard errors are clustered at the firm level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Distressed Firm | New Projects | Stalled $\text{Projects}_{t+1}$ | |
| *HelpReceivingFirm* | -0.0579*** | 0.0550** | 0.0560*** | 0.252* |
| | (-6.17) | (2.27) | (3.17) | (1.91) |
| Observations | 52021 | 52021 | 50060 | 1390 |
| Adjusted $R^2$ | 0.100 | 0.301 | 0.195 | 0.123 |
| Industry x State x Size x Year FE | Yes | Yes | Yes | Yes |
| Period | 2008-14 | 2008-14 | 2008-14 | 2008-14 |
| SubSample | All | All | All | New Investment |
| Std Error Cluster | ———Firm——— | | | |

# Appendix

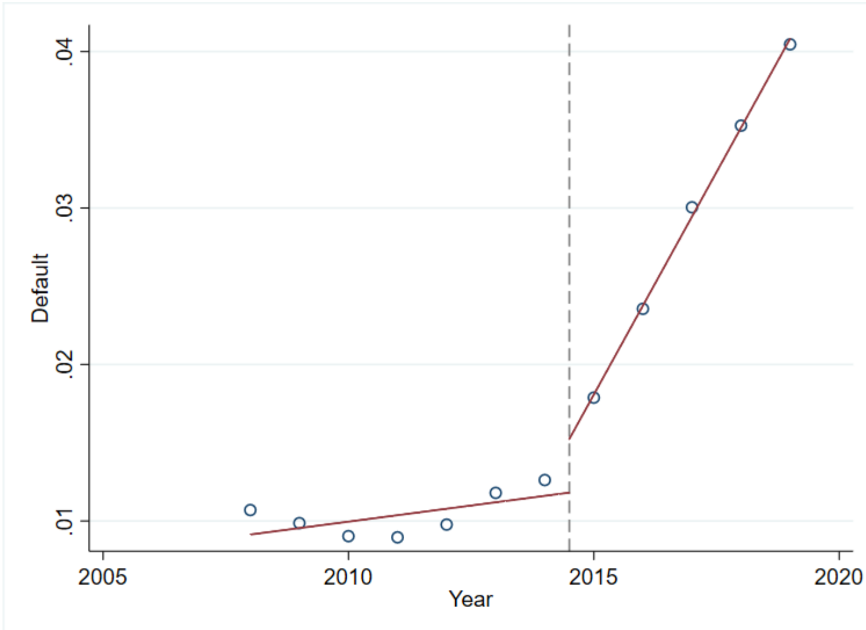


Figure A1: Overall Default: During and after regulatory forbearance

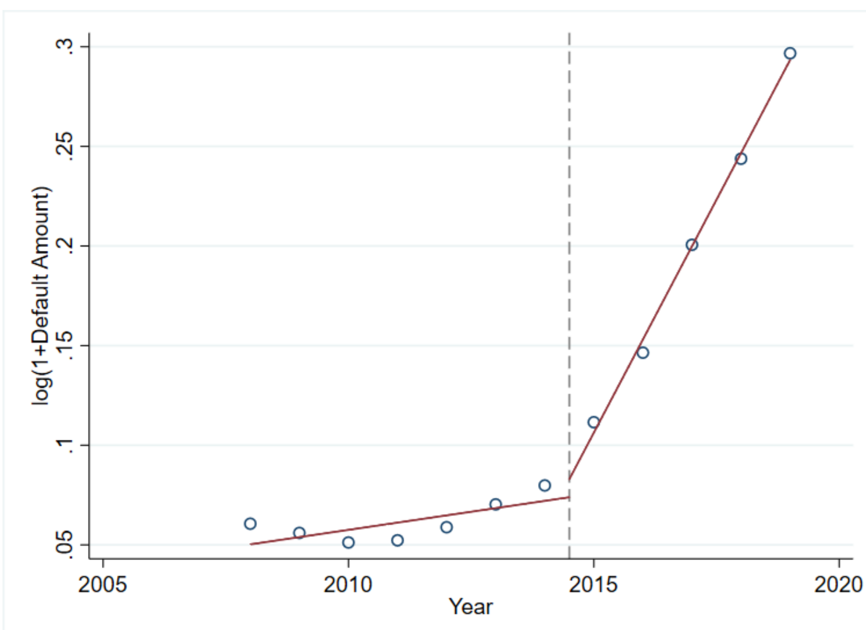


Figure A2: Overall Default Loan Amount: During and after regulatory forbearance

## TABLE A1: Variable Definitions

| Variable | Definition | Observation Level |
|---|---|---|
| *Period* | The dataset is divided into two periods: pre-period(2008-2014) and post-period (2015-19). Pre-period is also called forbearance period. | |
| $RelationshipStrength_{Num}$ | Weighted sum of year-wise number of loans, where the weights are inverse of time elapsed since the loan was given | Firm-Lender-Year |
| $RelationshipStrength_{Amt}$ | Weighted sum of year-wise amount of loans, where the weights are inverse of time elapsed since the loan was given | Firm-Lender-Year |
| $RelationshipStrength_{Dist}$ | Reciprocal of distance (kilometers) between headquarters of the firm and the bank | Firm-Lender |
| $Relationship_t$ | Indicator variable that equals one in a given year for a firm-lender pair if all the three relationship strengths (number, amount, and distance) of that pair for a given year lie above their respective (within firm-year) median values, and zero otherwise | Firm-Lender-Year |
| *Relationship* | Indicator variable that eqals one for a firm-lender pair if $Relationship_t$ equals one for at least one year during the pre-period (2008-14) for this pair | Firm-Lender |
| $Relationship_{t-1}$ | One year lagged value of $Relationship_t$ | Firm-Lender-Year |
| $Relationship_{2007}$ | Indicator variable that eqals one for a firm-lender pair if $Relationship_t$ equals one in year 2007 for this pair | Firm-Lender |
| $Relationship_{Dist}$ | Indicator variable that equals one in a given year for a firm-lender pair if $RelationshipStrength_{Dist}$ lies above the median value for that firm in that year, and zero otherwise | Firm-Lender-Year |
| *Post* | Indicator variable that equals one for each year starting 2015, and zero before that. | Year or Period |
| *Default* | Indicator variable that equals one if the firm fails to repay its dues for 90 days or more during that period. It could be categorized into wilful or non-wilful default. The period could also be one year. | Firm-Lender-Period (year) |
| *DefaultAmount* | Average (total) loan amount on which the firm defaulted for a given lender in that period (year) | Firm-Lender-Period (year) |
| *NewLoanAmount* | Total new loan amount borrowed by a firm from a given lender in that period (year) | Firm-Lender-Period (year) |
| *LoanAmount* | Total loan amount borrowed by a firm from a given lender which has not been repaid in full by the end of the period. This can also be referred as Outstanding Loan Amount. | Firm-Lender-Period |
| *NegativeLendingShock* | *NegativeLendingShock* is an indicator variable which takes the value of one if in a given year a lender sees an idiosyncratic decline in lending, and zero otherwise. Bank-specific year-wise idiosyncratic change in lending is calculated by following \citeAmiti2011. | Lender-Year |
| *InterestCoverageRatio* | Annual Interest Expense / Earnings Before Interest and Taxes | Firm-Year |
| *DistressedFirm* | Indicator variable which equals one if *InterestCoverageRatio* of a firm is less than one in that period (year). | Firm-Period (year) |
| $Help_t$ | Indicator variable that equals one in a given year for a firm-lender pair if the relationship lender makes a new loan to the firm or restructures an existing one in the same year, while the firm pays off a running loan from a transaction lender, and zero otherwise. | Firm-Lender-Year |
| *Help* | Indicator variable that equals one if $Help_t$ is one for at least one of the years during the pre-period and zero otherwise. | Firm-Lender-Period |
| *HelpReceivingFirm* | Indicator variable that equals one in a given year if a firm received $Help_t$ from a relationship lender in that year, and zero otherwise. | Firm-Year |
| $NewProject_t$ | Indicator variable that take the value one if the firm announces a new project in a given year, and zero otherwise. | Firm-Year |
| $StalledProject_{t+1}$ | Indicator variable that take the value one if the firm announces that an existing project gets stalled in the following year, and zero otherwise. | Firm-Year |

**TABLE A2: Types of Lenders**

| | Count | Percent | Relationship | Default | #New Loans | New Loan Amt (INR 10mn) | Distance (km) |
|---|---|---|---|---|---|---|---|
| Public Sector Banks | 279042 | 48.96 | 0.16 | 0.0285 | 0.21 | 21.52 | 265.70 |
| Private Sector Bank | 142364 | 24.98 | 0.12 | 0.0172 | 0.30 | 18.03 | 653.48 |
| NBFC | 76411 | 13.41 | 0.09 | 0.0009 | 0.51 | 128.89 | 821.86 |
| Foreign Bank | 35715 | 6.27 | 0.14 | 0.0078 | 0.23 | 14.08 | 535.38 |
| Financial Institutions | 10852 | 1.90 | 0.08 | 0.0101 | 0.36 | 75.62 | 696.27 |
| Co-operative Banks | 8443 | 1.48 | 0.18 | 0.0018 | 0.53 | 5.31 | 200.59 |
| Private Firm | 5858 | 1.03 | 0.12 | 0.0000 | 0.47 | 260.63 | 597.76 |
| State Govt Body | 5899 | 1.03 | 0.05 | 0.0000 | 0.12 | 3.21 | 288.63 |
| HFC | 5140 | 0.90 | 0.10 | 0.0016 | 0.36 | 33.05 | 696.15 |
| Govt Firm | 223 | 0.04 | 0.02 | 0.0000 | 0.22 | 1.94 | 949.28 |
| Regional Rural Bank | 28 | 0 | 0.07 | 0.0000 | 0.36 | 4.75 | 558.41 |
| Total | 569975 | 100 | | | | | |

## TABLE A3: Relationship Defined Using Seventy-Fifth Percentile

The table documents the difference in differences estimates of regressing $Default$ (or default amount) on *Relationship*. Columns (1) and (3) show results for equation (4) where the observations are collapsed into pre- and post-periods. Columns (2) and (4) show results for equation (5) where the data is arranged in firm-lender-year level observations. Default for a firm-lender pair takes the value of one if the firm defaults on this lender during the period, and zero otherwise. $log$(1+Default Amount) is the logarithmic value of the outstanding loan amount on which the firm defaulted in that year (Column (4)). For column (3), yearly values of the defaulted loan amount are aggregated (mean) over the pre- and post-periods before applying the log function. $Relationship_{75}$ takes the value of one if the firm and the lender are in a relationship (with a modified definition from section 4.1 by using 75th percentile instead of median to classify the three relationship strengths) for at least one year during the forbearance period, and zero otherwise. $Relationship_{t-1,75}$ is the value of *Relationship* from the previous year based on the definition in section 4.1 but using 75th percentile instead of median. $Post_t$ equals one starting 2015 and zero for all years before that. All regressions have Firm x Time and Lender fixed-effects. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | $log$(1+Default Amount) | |
| $Relationship_{75}$ | -0.000561 | | -0.0148 | |
| | (-0.37) | | (-1.58) | |
| $Relationship_{75} * Post$ | 0.0196*** | | 0.102*** | |
| | (4.90) | | (4.40) | |
| $Relationship_{t-1,75}$ | | -0.00154 | | -0.000408 |
| | | (-0.67) | | (-0.02) |
| $Relationship_{t-1,75} * Post$ | | 0.0143*** | | 0.117*** |
| | | (3.21) | | (3.37) |
| Observations | 112939 | 385668 | 112939 | 385668 |
| Adjusted $R^2$ | 0.256 | 0.217 | 0.134 | 0.187 |
| Firm x Period FE | Yes | | Yes | |
| Firm x Year FE | | Yes | | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | Lender | | | |

## TABLE A4: Separating Wilful and non-wilful defaults

This table documents the results which check if the main result differs by categorization of default: Wilful and Non-wilful Defaults. Lenders categorize a loan as a default if the borrower fails to make a repayment for over 90 days. The default is categorized as wilful only if the lender believes that the firm had the resources to repay but did not or used the funds for purposes not disclosed at the time of disbursal. I run regression (4) with dependent variables: non-wilful default, wilful default, outstanding loan amount of non-willful default, and that of wilful default, and document the results in columns (1) to (4) respectively. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Non-wilful Default | Wilful Default | $log$(1+Non-wilful Default Amt) | $log$(1+Wilful Default Amt) |
| *Relationship* | -0.00133 | -0.000306 | -0.00566 | -0.00334 |
| | (-1.01) | (-0.41) | (-0.70) | (-0.69) |
| $Relationship * Post$ | 0.0132*** | 0.00872*** | 0.0676*** | 0.0817*** |
| | (5.59) | (4.60) | (4.22) | (5.19) |
| Observations | 112939 | 112939 | 112939 | 112939 |
| Adjusted $R^2$ | 0.192 | 0.207 | 0.134 | 0.213 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | Lender | | | |

## TABLE A5: ANNOUNCEMENT EFFECT AND BANKRUPTCY LAW EFFECT

This table shows the results for robustness tests around the date of intervention, 2015, the year when forbearance was withdrawn. RBI announced the withdrawal of forbearance in 2013. So, I check for announcement effect by separating the years 2013 and 2014 using a dummy variable *Announcement*, which takes the value one if year equals 2013 or 2014 and zero otherwise. I run regression 4 after restricting the sample to 2008 to 2014 and show the result in column (1), and column (2) includes the post-period as well. In 2017, changes to bankruptcy laws (Insolvency and Bankruptcy Code or IBC) took effect. I divide the data into two periods, 2008-2012 as the pre-period, and 2013-2016 as the pre-IBC period, collapse the data into these periods, run a regression similar to equation (4) with $PreIBC$ dummy, which equals one for years 2013-16 and zero otherwise, instead of *Post* dummy. The results are shown in column (3), where the coefficient for $Relationship * PreIBC$ in the regression run for the period 2008-2016 is not significantly different from zero. Column (4) includes the post-IBC (2017-19) period as another dummy variable. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Default | | |
| *Relationship* | 0.000590 | -0.00205 | -0.00103 | -0.00294** |
| | (0.52) | (-1.48) | (-0.88) | (-2.02) |
| $Relationship * Announcement$ | -0.000667 | -0.00109 | | |
| | (-0.43) | (-0.71) | | |
| $Relationship * Post$ | | 0.0206*** | | |
| | | (5.24) | | |
| $Relationship * PreIBC$ | | | 0.00800*** | 0.00753*** |
| | | | (3.67) | (3.44) |
| $Relationship * PostIBC$ | | | | 0.0218*** |
| IBC | | | | (5.13) |
| Observations | 89508 | 145911 | 98622 | 147474 |
| Adjusted $R^2$ | 0.231 | 0.254 | 0.254 | 0.262 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Time Period | 2008-14 | 2008-20 | 2008-16 | 2008-20 |
| Std Error Cluster | | Lender | | |

## TABLE A6: PLACEBO TESTS

I run two placebo tests and document the results in this table. The first set of tests vary the year of the intervention to 2011 (from 2015) and show results for $Default$ and $log(1 + DefaultedLoanAmount)$ in Columns (1) and (2) respectively. Columns (3) and (4) randomly assign firm-lender pairs into a relationship and show that this random assignment does not reproduce the main results. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) Default | (2) $log$(1+Default Amount) | (3) Default | (4) $log$(1+Default Amount) |
|---|---|---|---|---|
| $Relationship$ | 0.00118 | 0.00171 | | |
| | (1.08) | (0.32) | | |
| $Relationship * Post2010$ | -0.000479 | 0.0102 | | |
| | (-0.23) | (1.18) | | |
| $RandomRelationship$ | | | 0.00201 | 0.00560 |
| | | | (1.48) | (0.77) |
| $RandomRelationship * Post$ | | | -0.000196 | 0.0140 |
| | | | (-0.10) | (1.17) |
| Observations | 82082 | 82082 | 112939 | 112939 |
| Adjusted $R^2$ | 0.232 | 0.199 | 0.255 | 0.133 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | Lender | | | |

## TABLE A7: DOES AQR TARGET ONLY RELATIONSHIP BANKING?

One concern could be that the AQR is biased against relationship banking. If this statement is true, the auditor pays disproportionate attention to the relationships of a bank. As AQR occurs at the lender level, I define $Relationship_{bank}$ at the level of the lender using the similar method as described in section 4.1, but instead of classifying lenders of a firm into a relationship, I classify borrowing firms of a lender into relationship or transaction. Then I replicate Table 3 using this new measure of *Relationship*. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default | | | |
| $Relationship_{bank}$ | 0.000773 | | 0.00102 | |
| | (0.64) | | (0.20) | |
| $Relationship_{bank} * Post$ | 0.00190 | | 0.0242 | |
| | (0.80) | | (1.61) | |
| $Relationship_{t-1,bank}$ | | -0.000807 | | -0.00334 |
| | | (-1.35) | | (-0.79) |
| $Relationship_{t-1,bank} * Post$ | | 0.00139 | | 0.0214 |
| | | (0.75) | | (1.31) |
| Observations | 112939 | 376580 | 112939 | 376580 |
| Adjusted $R^2$ | 0.255 | 0.220 | 0.133 | 0.188 |
| Firm x Period FE | Yes | | Yes | |
| Firm x Year FE | | Yes | | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Std Error Cluster | Lender | | | |

## TABLE A8: PRIVATE VS PUBLIC FIRMS

The table documents if the findings are restricted to government-owned firms. I take four subsamples: (i) government-owned firm borrowing from government lender, (ii) private firm borrowing from government lender, (iii) government-owned firm borrowing from a non-government lender, and (iv) private firm borrowing from a non-government lender. I run the main regression for each of these subsamples and show the results in Columns (1) to (4) in that order. Results indicate that privately owned firms, irrespective of the ownership status of the bank, default more on relationship lenders. Clearly, the sample mostly consists of privately owned firms, and it is difficult to make any comment about the repayment behavior of government-owned firms. T-statistics are reported in parentheses, and standard errors are clustered at the lender level.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Default | | |
| *Relationship* | -0.00519** | -0.00170 | 0 | -0.00135 |
| | (-2.53) | (-0.87) | (.) | (-0.82) |
| $Relationship * Post$ | 0.00125 | 0.0205*** | 0 | 0.0101*** |
| | (0.37) | (3.55) | (.) | (3.37) |
| Observations | 2556 | 37380 | 1128 | 56321 |
| Adjusted $R^2$ | 0.170 | 0.330 | . | 0.180 |
| Firm x Period FE | Yes | Yes | Yes | Yes |
| Lender FE | Yes | Yes | Yes | Yes |
| Subsample: Govt Lender | Yes | Yes | No | No |
| Subsample: Govt Firm | Yes | No | Yes | No |
| Std Error Cluster | | Lender | | |