Corporate Debt Restructuring, Bank Competition and Stability: Evidence from creditors' perspective

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ABSTRACT

This paper estimates the causal effect of a unique programme of corporate debt restructuring (CDR) on stability of Indian banks over the period 1992-2012. The banks who participated in the programme were extended regulatory forbearance on asset classification and provisioning on the restructured corporate loans. We find that banking stability of the participated banks increases substantially after the implementation of the programme. Using stochastic frontier analysis approach, we estimate two variant measures of market power and investigate the interactive effect of CDR on bank stability. The result shows that the positive effect of CDR on stability declines at higher level of market power, implying that the CDR mechanism is less effective for the participating banks beyond a threshold level of market power. We also find that the second phase of deregulation and the direct effect of market power have significant positive effect on the overall soundness of Indian banks. To provide unbiased treatment effects of CDR eliminating any sample selection bias, we further confirm the positive effect of CDR on bank stability using a number of alternative matching estimators. Our results (both parametric and non-parametric) remain insensitive to an array of robustness tests including quality of matching.

JEL Classification: G21; G28
Keywords: Risk analysis; Bank competition; Stability; Corporate debt restructuring; Deregulation

1. Introduction

Maintaining a reasonable level of banking competition and stability is the ultimate objective of regulators around the world, including central banks such as the Reserve Bank of India (henceforth RBI). Over the last two decades, the banking systems in many emerging market economies have passed through major reforms including restructuring programmes to reduce bank-level non-performing assets, and it is therefore important to understand the effectiveness of such institutional mechanisms in achieving bank stability. RBI initiated two phases of banking reforms in the 1990s to reduce market power and risk-taking attitudes of banks. However, in the beginning of 2000s, Indian corporates faced increasing challenges in meeting their debt servicing obligations to the banks/financial institutions. Since high corporate debt overhang[1] poses a risk to banks' balance

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[1] Myers (1977) demonstrated that 'debt overhang' is a state when corporates are discouraged of extending investments on new productive projects fearing of defaulting on existing outstanding risky debts, and thus impair economic growth.

sheets and financial stability due to increasing nonperforming loans (NPLs) and corporate bankruptcies (Goretti and Souto, 2013), RBI introduced an out-of-court restructuring programme in the form of 'Corporate Debt Restructuring' (henceforth CDR; see sub-section 2.2). The intention was to provide a speedy, cost effective, and market friendly alternative to in-court restructuring procedures (Claessens, 2005; Liu and Rosenberg, 2013) in order to bring the credit market out of a downward spiral and to assist in reviving viable corporates.

The net effect of CDR emanated in two ways: on the one hand, corporates were able to maintain their investments and firm value and forestall bankruptcy and on the other hand, the bank who participated in the restructuring of corporate debts (henceforth member banks) under CDR were able to minimise their exposures to those sick corporates and maintain banking stability through various channels. In this paper, we are interested in the latter aspect of CDR and investigate empirically whether member banks have benefited from restructuring corporate debts and enhanced their stability (or reduced their risk taking). As per CDR norms, member banks could retain the asset classification of restructured loans, and even could upgrade nonperforming restructured assets to standard (performing) category after a specified period and charge less to their net income for loan loss provisions (Working-Group, 2012 henceforth WG). This special regulatory forbearance on asset classification and provisioning gave more opportunities to member banks to understate nonperforming loans and overstate net income. Banks were benefited more after the global financial crisis as they restructured more loans during post crisis period. Figure 1 shows that the total restructured corporate loans as percent of total loans have reached to 12.5% from just 2% in 2006. It is documented both theoretically and empirically that by using *ex-ante* loan loss provisions, banks can reduce volatility of its current profitability i.e., smoothing income (e.g., Fudenberg and Tirole, 1995; Lobo and Yang, 2001; Goel and Thakor, 2003; Shrieves and Dahl, 2003). Through income smoothing banks can also reduce the possibility of depleting its capital (Laeven and Majnoni, 2003). Therefore, we expect a positive correlation between member banks' participation and their stability.

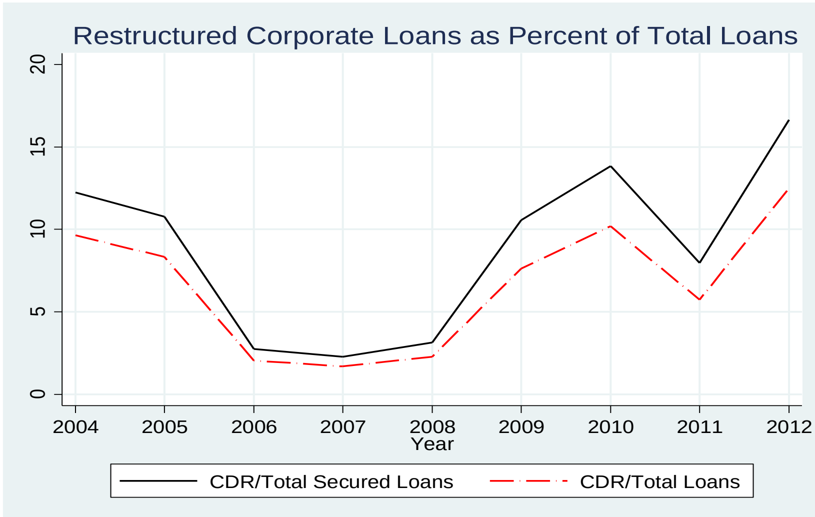

Figure 1: Restructured corporate loans as percent of total loans after the genesis of CDR.

The question of whether greater competition is good or bad for banking stability has been at the epicenter for the last two decades and recently, after the global financial crisis in 2008, it attracts renewed attention of the academics and regulators (Keeley, 1990; Allen and Gale, 2004; Schaeck, Cihak and Wolfe, 2009; Martinez-Miera and Repullo, 2010; Chortareas, Girardone and Ventouri, 2011; Beck, De Jonghe and Schepens, 2013; Anginer, Demirguc-Kunt and Zhu, 2014). The findings of the existing studies are contradictory because of cross country variation and methodology adopted in measuring market power.[2] Therefore, in this study we also investigate how banking competition impacts risk-taking behaviour of Indian banks.

We contribute to the existing literature mainly in two ways. First, given the limited number of studies that analyse the changes within Indian banking industry after two important financial reforms in the last two decades, we contribute to the literature exploring the ambiguous nexus between bank competition and stability using the largest panel data taken from the RBI for the period 1992-2012.[3] To eradicate any endogeneity problems between market power and bank stability, we employ instrumental variable technique with a Generalised Method of Moments (GMM) estimator using the kernel-based heteroskedasticity and autocorrelation consistent (HAC) variance estimation of Newey and West (1987).

Second, we attempt to add to the literature on corporate debt restructuring from the creditors' perspective by investigating the impact of a unique institutional mechanism in India on bank stability of the treatment group while using a 'natural experiment' type difference-in-

[2] See for example Beck, De Jonghe and Schepens (2013) and Anginer, Demirguc-Kunt and Zhu (2014).
[3] See for example Tzeremes (2015).

differences (DD) approach (see Bertrand and Mullainathan, 2003) and nonparametric matching estimators (see Abadie and Imbens, 2006; Imbens and Wooldridge, 2009). Using this modeling strategy is appropriate to establish causal claims and to investigate the effects of a programme implementation among treated and control groups. This approach allows us to capture the mean difference in the outcome variable between treated and control groups after implementation of the programme removing biases due to economic trend of the two groups. In our case, it captures the mean difference of bank-level stability between member banks and non-member banks after the genesis of CDR programme in India. Comparing the performance of the treated group allows us to capture the effect of the programme removing any bias due to other omitted time invariant factors (Imbens and Wooldridge, 2009; Fang, Hasan and Marton, 2014). As a robustness test, to eliminate any sample selection bias, we also employ alternative estimators including the bias-corrected covariate matching methods recently developed by Abadie and Imbens (2006). Since the matching methods are nonparametric in nature, they can alleviate sample selection bias by formally controlling for the non-random selection problem and avoid the specification of the functional form (Imbens and Wooldridge, 2009).

From the economic policy standpoint, it is important to investigate the impact of the regulatory forbearance under the guise of CDR system on the member banks' stability so that appropriate action can be taken to reduce excessive risk-taking not only by the Indian policymakers but also in other emerging market economies in case of such widespread corporate sickness. In addition, since bank competition is one of the important determinants of banking stability, we also investigate the interactive effects of CDR on stability at different levels of bank competition. Considering the recent development in measuring bank competition, we estimate two variant measures of market power proxied by conventional Lerner indices (Berger, Klapper and Turk-Ariss, 2009) and efficiency-adjusted Lerner indices from a stochastic frontier analysis approach (Koetter, Kolari and Spierdijk, 2012), which allow us to dispel any concern about the incorrect measures of market power, and thus provide robust analysis aiming at facilitating reliable policy decision making.

The rest of the paper is organised as follows. Section 2 provides a brief overview of the regulatory framework and CDR mechanism in India. In section 3, we develop theoretical hypotheses. Section 4 outlines the empirical models and Section 5 describes the data and descriptive statistics. Section 6 explains the estimation results, discussing the effects of competition on stability of banks, and presents the results of the causal effect of CDR on stability with all sensitivity analyses. The concluding remarks are provided in Section 7.

2. Deregulation and corporate debt restructuring in India

2.1 Deregulation

Indian banking sector comprises of public sector banks, private sector banks and foreign banks. In the 1950s, the limited regulatory control over interest rates and trivial pre-emption of funds in the financial system resulted inequitable distribution and misallocation of credit (Das and Kumbhakar, 2012). To ensure proper allocation of credit in the priority sectors, Indian government tightened its control over credit allocation and introduced administered interest rates both on deposits and loans, high reserve requirements and rigorous statutory liquidity restrictions, which culminated with the nationalisation of 20 major commercial banks between 1969 and 1980 (Das, Nag and Ray, 2005; Bhattacharyya and Pal, 2013). The net effect of this overregulation resulted in an inefficient allocation of resources, high operating costs, declining profitability and deteriorated asset quality.

In 1992, the RBI started the liberalisation process stressing deregulation and opening up of the banking sector to market forces aimed at providing operational flexibility and functional autonomy. Since then it has been consistently working to establish a sound regulatory framework in order to facilitate effective supervision and institutional infrastructure. The diversification of ownership through considerable dilution of capital by the government reduced overpowering of state-owned banks, and yields a level-playing field for all. This first phase of reforms improved the competitiveness and efficiency in the resource allocation process of the banking sector and strengthened the transmission mechanism of monetary policy including reduction in statutory liquidity ratio (SLR), cash reserve ratio (CRR), permission for de novo entry of banks in the private sector, and deregulation of interest rates.

The second phase of reform started in 1998 with the aim of enhancing banking stability through improved banking regulation, increasing competitiveness, adoption of capital adequacy norms, prudential norms for asset classification and provisions for delinquent loans in line with global practices. To adhere to the stipulated capital adequacy norms, substantial amount of capital were injected by the government of India to the public sector banks. To this end, there has been a wave of mergers and acquisitions conducted both according to the market principles and with the assistance of government (Fujii, Managi and Matousek, 2014). In the recent past, the strengthening of Debt Recovery Tribunals (DRTs), the inauguration and successful implementation of new institutional mechanisms *viz.* SARFAESI (Securitisation and Reconstruction of Financial Assets and Enforcement of Securities Interest) Act' 2002 and CDR system facilitated the expedition of recovery of loan arrears. In the case of DRT Act, special tribunals were set up by the government of

India to facilitate speedy recovery of defaulted loans without needing Civil Procedure Code. In the case of SARFAESI Act, the rights of the secured creditors were strengthened and thereby banks were allowed to seize and liquidate the assets of the defaulted firm without much delay. Visaria (2009) and Vig (2013) provide detailed discussion on DRT and SARFAESI Acts, respectively. In the following sub-section we discuss in detail about the CDR.

2.2 Corporate debt restructuring

In the late 1990s, Indian corporates faced unprecedented financial distress to be able to meet the repayment obligations. To reduce the 'debt overhang' problem of corporates as well as bringing the credit market out of the downward spiral, RBI sponsored a restructuring mechanism in the form of CDR in 2002. However, prior to CDR, in case of in-court restructuring of corporate debts, the Board for Industrial and Financial Reconstruction (BIFR), an agency of the government of India, similar to the US Chapter 11 Bankruptcy Code, was set up under the Sick Industrial Companies Act 1985 to determine the sickness of industrial companies and to help in reviving the viable economically efficient entity and shutting down the economically inefficient ones. In recent years, the misuse and the Indian law's indefinite nature of respite made it a haven for promoters of sick companies.

CDR is an efficient out-of-court institutional mechanism for banks/financial institutions to restructure corporate debts (e.g., secured by tangible assets). To participate in the restructuring bank needs to be member of the system and sign debtor-creditor agreement (DCA) and inter-creditor agreement (ICA), which extend legal supports for the CDR.[4] The CDR aims at speedy restructuring of the dues of banks/financial institutions in a transparent manner to minimise their losses where they have an exposure of Rs. 100 million and above in the multiple banking/syndicates/consortium accounts.[5] It is a three-tiered mechanism with a standing forum, empowered group and the CDR cell. While standing forum sets comprehensive policies and guidelines, the CDR cell in conjunction with the lenders does the preliminary analysis of proposals and provides a detailed restructuring plan, and finally, empowered group deliberates and approves the restructuring proposals. Corporate loans will go ahead for restructuring if it has support of 75% of the creditors by value, and 60% by number (RBI, 2005). In 2003, in order to make CDR mechanism more efficient and barring the

[4] In the former case, both debtor and creditor(s) agree to stay away from recourse to any legal action during restructuring period of 90/180 days, and in the latter case, all member banks/institutions of CDR system sign an agreement whereby they are legally binding with necessary enforcement and penal clauses.

[5] For more information about corporate debt restructuring please see various circulars of RBI compiled at: http://www.cdrindia.org/rbi.htm

willful defaulters CDR scope was extended to include 'standard' loan assets, 'doubtful' loan assets and the cases of BIFR of just 'sub-standard' loan assets previously.[6]

Special regulatory forbearance on asset classification and provisioning was extended to the restructured assets. Any standard assets can retain its assets classification upon restructuring without slipping into lower asset categories as per the CDR scheme. Banks were also allowed to make concessional provisions of 2% on any restructured standard assets.[7] In addition, if any restructured account had nonperforming assets (i.e., sub-standard and doubtful), it can be upgraded into standard (performing) assets category after a specified period (i.e., one year); if it can be shown that the obligations are met by the borrowers as per CDR norm.[8] According to guidelines of RBI, if restructured nonperforming assets remain in the same category, provisioning has to be made and income can be recognised only on cash basis (realisation) (Vaidyanathan, 2013). However, a recent report by Working Group reveals that according to the global practice any assets restructured should fall into lower asset category and loan loss provisions should be made accordingly (WG, 2012).

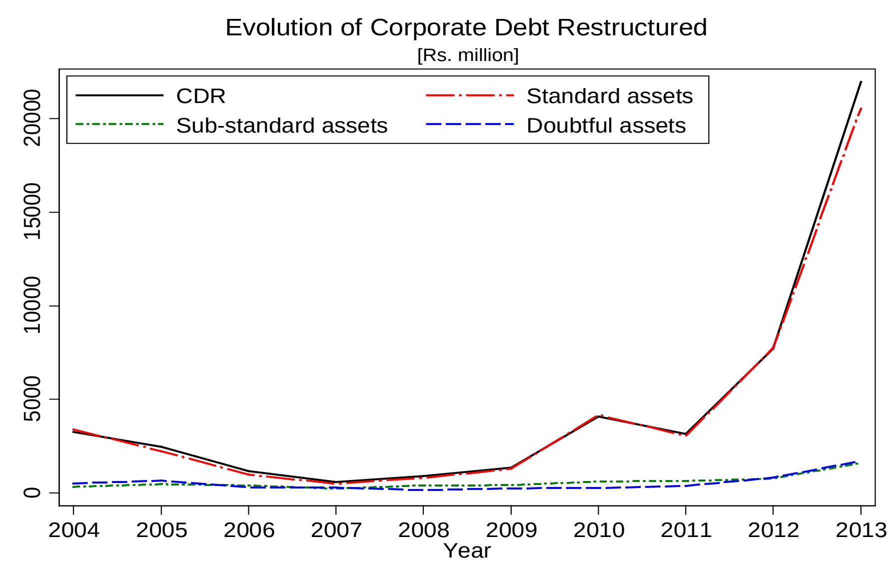

Figure 2: the evolution of CDR in India from 2004 to 2013

[6] Based on assets classification, accounts classified as 'standard' and 'sub-standard' were in the Category 1 CDR and accounts classified as 'doubtful' were in the Category 2 CDR.
[7] According to provisioning norms, in respect of sub-standard assets of secured category, banks are required to keep 10 per cent provision, and for the unsecured exposures, additional 10 per cent, totaling 20 per cent is required to be made (for details, Vaidyanathan, 2013).
[8] It is noted that specified period is defined as a period of one year from the date when the first payment of interest or instalment of principal falls due under the terms of restructuring package (WG, 2012).

We can see from the Figure 2 that after global financial crisis in 2008 the corporate loan restructured increased by 744% from Rs. 913.4 million in 2008 to Rs. 7718.5 million at the end of 2012. Against this backdrop of substantial increase of restructured loans, on November 2012, RBI has raised provision on restructured standard loans to 2.75% from just 2% previously. Provisioning on any new restructured standard loans is 5% from June 1, 2013. It has also decided to do away with the regulatory forbearance on asset classification and provisioning from April 1, 2015 (RBI, 2013).

A plethora of anecdotal evidence suggests that the CDR system has significant effect on the bottom lines of the member banks. A report of Standard Chartered Securities published on many local newspapers stating that the increased provisioning requirement is likely to erode 18% profitability of the public sector banks.[9] Many critics expressed concerns about CDR system that it is a conduit for bankers to hide NPLs and hike income, which will have a deleterious effect on the impairment of asset in the future. It was also echoed by the deputy governor of RBI, K.C. Chakrabarty that “If the reason for the recent increase in restructured accounts is indeed the economic downturn, it should have been reflected across all bank groups and not just public sector banks." It was reported that there were forced debt restructuring of loss making public sector entities and retaining those potential NPLs as standard restructured assets.

3. Review of Related Literature

The main research questions in this article are whether market power influences the risk of banks and whether CDR reduces risk of member banks under CDR mechanism. We develop hypotheses based on the literature regarding market power-stability nexus and *ex-post* credit risk and CDR.

3.1 Market power-stability nexus

From a theoretical and empirical point of view, there is an ambiguous relationship between market power and stability of a bank. The stability in banking sector is heavily relied on the degree of competition that banking sector possesses. The first theoretical model in Marcus (1984) shows that if there is competition in the deposit market, banks undertake risk taking strategies because of the contraction in the banks’ franchise value, which is well-known as the ‘franchise value’ hypothesis in banking. The first empirical study of Keeley (1990) on U.S. banking industry in the aftermath of financial deregulation shows that greater competition reduces the franchise value of banks and then increases the banks’ incentive to take excessive risk. The advocates of ‘market

[9] http://articles.economictimes.indiatimes.com/2012-07-24/news/32828003_1_state-run-banks-cent-private-sector-banks

power-stability' view argue that more concentrated and less competitive banking systems are more stable because the excessive profit they make provides a "buffer" against fragility and provides incentives against excessive risk taking (Beck, 2008).

However, the relationship between market power and stability can also be negative. Boyd and De Nicolo (2005) introduce 'competition-stability hypothesis' and argue that greater competition contributes to sustain stability in the banking market. The basis of their arguments expounds moral hazard and adverse selection problems of customers in deposit market. They argue that higher market power of banks increases the borrowing cost for entrepreneurs which induces borrowers to opt for risky projects to mitigate the extra repayment they incur from the loans which in turn increases entrepreneurial default risk. In other words, this harder repayment strategy exacerbates moral hazard incentives of borrowers and banks end up with riskier set of clients due to adverse selection considerations (Berger, Klapper and Turk-Ariss, 2009; Turk Ariss, 2010). More recently, using cross-country data, Beck, De Jonghe and Schepens (2013) find negative relationship between bank competition and stability while the finding of Anginer, Demirguc-Kunt and Zhu (2014) is completely opposite. Therefore, the findings based on cross-country analysis or from developed market economies would be hard to generalise in the case of emerging market economies, especially for India, which has undergone substantial regulatory changes in the recent past.

Hypothesis 1: Market power effect can be positively associated with bank stability.

3.2 Debt restructuring and banking stability

In this section, we argue for a positive relationship between banking stability and member banks of CDR who relished substantial regulatory forbearance on asset classification, provisioning and capital adequacy. We measure bank stability with bank-specific Z-scores, which are calculated as the sum of the return-on-assets (ROA) and capital ratios, scaled by standard deviation of the ROA (for details see section 5).

Since member banks of CDR system were extended regulatory forbearance on asset classification and provisioning, we assume that they reduce risk through changes in profitability, capital adequacy, or a combination of both. Unlike the literature on performance evaluation of corporates after restructuring debts, no general model exists from the creditors' perspective (Kang and Shivdasani, 1997). However, existing literature implicitly indicates how member banks could affect profitability and capital adequacy via loan loss provisioning, and thereby their stability.

Regarding the profitability channel, member banks may have increased profitability and thus stability because they had more opportunities to understate nonperforming loans and overstate net income through exploitation of CDR system. As per CDR norms, member banks could retain the asset classification of restructured loans and charge less to their net income for loan loss provisions (WG, 2012) which should have been higher if they did not have regulatory forbearance on asset classification and provisioning, and thus would have lower net income. Previous literature on income smoothing argues that banks can use its loan loss provisions to increase its current profitability (e.g., Fudenberg and Tirole, 1995; Lobo and Yang, 2001; Shrieves and Dahl, 2003).[10] According to Fudenberg and Tirole (1995), bank managers during lean (fat) years charge less (more) loan loss provisions to the net income by shifting future (current) earning to the current (future) period in order to increase (decrease) profitability. Ghosh and Nachane (2003) find an evidence of income smoothing in India for a sample of state-owned banks for the period 1997-2002.

By smoothing income banks not only can reduce volatility of its revenue but also it can reduce the possibility that it may have to eat into its capital (Laeven and Majnoni, 2003). According to the new Basel capital adequacy framework, general provisions are included in the calculation of Tier-2 capital not exceeding to an amount of 1.25 per cent of risk-weighted assets. Therefore, if member banks are not capital-constrained they will have less incentive to charge higher loan loss provisions to manage regulatory capital. On this issue Bikker and Metzemakers (2005) and Bushman and Williams (2012) find negative relationship between loan loss provisions and capital ratios.

In the context of multiple/consortium/syndicate accounts, creditors coordinate and cooperate regularly and intensively in the restructuring of distressed borrowers (e.g., Franks and Sussman, 2005; Brunner and Krahnen, 2008). Vig (2013) did not find any evidence of creditor run or coordination problems among Indian banks in case of multiple banking accounts for a sample of banks during 1997-2004. Rajan (1992) shows that banks realise more benefits through multiple banking than single banking account financing. It is noted that in the CDR mechanism creditors are the close monitors of the restructured corporate loans. By using out-of-court restructuring of corporate loans, member banks not only get respite from expensive and unending legal proceedings but also they can free up additional resources to invest in more productive intermediation activities, and thus earn more profits. They can turn potential nonperforming assets (i.e., non-income yielding assets) into performing assets (income yielding assets), and by so doing, member banks can increase

[10] Income smoothing refers to the practice of minimising variations in earnings over time through a deliberate damping of fluctuations.

profitability and simultaneously reduce stress on provisioning, capital adequacy, liquidity and net interest margin, and thereby increase competitiveness with reduced operating costs.[11]

Summing up, the increasing profitability because of favorable regulatory forbearance on asset classification and provisioning as well as costs savings in managing nonperforming loans enable member banks of CDR system to enhance their stability. However, the alluded concessional loan loss provisions on restructured corporate loans have direct implications on the mark-up of the banks and their market power. Due to increasing market power, member banks may have shown delinquency in determining the riskiness of their portfolios. Besides, since the aim of the financial reforms was to enhance market mechanism, transparency and banking competition, we may expect individual banks' pricing power can channel through CDR and induce excessive risk-taking, which is an empirical issue.

Hypothesis 2a: CDR can have a positive effect on stability of member banks.

Hypothesis 2b: The positive effect of CDR on stability reduces at higher degree of market power.

4. Methodology

4.1 The impact of competition on bank risk-taking

We test whether bank competition impact the stability of Indian banks using bank-level data. To circumvent the potential endogeneity issue with the measure of market power we follow recent empirical studies (e.g., Berger, Klapper and Turk-Ariss, 2009; Tabak, Fazio and Cajueiro, 2012; Fu, Lin and Molyneux, 2014) and employ an instrumental variable technique with a GMM estimator using the kernel-based heteroskedasticity and autocorrelation consistent (HAC) variance estimation of Newey and West (1987). The advantage of using this method is twofold. First, it is robust to the presence of some unobserved characteristics, influencing both market power and stability, or by reverse causality, and second, it does not require any assumptions about error distributions and, therefore, it is robust to the arbitrary heteroskedasticity and autocorrelation of disturbance terms (Hansen, 1982). The regression model is as follows:

[Insert Table 1]

$$Bank\ risk_{it} = \alpha_i + \alpha_t + \beta_1 Lerner_{it} + \beta_2 dreg_t + \sum \gamma \cdot (Bank\ Controls)_{it} + \sum \delta \cdot (Macro)_{it} + \varepsilon_{it} \qquad (1)$$

where i denotes individual banks and t indexes years. The dependent variable is the individual bank risk at time t. The main independent variable of interest is the Lerner index, a proxy for individual bank market power at time t. We use either conventional Lerner index i.e., C-Lerner or

[11] See Jensen and Meckling (1979) for details on direct and in-direct costs related to bankruptcy by firms.

efficiency-adjusted Lerner index i.e., E-Lerner. The second variable of interest is the deregulation dummy (i.e., dreg) takes a value equal to one for the year 1998 and thereafter, or else zero. We control for various bank-specific characteristics as well as macroeconomic variables. The detailed definition of these variables can be found in Table 1.

4.2 The impact of corporate debt restructuring (CDR) on bank stability

We examine the effect of CDR on bank stability by using a difference-in-differences (DD) approach following Bertrand and Mullainathan (2003) and Koetter, Kolari and Spierdijk (2012).[12] This methodology is simple yet powerful enough to identify the effect of an event (in our case, it is the emergence of the CDR mechanism) on groups who are affected by the institutional mechanism (henceforth treated) with those that are unaffected (henceforth control). For our case, the variable of interest is the stability of banks. To understand the effect of CDR on stability, we could simply get the difference between the stability (i.e., Z-Score) of treated banks before and after the CDR mechanism. The difference would suggest the effect of CDR mechanism increasing/decreasing banking stability. However, the factors other than CDR, both observable and non-observable, potentially impacting banking stability may have changed as well. Therefore, the common economic shock warrants having a control group, which is likely to eliminate the bias that emanates from changes other than the CDR mechanism that could have affected the treated group (Imbens and Wooldridge, 2009; Vig, 2013; Fang, Hasan and Marton, 2014). The bank-level estimation of this approach is as follows:

$$Bank\ risk_{it} = \alpha_0 + \alpha_i + \alpha_t + \beta_1 \cdot CDR_{it} + \beta_2 Lerner_{it} + \sum \gamma \cdot (Bank\ Controls)_{it} + \sum \delta \cdot (Macro)_{it} + \varepsilon_{it} \qquad (2)$$

The dependent variable is individual banks risk at time t . The CDR is an indicator variable that takes a value equal to one if a bank signs inter-creditor agreement (ICA) and becomes a member of CDR program in 2003 and thereafter or else zero.[13] Since there is a time lag reaping the benefit of restructured loans we use lag of one period of CDR (see Gertler, Martinez, Premand, Rawlings and Vermeersch, 2011; Fang, Hasan and Marton, 2014). We are interested in estimating β_1, which captures the treatment effects of CDR on banking stability.[14] In other words, it captures

[12] The key assumption "parallel trends" requires that the average changes of the outcome variable between the controls and treated are symmetrical in absence of treatment. Therefore, following Lemmon and Roberts (2010) we run the two-sample Wilcoxon test to check for the parallel trends in the pre-implementation period of CDR. We cannot reject the null hypothesis at 5% level that the two samples are taken from populations with the same median.

[13] 47 institutions/banks signed ICA on February 2002, and CDR became operational on March 2002. In February 2003, CDR's scope was widened to include doubtful and BIFR cases and even standard loan assets. Therefore, we have constructed the CDR indicator variable based on financial year 2002-2003.

[14] It is important to note that CDR mechanism only applies to the banks that are signatories of inter-creditor agreement (ICA). However, there are a small number of banks who adopted a transaction-based membership and signed ICA for a

the mean difference in the stability between member banks and non-member banks after the genesis of CDR system. Lerner is either C-Lerner or E-Lerner for bank i at time $t-1$ to account for any endogeneity issue. We specify the analogous bank-specific and macroeconomic control variables as in Eq. (1).

While CDR, all else equal, has direct impacts on bank stability, it may also have contingent effects with bank competition. To examine whether Lerner indices interact with CDR as a mechanism to induce excessive risk-taking, we use difference-in-difference-in-differences (DDD) approach.[15] This approach allows us to investigate the cross-sectional heterogeneity in the competition of treated and control groups and examines the magnitude of the effect of individual bank's competition on stability since the genesis of CDR mechanism.

$$\begin{aligned} Bank\ risk_{it} &= \alpha_0 + \alpha_t + \beta_1 \cdot (CDR)_{it} + \beta_2 Lerner_{it} + \beta_3 \cdot CDR_{it} \times Lerner_{it} + \sum \gamma \cdot (Bank\ Controls)_{it} \\ &\quad + \sum \delta \cdot (Macro)_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

where the coefficient β_3 captures the DDD effect and represents the difference in the effect of individual bank's competition on stability between before and after CDR mechanism and between member and non-member banks.[16] This approach captures the time change in the average impact of individual bank's competition for member banks by netting out the change in the average effect for non-member banks.

5. Data and descriptive statistics

To investigate the relationship between CDR, market power, and risk, we draw data from a number of sources: (1) the bank level dataset compiled from the RBI, from the Reports on trend and Progress of Banking in India for various years, (2) the macro data compiled from the World Bank World Development Indicators (WDI), and (3) IV instrument, Business Freedom is from the Heritage Foundation. Our dataset comprises of an unbalanced panel of up to 110 commercial banks from 1992-2012. We dropped banks that had information for fewer than three consecutive years, as the risk measures computed in this study based on rolling windows over the past three years. We deflate all monetary values to 1994 (1993-94 = 100) prices using the wholesale price index (WPI)

single transaction of restructuring of corporate debts at different point in time after the genesis of CDR. Since most of the restructuring of corporate debts is undertaken by the ICA members (almost 98.3%), in reality, this distinction is trivial. However, we constructed another CDR indicator where transaction-based members were also taken into consideration by taking a value equal to one for that particular bank for that particular year, and the overall results remain unchanged and are available from the authors upon request.

[15] See for example Long, Yemane and Stockley (2010) and Vig (2013).

[16] The advantage of using this approach is that it controls (nonparametrically) for any group-specific trends by adding interaction between group and year fixed effects (Vig, 2013).

obtained from the Office of the Economic Advisor, Ministry of Commerce and Industry, Government of India, and the deflated series are reported in millions of Indian Rupees (INR).

5.1 Measuring bank risk

We follow Turk Ariss (2010) to measure $Z-score$ which is widely used in the literature and considered to be an unbiased and complete indicator of bank riskiness (see, for instance, Laeven and Levine, 2009; Fang, Hasan and Marton, 2014). Using assets returns, its volatility and leverage, we calculate $Z-score$ as follows:

$$Z-score_{it} = \frac{ROA_{it} + EQA_{it}}{\sigma_{it}^{ROA}} \tag{4}$$

where ROA and EQA are the average return-on-assets and the equity-to-assets ratio, respectively and σ^{ROA} is the standard deviation of return-on-assets. We can interpret this score as the number of standard deviation below the mean by which returns would have to drop before all equity in the bank gets depleted (Boyd and Runkle, 1993; Beck, De Jonghe and Schepens, 2013). If banks' profitability is normally distributed, the inverse proxy of $Z-score$ can be considered as bank's probability of default (Fu, Lin and Molyneux, 2014). In other words, higher returns and capitalisation would increase but volatile returns would decrease the stability of banks. It can also be measured by estimating the ratio of nonperforming loans and loan loss provision. However, these measures only reflect the credit risk of banks (Delis and Kouretas, 2011).

5.2 Measuring market power

We employ the Lerner index as a measure of market power of individual bank for the sample. The index is more accurate measure of bank-specific market power than the so-called Panzar-Rosse H-statistics or the asset shares of the three largest banks (Brissimis, Delis and Papanikolaou, 2008). The essence of pricing power is reflected through Lerner index because it measures the disparity between price and marginal cost expressed as a percentage of price. In other words, it captures the degree to which a bank can increase their marginal price beyond their marginal cost. According to Berger, Klapper and Turk-Ariss (2009), the Lerner index is the only measure of market power calculated at the bank level as:

$$Lerner_{it} = \frac{P_{it} - MC_{it}}{P_{it}} \tag{5}$$

where P_{it} is the price of total assets proxied by the ratio of total revenue (interest and non-interest income) to total assets for bank i at time t. MC_{it} is the marginal cost of producing an additional unit of output. Following conventional bank efficiency studies, in this paper we use stochastic frontier analysis (SFA) to estimate marginal cost and hence Lerner Index. The inputs and outputs choices are specified according to the intermediation approach of Sealey and Lindley (1977), where a bank uses labour and physical capital to accumulate deposits, and deposits are used to fund loans and other earning assets. Similar to Koetter, Kolari and Spierdijk (2012), a production technology is specified with three inputs (i.e. labour, capital and borrowed funds) and two outputs (i.e. loans and securities). Since equity can be used to fund loans it is commendable to include equity in the production function to account for various risk attitudes of banks. The assumption is that there is perfect competition in the factor markets and banks have no other choice but accepting the given factor prices in order to supply a certain amount of outputs. The following translog total cost function is specified for bank $i=1,...,N$ at time $t=1,...,T$ as:

$$
\begin{aligned}
\ln TOC_{it} &= \beta_0 + \sum_{j=1}^{3}\beta_j \ln \mathrm{W}_{j,it} + \sum_{p=1}^{2}\gamma_p \ln \mathrm{Y}_{p,it} + \delta \ln(\mathrm{Z}_{it}) + \sum_{j=1}^{3}(\frac{\varsigma_j}{2})(\ln W_{j,it})^2 \\
&+ \sum_{j}^{3}\sum_{k}^{3}\eta_{jk} \ln W_{j,it} \ln W_{k,it} + \sum_{p=1}^{2}(\frac{\theta_p}{2})(\ln \mathrm{Y}_{p,it})^2 + (\frac{\kappa_{12}}{2}) \ln Y_{1,it} \ln Y_{2,it} \\
&+ \sum_{j=1}^{3}\sum_{p=1}^{2}\lambda_{jp} \ln W_{j,it} \ln Y_{p,it} + \sum_{k=1}^{2}\rho_k trend^k + \sum_{j=1}^{3}\varepsilon_j \ln W_{j,it} trend + \sum_{p=1}^{2}\omega_p \ln \mathrm{Y}_{p,it}\, trend + \varepsilon_{it}
\end{aligned}
\tag{6}
$$

where TOC_{it} is the total costs including financial and operating cost; Y_{it} represents for two outputs i.e., total loans $Y_{1,it}$ and total securities $Y_{2,it}$, and $W_{j,it}$ ($j=1,2,3$) are input prices where W_1 is the price of funds; W_2 is the price of labour; W_3 is the price of capital of bank i at time t ; Z_{it} is total equity of bank i at time t ; and *trend* is the time trend to capture technical change. We impose homogeneity of degree one on input prices and divided all factor prices and TOC_{it} by W_3 . After estimating cost function, we take the first derivative with respect to outputs for each bank in the sample and estimate marginal cost as:

$$
\begin{aligned}
\mathrm{MC}_{it} &= \frac{TOC_{it}}{\mathrm{Y}_{1,it}}\left[\gamma_1 + \theta_1 \ln \mathrm{Y}_{1,it} + (\frac{\kappa_{12}}{2}) \ln Y_{2,it} + \sum_{j=1}^{3}\lambda_{1j} \ln W_{j,it} + \omega_1 trend\right] \\
&+ \frac{TOC_{it}}{\mathrm{Y}_{2,it}}\left[\gamma_2 + \theta_2 \ln \mathrm{Y}_{2,it} + (\frac{\kappa_{12}}{2}) \ln Y_{1,it} + \sum_{j=1}^{3}\lambda_{2j} \ln W_{j,it} + \omega_2 trend\right]
\end{aligned}
\tag{7}
$$

The Lerner index is interpreted as inverse of competition; the higher the index greater is the pricing power and implies less competitive market conditions. The conventional Lerner index estimated above is measured assuming full bank efficiency and therefore does not account for the possibilities of bankers failing to exploit output pricing opportunities resulting from market power. Following Koetter, Kolari and Spierdijk (2012), we estimate efficiency-adjusted Lerner indices from a single structural model as:

$$(\widehat{AR}_{it} - MC_{it}) / \widehat{AR}_{it} \qquad (8)$$

where $\widehat{AR}_{it}$ is the average revenue computed as $\widehat{TR} / TA,$ where, $TR = \widehat{PBT} + \widehat{TOC}$. In order to obtain efficiency-adjusted Lerner indices we have to estimate expected profit $\widehat{PBT}$ from an alternative profit function[17] and expected total costs $\widehat{TOC}$ from Eq. (6). Dissimilar to conventional Lerner indices in Eq. (5), the estimation of efficiency-adjusted Lerner accounts for both bank efficiency and degree of market power simultaneously.

5.3 Bank-specific and macro control variables

Following recent banking studies, we also control for an array of bank-specific characteristics and macroeconomic variables. We control for bank size by using the logarithm of total assets to account for potential size effect on risk taking behaviour of individual banks. It is argued in the literature that the vanity of being too-big-to-fail can invigorate risk taking attitude of large banks than their small counterparts (Iannotta, Nocera and Sironi, 2007). However, it is also evident that large banks can exploit economies of scale and enhance diversification opportunities, which in turn reduce the riskiness of their operations (Lepetit, Nys, Rous and Tarazi, 2008). Illiquid banks assume more risk as they are less aggressive towards profitability. To account for liquidity risk of individual banks, we use ratio of net loans over total assets (Fang, Hasan and Marton, 2014). To control for individual bank's loan portfolio risk we include the ratio of loan loss provision to total loans. Net interest margin is employed in the model to control for individual bank's lending attitude. The impact of income diversification on stability is ambiguous; therefore income diversification is used to capture the effect of off-balance sheet activities of banks. It is demonstrated in the literature that capital requirement and restrictions on interest rates and bank's activities are likely to increase bank stability (Hellmann, Murdock and Stiglitz, 2000). In addition, a well-capitalised bank is assumed to take less risk; therefore we use equity ratio to control for capital risk.

The study also includes several macroeconomic variables to control for economic development and business cycle of the economy. We include GDP per capita to capture the level of economic development. Since, in the last two decades, Indian economy observed substantial volatility, we use standard deviation of GDP (measured using 5-year rolling-window period) to control for volatility of economic growth. Lastly, since any major fluctuation in inflation can have

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[17] To estimate expected profits ($\widehat{PBT}$) we use PBT (i.e. profit before tax) instead of TOC in Eq. (6) as the dependent variable. Following Bos and Koetter (2011), to account for individual bank losses, we use a negative profit indicator (NPI) in the profit function as many banks in our sample period incurred losses.

serious implication towards banking profitability, and hence to the banking stability (Revell, 1979), we include inflation (i.e. consumer price index) to control for this economic uncertainty.

5.4 Descriptive statistics

Table 2 presents the descriptive statistics of the variables used in this study. We have 1798 bank-year observations for 110 banks and 21-year sample. The mean value of Z-score is 3.3, implying that on average; return on assets (ROA) would have to fall by 3.3 times their standard deviation to wipe out bank equity. The mean volatility of return (σ_{ROA}) is 0.01. The mean value of conventional Lerner (i.e., C-Lerner) is 32% and efficiency-adjusted Lerner (i.e., E-Lerner) is 42%, indicating that banks are pricing their product on average 32% and 42% above the marginal costs, respectively. The mean of total assets is Rs. 140,139 million; the loan ratio is 43%; LLP is 2% and net interest margin is 4%.[18] The mean of income diversification is 17% where equity ratio is around 12%. Regarding macroeconomic control variables, the mean of GDP per capita is Rs. 61,715. The mean value of GDP growth rate volatility is 2.08, indicating serious fluctuations in the economic growth of India for the last two decades. To control for economic stability, inflation is used which has a mean of 7.4%. To circumvent the issue of endogeneity between market power and stability, three instruments are used in the IV regression technique: business freedom, merger and lagged Lerner indices. The mean value of business freedom is 51.66% with a standard deviation of 6.45%.

Table A1 reports the pairwise correlations and their significance levels among the independent variables used in this paper. Our first research question is whether market power is positively related to bank's risk taking attitude; the significant positive correlation between Lerner indices and equity ratio is an indication of evidence in support of competition-fragility hypothesis for India (see, for example Beck, De Jonghe and Schepens, 2013). The variance inflation factors (VIF) are computed for each of our model estimates. The average VIF never exceeds 3, indicating that multicollinearity is not a cause of concern for our results.[19]

[Insert Table 2]

6. Empirical results

First, we report the specification tests and results for competition-fragility hypothesis based on the IV regression model in Eq. (1). Second, we then report the treatment effects of the CDR system on bank stability based on difference-in-differences estimation in Eq. (2). Finally, we report

[18] Loan ratio is measured as performing loans divided by total assets. Performing loans is the difference of total loans and nonperforming loans. Therefore, few banks showed negative loan ratio.

[19] VIF is equal to 1/ (1-r^2), where r^2 is from the regression of an independent variable on rest of the independent variables (see Anginer, Demirguc-Kunt and Zhu, 2014).

the contingent effects of CDR system with bank competition on stability based on difference-in-difference-in-differences estimation in Eq. (3).

6.1 Bank competition and stability

Table 3 reports the impact of competition on bank's risk taking attitudes. Two different measures of risk indicators are employed as the dependent variables that proxy for stability of individual bank: the distance to default measured by logarithm of Z-score (column 1 and 2), and the negative of return volatility measured by the standard deviation of ROA (column 3 and 4). For the latter case, we follow Beck, De Jonghe and Schepens (2013) and transform this dependent variable to make it directly proportional to banking stability (i.e., $Volatility = [-\log(\sigma_{ROA})]$. Before choosing which estimator should we use for Eq. (1), we conduct endogeneity test for the competition measures i.e., Lerner indices, which is reported at the bottom of Table 3. Under conditional homoscedasticity, this endogeneity test statistic is equivalent to a Hausman test statistic (Tabak, Fazio and Cajueiro, 2012). In case of rejecting the null hypothesis of exogeneity, we employ the GMM estimator. In case we cannot reject the null hypothesis, we use the OLS fixed effects estimator. In both cases, we calculate heteroskedasticity and autocorrelation consistent (HAC) standard errors which are reported in the square brackets. The relevance and validity of the instruments used for the Lerner indices are confirmed by the First Stage *F-test* (> 10) and Hansen's *J-test (>0.05)*, respectively. The goodness of fit of all regression models are confirmed by the Second Stage *F-test*.

[Insert Table 3]

Based on column 1 and 2 of Table 3, we find that both C-Lerner and E-Lerner have significant positive relationship with Z-score, indicating that higher degree of bank pricing power is positively associated with individual bank soundness in India. Since the dependent variable is the natural logarithm of Z-score, we can interpret the effect of market power on stability as semi-elasticity. The highly significant coefficient of Lerner index has substantial economic importance that a one standard deviation of decrease in the E-Lerner (0.253) is concomitant with a fall in the Z-score of 70%. In the case of C-Lerner, a one standard deviation (0.179) reduction is equal to 128% drop in the Z-score.

This result also corroborates with the additional risk measures used in this study. The negative of return volatility, in columns 3 and 4, is also positively related to both competition measures, suggesting an increase in market power associated with reduction in return volatility. These results lend support to the traditional view of competition-fragility hypothesis that lower bank pricing power leads to bank fragility. The findings of this study is in line with existing literature that uses Lerner index as a proxy for competition measure (see, e.g., Berger, Klapper and Turk-Ariss, 2009; Beck, De Jonghe and Schepens, 2013; Fu, Lin and Molyneux, 2014).

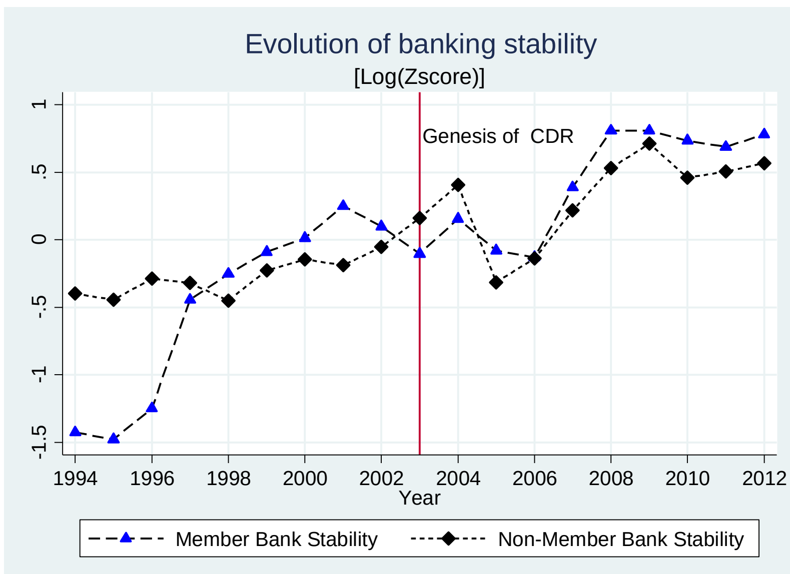
6.2 The impact of deregulation on banking stability

After the first phase of deregulation in 1992, India initiated a second phase of deregulation in order to augment financial stability. Various financial reforms were initiated to improve capital adequacy and to bring forth provisioning norms at par with international best practice. Table 3 also reports the impact of deregulation dummy on the banking stability. It shows that after 1998, the stability of Indian banks improves significantly. This is in accordance with a recent study of Das and Kumbhakar (2012) who find significant impact of second phase deregulation on efficiency and total factor productivity. They argue that the substantial increase in the capital adequacy ratio played a vital role in the improvement of efficiency.

6.3 The impact of CDR on banking stability

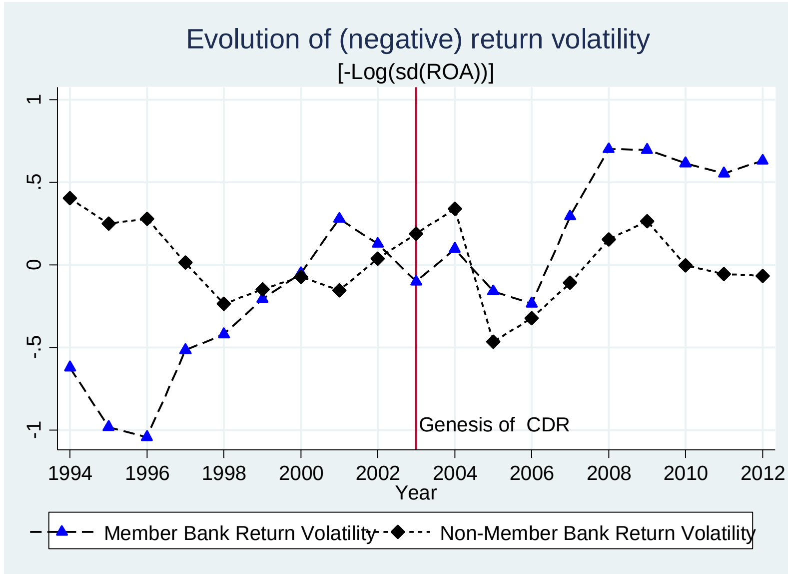
We examine the effect of CDR on bank stability employing a difference-in-differences approach. The results are reported in Table 4a and 4b. Before we begin DD analysis, we provide a graphical illustration of our results. In Figure 3a-d, we separately plot the de-meaned time series of Zscore, (negative) return volatility, NPLs, and LLP for both the member (i.e., treated) and non-member (i.e., control) groups. It can be seen from these figures that the ratios especially Zscore for the treated and control groups moved roughly together before the inception of CDR mechanism. After the CDR, the treated banks were able to increase (decrease) stability (NPLs and LLP). In addition, in Figure 3e we plot the Epanechnikov kernel densities of Zscore for both the treatment and control groups before and after the CDR. It can be seen that there is a rightward shift of the kernel density for the treated group after the genesis of CDR system where multi-modality in the distribution is less apparent, whereas there is a negligible shift in the density of the control group post-implementation of CDR.

We start with a simple comparison of means of the dependent variables in Table 4a. We collapse the data (averages) to get two data points per bank; one for the pre-implementation and other for the post-implementation of member and non-member banks of CDR. We report the before-after results for the variable *Z-score* and *return volatility*. As can be seen, banking stability increased for both groups, but it increased 36.9% (*Z-score*) more in the member banks. Similar result can be seen for the *return volatility*. We next run ten different regressions using analogous dependent variables with both competition measures. In all regressions, we include bank fixed effects and year fixed effects to control for bank-specific heterogeneity and aggregate economic shocks, respectively. In column 1, we show the results of basic regression without using any controls. The positive and significant coefficient of CDR indicates that banking stability increased by 43.6% after the implementation of CDR mechanism in India. In column 2-3, we add all the control variables it also shows positive and statistically significant at 10% level. We use negative volatility of return and it confirms our results that after implementation of CDR system, there is a significant improvement in risk-reduction.[20]

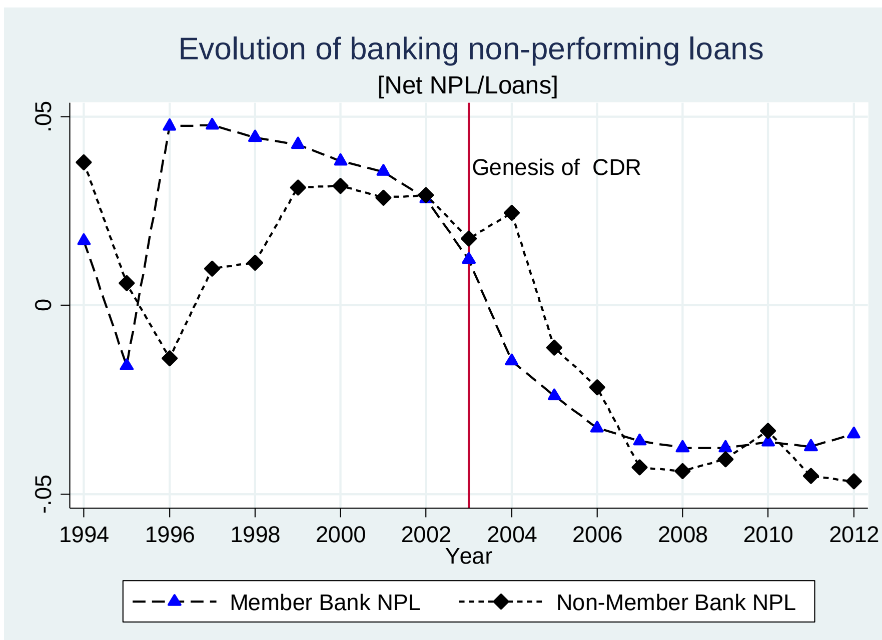


Note: Figure 3a. **Evolution of banking stability**. Following Vig (2013), de-meaning of Z-score is done for each groups (Member and Non-Member), and then we plot the time series of de-meaned values of Z-score. It clearly shows before entering into CDR, member banks had a declining trend from the year 2001 to 2003. From 2004 to 2012, stability of the member banks increased as compared to non-member banks given CDR fully operationalized in the year 2004.

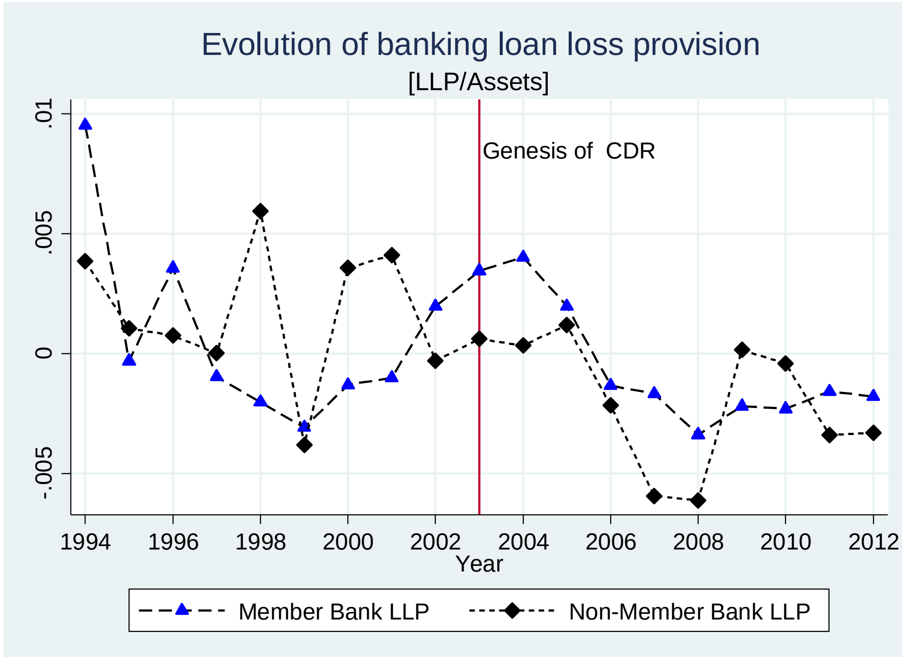
[20] In DD, same firm is observed before and after a program, in doing so, we are cancelling out (or controlling for) both the effect of observed time-invariant characteristics as well as the effect of unobserved time-invariant characteristics (see Gertler, Martinez, Premand, Rawlings and Vermeersch, 2011, p99). For example: the SARFAESI act' 2002 strengthened the rights of secured creditors and may have had some effect on the stability of banks. Since this legal reform happened at the country level and applied to all banks in India, we assume that this time-invariant characteristic does not have any influence on the DD effect in this study (see Vig, 2013, for details on SARFAESI act). However, we check the sensitivity of our results using a dummy of SARFAESI act (taking a value equal to one for the year 2002 and thereafter, or else zero), and the results (unreported) remain unaltered.



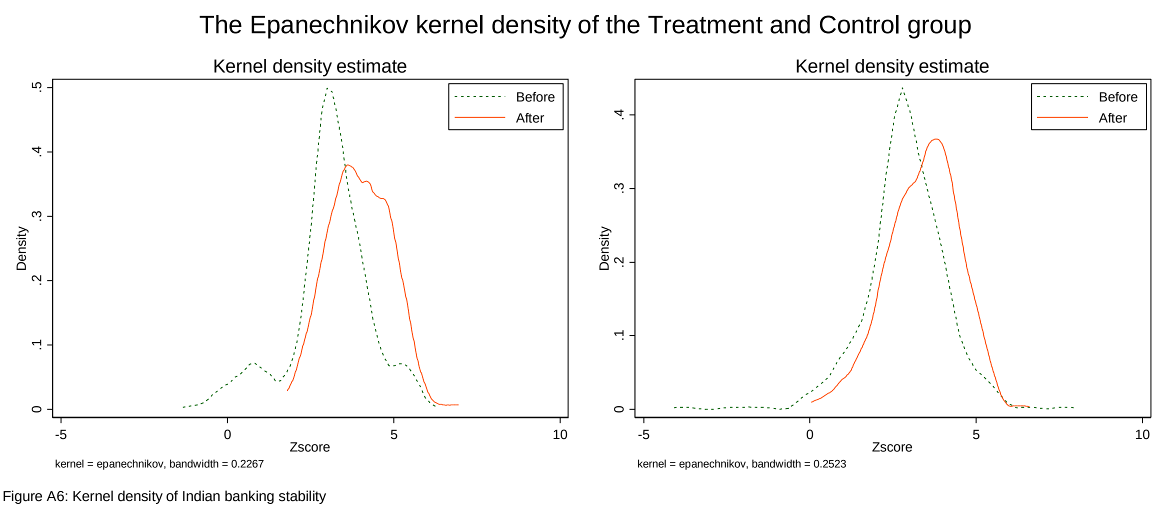
Note: Figure 3b. **Evolution of banking (negative) return volatility**. Following Vig (2013), de-meaning of return volatility is done for each groups (Member and Non-Member), and then we plot the time series of de-meaned values of return volatility. Following Beck et al., (2013), we transform (logarithm) return volatility to make it proportional to bank stability.



Note: Figure 3c. **Evolution of non-performing loans**. Following Vig (2013), de-meaning of non-performing loan ratio is done for each groups (Member and Non-Member), and then we plot the time series of de-meaned values of non-performing loan. It clearly shows that before entering into CDR, member banks had higher non-performing loans, which was decreased in the treatment period. NPL is rising again may be because 20-25% of restructured loans are assumed to be bad gradually.



Note: Figure 3d. **Evolution of loan loss provisions**. Following Vig (2013), de-meaning of loan loss provision is done for each groups (Member and Non-Member), and then we plot the time series of de-meaned values of non-performing loan. It clearly shows that before entering into CDR, member banks had higher loan loss provision, which is decreased in the treatment period may be due to regulatory forbearance on asset classification and provisioning.



Note: Figure 3e. **Kernel density of Indian banking stability (Zscore).** This figure depicts the Epanechnikov kernel density of the logarithm of Z-score for both the member banks ("treatment") group and non-member banks ("control") group. It shows that stability of the treated banks has increased more (left graph) compared to control groups (right graph).

[Insert Table 4a and 4b]

The results of the interaction between CDR and Lerner indices are reported in the column 4, 5 and 9, 10 of Table 4b. For column 5, we find significant negative interaction effect (-0.926) on stability. The evidence suggests that the magnitude of the positive impact of CDR on stability diminishes for the member banks at higher degree of market power In terms of economic magnitudes, it implies that a one standard deviation reduction in market power (0.253) leads to a 23% increase in the soundness of member banks. This finding is corroborated by the significant negative coefficient (-0.776) of the interaction terms in column 10. It should be noted that, in the case of multiplicative terms in the models, based on simple t-statistics we cannot make accurate inference because model parameter does not provide adequate information (Brambor, Clark and Golder, 2006). Therefore, following Brambor, Clark and Golder (2006), we use marginal effect to show the influence of different level of market power (competition) in the impact of CDR on stability.

[Insert Figure 4]

The estimated total marginal effects and standard errors of CDR on stability are graphically illustrated in Figure 4. The upper (lower) panel, Panel A (Panel B) shows the total effect of CDR on Z-score (negative return volatility) for both conventional and efficiency-adjusted Lerner indices (i.e. C-Lerner and E-Lerner). The marginal effect of CDR on Z-score is statistically different from zero before a threshold level of E-Lerner Index of around 38 points, with stability loss of up to 9% at higher market power levels. In other words, the positive impact of restructuring of corporate loans diminishes as market power increases, and this effect on Z-score becomes insignificant once E-Lerner index reaches beyond 38 points. We find similar results from column 10 that the marginal effect of CDR on negative return volatility is statistically different from zero before a threshold level of efficiency-adjusted Lerner Index of around 39 points, with loss of stability of up to 5% at higher market power levels. Caminal and Matutes (2002) show that banks with greater market power tend to incur higher monitoring costs and originate risky loan portfolios. Therefore, the probable explanation of our finding is that member banks may have shown delinquency in determining the riskiness of their portfolios. It could also be that the de jure implementation of CDR system and benefit through regulatory forbearance on asset classification and provisioning de facto impacted margin of the member banks and hence market power (see Figure A1), as a result, they could get some extra leeway taking excessive risk which resulted in diminishing benefits of CDR on stability. This favorable effect of CDR on the performance of the Indian banking sector remains consistent with the increasing efficiency change after 2002 reported in Sahoo and Tone (2009), across all ownership groups.

6.4 Sensitivity analysis

It is possible that relationship between market power and stability is due to poorly specified Lerner indices. According to Maudos and de Guevara (2007), the estimated MC_{it} through Eq. (7) may be prone to some form of monopoly power originating from deposit markets due to bank's ability to fund at a cheaper rate. Since a form of deposit market power is already reflected in the loan pricing, including the factor funding cost in the Eq. (6) may provide biased results. Therefore, to eliminate the deposit market distortions we re-specified Eq. (6) with only two factors (i.e., cost of labour and cost of capital) and calculated marginal costs (MC_{it}) for bank i at time t following Eq. (7). This Lerner index, which is a 'raw' pricing power of individual bank, is then derived from the structural model specified in Eq. (5). Table A2 shows results of the funding-adjusted Lerner index and risk-taking attitudes. We also use ex-post credit risk as a risk indicator and the results remain unaltered supporting competition-fragility hypothesis.

[Insert Table 5]

To check the sensitivity of these results we also construct three different market power dummy variables for the different level of market power of banks following Tabak, Fazio and Cajueiro (2012). These dummies are High $(\geq \overline{\text{Lerner}}+0.5\sigma_{\text{Lerner}})$, Average $(<\overline{\text{Lerner}}+0.5\sigma_{\text{Lerner}}$ and $>\overline{\text{Lerner}}-0.5\sigma_{\text{Lerner}})$, and Low $(\leq \overline{\text{Lerner}}-0.5\sigma_{\text{Lerner}})$. Since we have different variants of Lerner indices i.e. C-Lerner and E-Lerner, six market power dummies are created in order to check the impact of different levels of market power on stability. Results are reported in Table 5. Based on the results of market power dummy we can see that High and Average market power dummies of both Lerner indices are positively and significantly related with Z-score. However, the Low market power dummy is always negatively and significantly associated with Z-score. Similar results are obtained when we use negative return volatility as the dependent variable. These results suggest that banks with less market power (i.e. <29 points) are likely to take more risk. In other words, banks operating with higher competition are likely to adopt more aggressive risk-taking attitudes. These findings lend support to our earlier results that greater competition enhances risk-taking behaviours, alluding to the competition-fragility hypothesis.[21]

[Insert Table 6]

[21] In addition, a possible nonlinear relationship between competition and financial stability is also captured by using quadratic term for the Lerner indices following Berger, Klapper and Turk-Ariss (2009). The unreported results based on the calculated inflection points remain unchanged.

To alleviate any selection bias, that might yet remain in our DD result, we use propensity score matching (PSM) (see Rosenbaum and Rubin, 1983). This matching technique allows us to identify a group of non-member banks which are similar to the member banks on the basis of some observables characteristics, and then compare the banking stability between the control and treated groups. By doing this, it can avoid any selection bias and provide unbiased estimates of treatment effects (Abadie and Imbens, 2006; Imbens and Wooldridge, 2009). In the first stage of PSM, we estimate the probability (i.e., propensity score) that a bank enters into CDR mechanism by using a logit model. In the second stage, we match each member banks of CDR with non-member banks with a similar propensity score. For this procedure, we consider two matching techniques include kernel marching and stratified matching. Furthermore, following Abadie and Imbens (2006), we also estimate the average treatment effect using the bias-corrected covariate matching estimator adjusted for heteroskedasticity, matching on four nearest neighbours as recommended in Abadie, Drukker, Herr and Imbens (2004). Unlike PSM, this method uses covariates to match treatment group and control group, corrects for bias when matching is not perfect, makes no assumption about functional form, and provides standard errors for matching estimators. The results are reported in Table 6, and it is consistent with the earlier findings. In all matching estimators, the average treatment effect for the treated (ATT) remains significant at the 1% level, indicating a significant improvement in the stability of member banks of CDR.

7. Conclusions

Following widespread corporate distress in servicing debt obligations to the creditors, Reserve Bank of India implemented a debt restructuring programme in the form of 'corporate debt restructuring' in 2002. This institutional mechanism was intended to mitigate debt overhang of corporates and NPLs overhang of banks. In this paper, we contribute to the literature on debt restructuring from the creditors' perspective by investigating the impact of CDR system on bank stability. We exploit the membership variation of banks of CDR programme to find the causal relations of the treated banks on stability while using a 'natural experiment' type difference-in-differences (DD) approach. To eliminate any sample selection bias, we deploy a number of matching estimators including recently developed bias-corrected covariate matching estimator proposed by Abadie and Imbens (2006). Given the scarcity of empirical research on Indian banking sector (Fujii, Managi and Matousek, 2014; Tzeremes, 2015) despite its importance in the international economy, and the contradictory existing literature necessitates this study also to investigate the impact of bank competition on stability over the period 1992-2012, which covers a number of financial reforms including consolidation and liberalisation process.

The balance of evidence suggests that market power, proxied by two variants of Lerner indices i.e. conventional and efficiency-adjusted Lerner indices, enhances stability of Indian banks where greater competition induces excessive risk-taking of individual banks, supporting competition-fragility relationship. It also appears that although the second phase of deregulation improved overall banking stability significantly, there is a threshold level of market power below which banks experience a higher risk of fragility. The result from the DD approach suggests that after the genesis of CDR, member banks with generous regulatory forbearance on asset classification and provisioning experience an improvement in stability. It indicates that soundness of member banks increased by 43.6% after the implementation of CDR mechanism. The findings of the matching estimators are also consistent with the result of DD approach and show a positive treatment effect of CDR. This finding on the causal relationships point to a channel through which timely and efficient out-of-court restructuring mechanism with minimum regulatory forbearance can have a positive impact on banking stability. However, the finding of the interactive effect is alarming for the regulator as the marginal effect of CDR on Z-score is statistically different from zero before a threshold level of E-Lerner Index of around 38 points, with stability loss of up to 9% at higher degree of market power. As member banks were able to gain market power substantially (21%)[22] due to generous regulatory forbearance, it might have provided them some extra leeway to show delinquency in determining the riskiness of their portfolios (see Caminal and Matutes, 2002).

Based on the overall results, we can say that by reducing NPLs overhang under the guise of CDR system, RBI's intention of having stable banking sector have largely achieved. However, the recent up-trend in restructuring corporate debt is worrisome and therefore, regulators should tighten the macroprudential norms and emphasise on international best practice in asset classification and provisioning of restructured corporate loans ensuring no scope for ever-greening (Peek and Rosengren, 1995). Since it is predicted that at least 20-30% restructured standard corporate loans will slip into sub-standard loan eventually (WG, 2012), banks should increase provisioning on existing restructured loans gradually, otherwise any substantial losses might lead them to exhaust capital base at a point where insolvency or illiquidity would be inevitable.

[22] Based on preliminary data analysis, we find that the average E-Lerner of member banks for the post-CDR period has increased to 41 point compared to 34 in Pre-CDR period (see Figure A1).

Table 1: Variable Definitions and Sources

Variables	Notation	Definitions	Source
Frontier Arguments			
Costs of funds	w1	Sum of interest expenses on deposits, interest expenses on RBI and inter-bank funds divided by sum of deposits and borrowings from RBI and others	RBI
Cost of labour	w2	Payments to and provisions for employees divided by total assets	RBI
Cost of capital	w3	Other operating expenses divided by fixed assets	RBI
Total loans	y1	Total loans and advances	RBI
Other earning assets	y2	Total investments	RBI
Equity	z	Sum of capital and reserves and surplus	RBI
Operating costs	TOC	Sum of Interest Expenses and Operating Expenses	RBI
Profit before tax	PBT	Operating income less TOC	RBI
Negative profit	NPI	Takes 1 for the negative profit or else 0	Own
Bank risk measures			
Z-score	Z-score	Sum of return-on-assets (ROA), defined as net profit over assets, and equity ratio (EQA), defined as equity over assets, divided by standard deviation of (ROA) of each bank over past three years (calculated using a rolling window)	Own
Return Volatility	Sd(ROA)	Standard deviation of ROA for each bank, calculated over past 3 years	Own
Credit risk	NPL	Non-performing loans divided by total loans	RBI
Market Power			
C-Lerner	C-Lerner	A bank-level non-structural indicator of bank competition, measured by using fixed-effects method, with lower values indicating higher competition in the banking sector	Own
E-Lerner	E-Lerner	A bank-level non-structural indicator of bank competition, an efficiency-adjusted Lerner index, measured by using a stochastic frontier analysis approach, with lower values indicating higher competition in the banking sector	Own
Bank characteristics			
Bank Size	Size	Logarithm of total assets	RBI
Loan ratio	Loan	Total performing loans divided by total assets	RBI
Provision ratio	LLP	Total loan loss provision divided by total assets	RBI
Net interest margin	NIM	Net interest income to total earning assets	RBI
Income diversification	DIV	Non-interest income divided by total operating income	RBI
Equity ratio	EQA	Total equity divided by total assets	RBI
IV Instruments			
Merger	Merger	Takes value equal to one for the year and thereafter if a bank enters into mergers and acquisitions activity or else zero	Own
Business Freedom	BusFree	The business freedom is taken from Heritage Foundation, it is a number between 0 and 100, with 100 equaling the freest business environment	HF
Macroeconomic variables			
GDP per capita	GDP	Logarithm of GDP per capita	WDI
Volatility of GDP	sd(GDP)	Standard Deviation of real GDP growth rate calculated over past five years using a rolling window	WDI
Inflation	INF	Annual growth rate of consumer price index	WDI

Note: RBI, HF and WDI stand for the Reserve Bank of India, the Heritage Foundation and the World Development Indicator, respectively. Own stands for author's own calculation.

Table 2: Summary Statistics

This table shows the total sample summary statistics for the bank-specific variables, macroeconomic variables and the variables that are used as instruments in the instrumental variable regressions throughout the paper. Bank-level data is compiled from the RBI, from the Reports on trend and Progress of Banking in India for various years. Macroeconomic data is retrieved from the World Bank World Development Indicator (WDI). The IV instrument business freedom is obtained from the Economic Freedom Indicators of Heritage Foundation (2013). The full sample contains 1798 observations. This table consists of six parts. The descriptive statistics of the variables used for translog costs function is in the first part. The dependent variables which are used to proxy for stability of individual banks are in the second part of this table. The third part is contains market power variables, which is proxied by two variants of Lerner indices: conventional Lerner (i.e., C-Lerner) and efficiency-adjusted Lerner (i.e., E-Lerner). Bank-specific variables are in fourth part. IV instruments are in fifth part of this table followed by the macroeconomic variables in six.

Variable	Mean	Median	SD	Min	Max	N
Frontier Arguments						
Costs of funds	0.07	0.06	0.15	0	6.3	1798
Costs of labour	0.01	0.01	0.01	0	0.13	1798
Costs of capital	0.64	0.33	1.18	0.01	15.58	1798
Total loans	73096	14129	193917	0.3	2967979	1798
Other earning assets	43712	11073	102235	3	1207346	1798
Operating costs	9875	2598	22804	6	305492	1798
Profits before tax	2775	556	7024	-4422	108013	1798
Equity	9067	2034	22475	5	287196	1798
Total revenue	12650	3369	29558	4	413505	1798
Dependent Variables						
Z-score	3.3	3.29	1.18	-3.84	7.68	1572
Volatility of ROA	0.01	0	0.01	0	0.16	1578
Credit risk	0.05	0.02	0.08	-0.45	1.22	1792
Market Power						
C-Lerner	0.32	0.3	0.18	-1.99	0.9	1798
E-Lerner	0.42	0.44	0.25	-2.21	0.97	1798
Bank-specific variables						
Total asset	140139	31628	342239	106	4568799	1798
Loan ratio	0.43	0.44	0.14	-0.03	0.82	1792
LLP ratio	0.02	0.01	0.02	-0.23	0.28	1786
NIM	0.04	0.04	0.04	-0.41	0.58	1798
Diversification	0.17	0.14	0.13	-1.66	0.87	1798
Equity ratio	0.12	0.07	0.15	0	0.98	1798
Reregulation	0.73	1	0.45	0	1	1798
CDR	0.24	0	0.43	0	1	1798
IV Instruments						
Merger	0.09	0	0.29	0	1	1798
Business Freedom	51.66	55	6.45	35.5	55	1650
Macroeconomic variables						
GDP per capita	61715	36189	61301	7093	236651	1798
Volatility of GDP	2.08	2.03	0.53	0.88	3.07	1798
Inflation	7.4	7.16	3.07	3.68	13.23	1798

Table 3: The effect of bank competition on stability

The dependent variable is the Z-score, reported in columns 1and 2, standard deviation of return on assets, reported in columns 3 and 4. Bank competition is proxied by two variants of the Lerner indices i.e., conventional Lerner (C-Lerner) and efficiency-adjusted Lerner (E-Lerner). De-regulation dummy takes one for the year 1998 and thereafter and otherwise zero. Bank size is the logarithm of total assets valued in million rupees. Bank's liquidity is proxied by the ratio of net loan over assets. LLP ratio is measured as loan loss provision as a percentage of total assets, where income diversification is the ratio of non-interest income over total income. The profitability measure NIM is measured as the net interest income over total earning assets. Banks' equity is the bank total equity to asset ratio. To control for economic development, logarithm of GDP per capita is used, and volatility of GDP growth rate, measured as the standard deviation of GDP growth rate using 5-year rolling window, is used to account for precariousness of business cycle for the last two decades. Inflation is used to capture the economic uncertainty. Before deciding which estimator to apply, we run an endogeneity test for the Lerner indices, if we reject the null hypothesis of exogeneity, we use GMM estimator, or else use OLS fixed effects estimator. In both cases, we consider heteroskedasticity-autocorrelation robust standard errors (HAC). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: RBI and WDI. Coverage: 1992-2012.

	1	2	3	4
VARIABLES	Z-score [log(ROA+EQA)/(sd(ROA)]		Return volatility [-log(sd(ROA))]	
C-Lerner	7.145***	-	5.371***	-
	[1.338]	-	[1.271]	-
E-Lerner	-	2.783***	-	1.846***
	-	[0.640]	-	[0.531]
Deregulation	3.652***	1.567	3.209***	1.662
	[1.083]	[1.109]	[1.080]	[1.066]
Size	0.170**	0.162*	0.215***	0.223***
	[0.079]	[0.084]	[0.075]	[0.075]
Loan ratio	2.794***	1.050**	2.472***	1.333***
	[0.358]	[0.410]	[0.324]	[0.367]
LLP ratio	-21.546***	-12.256***	-17.346***	-10.930***
	[3.708]	[2.935]	[3.882]	[1.903]
Diversification	-3.400***	0.238	-2.495***	0.355
	[0.955]	[0.488]	[0.897]	[0.431]
NIM	-8.433***	0.185	-6.040**	0.720
	[3.006]	[1.193]	[2.678]	[1.025]
Equity ratio	0.891	-1.019	-1.989***	-3.201***
	[0.601]	[0.755]	[0.574]	[0.673]
GDP Per Capita	-2.510***	-0.588	-2.174***	-0.769
	[0.778]	[0.790]	[0.777]	[0.764]
Volatility of GDP	1.931***	0.085	1.578**	0.231
	[0.691]	[0.714]	[0.690]	[0.690]
Inflation	-0.035	-0.008	-0.038	-0.018
	[0.047]	[0.047]	[0.046]	[0.045]
Diagnostic Test				
Estimator	GMM	GMM	GMM	GMM
First Stage F-test	10.54***	35.81***	11.23***	38.60***
Hansen's J Chi2	0.834	0.0330	1.607	0.317
Hansen's J [p-value]	0.361	0.856	0.205	0.573
Second Stage F-test	15.31***	13.03***	9.428***	9.980***
No. of Obs.	1,561	1,561	1,566	1,566
No. of banks	106	106	106	106

Table 4a: This table provides basic empirical strategy.

Member banks are those who participated and Non-member banks are those who did not participate in the CDR programme. 'Before' refers to 1992-2003 and 'After' refers to period from 2004 to 2012. DD refers to Difference-in-Differences. Diff is interpreted as the percentage change form period before to after. DD is the percentage change in the member banks compared to non-member banks. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Outcome variable	**Before**			**After**			
	Non-Member	Member	Diff	Non-Member	Member	Diff	**DD**
Z-Score	2.881	3.079	0.197***	3.407	3.973	0.566***	**0.369*** **
Std. Error	0.051	0.057	0.076	0.059	0.058	0.083	**0.113**
Return volatility	5.218	5.984	0.766***	5.156	6.671	1.516***	**0.75*** **
Std. Error	0.05	0.056	0.075	0.058	0.058	0.082	**0.111**

Table 4b: The effect of corporate debt restructuring (CDR) on bank Stability

This table reports results from the regression $Bank\ risk_{it} = \alpha_0 + \alpha_t + \beta_1 \cdot (CDR)_{it} + \beta_2 Lerner_{i,t} + \sum \gamma \cdot (Controls)_{it} + \sum \delta \cdot (Macro)_{it} + \varepsilon_{it}$

And $Bank\ risk_{it} = \alpha_0 + \alpha_t + \beta_1 \cdot (CDR)_{it} + \beta_2 Lerner_{i,t} + \beta_3 \cdot (CDR)_{it} \times (Lerner_{i,t}) + \sum \gamma \cdot (Controls)_{it} + \sum \delta \cdot (Macro)_{it} + \varepsilon_{it}$. The dependent variable is the Z-score, reported in columns 1-5, standard deviation of return-on-assets, reported in columns 6-10. Following Beck et al. (2013) we transform the latter to interpret as an indicator of financial stability. Here, CDR is an indicator variable equal to one in the year and thereafter when bank i enters an inter-creditor agreement to pursue restructuring of corporate debt (i.e., treated group) and otherwise zero (i.e., control group). $Lerner_{it}$ is either conventional Lerner (i.e., C-Lerner) or efficiency-adjusted Lerner (i.e., E-Lerner) for bank i at time t . The variable of interest is β_1 and β_3 where the former captures the difference-in-differences (DD) effect and the latter captures the difference-in-difference-in-differences (DDD) effects. Bank-level and macroeconomic control variables are included in the both equations. We clustered standard error at bank-level and reported at the square brackets. ***, **, and * implies significance at the 1%, 5%, and 10%, respectively. Source: RBI and WDI. Coverage: 1992-2012.

	Z-score [log(ROA+EQA)/(sd(ROA)]					Return volatility [-log(sd(ROA))]				
VARIABLES	1	2	3	4	5	6	7	8	9	10
CDR	0.436**	0.322*	0.312*	0.638*	0.657***	0.682***	0.346**	0.318*	0.947**	0.608***
	[0.183]	[0.170]	[0.188]	[0.365]	[0.213]	[0.172]	[0.171]	[0.186]	[0.384]	[0.191]
C-Lerner		2.647***		2.723***			1.687***		1.797***	
		[0.305]		[0.314]			[0.222]		[0.240]	
E-Lerner			1.085***		1.307***			0.709***		0.888***
			[0.214]		[0.181]			[0.167]		[0.162]
CDR x C-Lerner				-1.077					-2.043*	
				[1.006]					[1.067]	
CDR x E-Lerner					-0.926***					-0.776***
					[0.285]					[0.254]
Size		0.094	0.126	0.092	0.123		0.154	0.182*	0.150	0.178*
		[0.087]	[0.090]	[0.086]	[0.091]		[0.093]	[0.097]	[0.093]	[0.097]
Loan ratio		1.853***	1.504***	1.826***	1.462***		1.714***	1.563***	1.657***	1.522***
		[0.367]	[0.377]	[0.368]	[0.379]		[0.346]	[0.365]	[0.343]	[0.363]
Loan Loss Provision		-10.176*	-8.429	-10.226*	-8.595		-10.218**	-9.205*	-10.273**	-9.291**
		[5.522]	[6.172]	[5.519]	[6.106]		[4.272]	[4.712]	[4.249]	[4.636]
Diversification		0.059	0.753	0.070	0.686		0.306	0.728	0.337	0.672
		[0.410]	[0.490]	[0.405]	[0.492]		[0.425]	[0.469]	[0.422]	[0.470]
Net interest margin		-0.131	1.307	-0.096	1.157		0.517	1.552	0.600	1.413
		[1.137]	[1.627]	[1.134]	[1.555]		[1.167]	[1.462]	[1.171]	[1.398]
Equity ratio		1.111*	0.846	1.100*	0.771		-1.821***	-1.968***	-1.840***	-2.030***
		[0.623]	[0.717]	[0.628]	[0.704]		[0.589]	[0.655]	[0.588]	[0.649]
GDP per capita		-0.066	0.010	-0.072	0.008		-0.174	-0.131	-0.184	-0.130
		[0.133]	[0.134]	[0.134]	[0.133]		[0.119]	[0.119]	[0.119]	[0.118]
Volatility of GDP		0.146*	0.081	0.141*	0.102		0.191**	0.149**	0.180**	0.166**
		[0.077]	[0.075]	[0.077]	[0.074]		[0.073]	[0.072]	[0.073]	[0.071]
Inflation		-0.015	-0.024*	-0.016	-0.025*		-0.028**	-0.034**	-0.029**	-0.034**
		[0.014]	[0.014]	[0.014]	[0.014]		[0.013]	[0.013]	[0.013]	[0.013]
Constant	3.730***	1.244	0.651	1.333	0.629	5.779***	4.828***	4.394***	4.992***	4.375***
	[0.143]	[1.099]	[1.205]	[1.111]	[1.208]	[0.120]	[1.015]	[1.102]	[1.018]	[1.107]
Diagnostic Test										
Observations	1,569	1,564	1,564	1,564	1,564	1,574	1,569	1,569	1,569	1,569
No. of banks	110	109	109	109	109	110	109	109	109	109
Bank fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.188	0.281	0.246	0.282	0.251	0.121	0.218	0.191	0.221	0.195
F	14.15***	22.03***	18.12***	23.56***	19.03***	9.487***	12.52***	10.50***	14.44***	10.98***

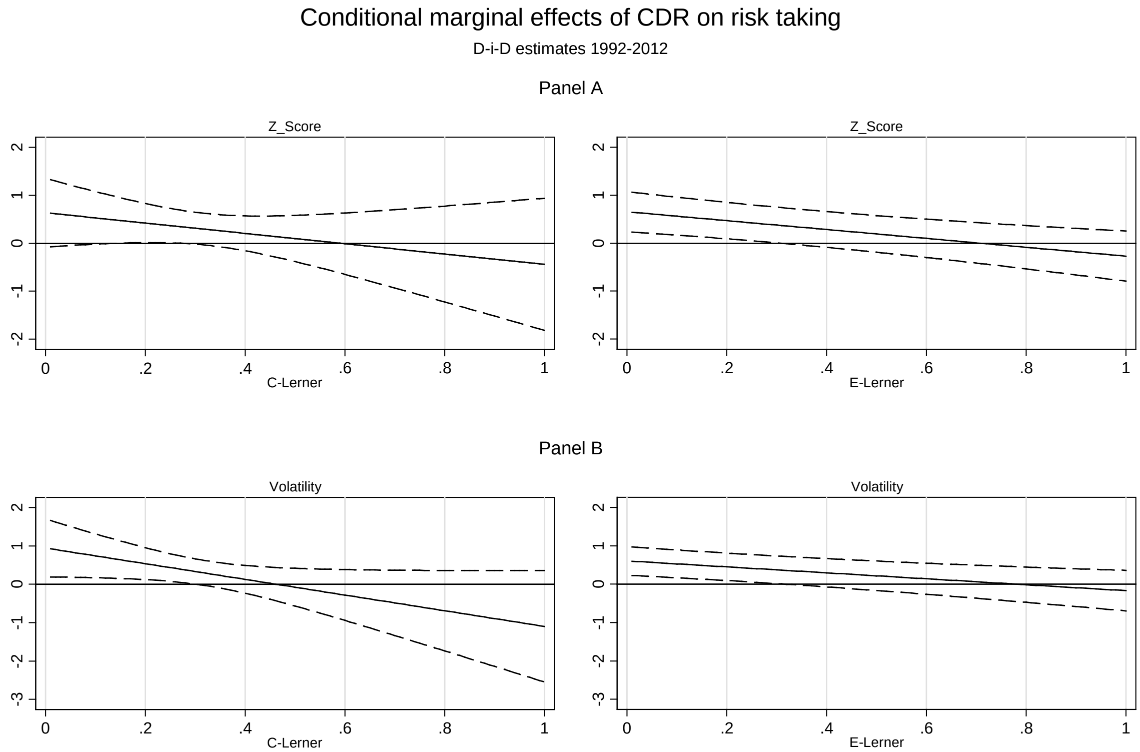


Figure 4: Marginal effect of CDR on banking stability; it corresponds with our results in Table 4b. The graphs on the upper panel display the marginal effect of CDR on Z-score at different levels of market power i.e., C-Lerner (left) and E-Lerner (right). It shows that the positive impact of CDR diminishes as market power increases with a loss of Z-score at 9%. The graphs on the lower panel display the marginal effect of CDR on negative return volatility at different levels of market power i.e., C-Lerner (left) and E-Lerner (right).). It shows that the positive impact of CDR diminishes as market power increases with a loss of volatility at 5%.

Table 5: The relationship between different level of bank competition and stability

To check the sensitivity of the earlier results that higher market power is congenial to reducing risk we have constructed three different level of market power dummies following Tabak et al. (2012) as for High ($\geq \overline{\text{Lerner}}+0.5\sigma_{\text{Lerner}}$) , Average ($<\overline{\text{Lerner}}+0.5\sigma_{\text{Lerner}}$ and $>\overline{\text{Lerner}}-0.5\sigma_{\text{Lerner}}$) , and Low ($\leq \overline{\text{Lerner}}-0.5\sigma_{\text{Lerner}}$) . Six market power dummies of C-Lerner and E-Lerner are regressed with Z-score and return volatility. Bank fixed effects and year fixed effects are included in all regressions. Unreported bank controls and macro controls are also included in all regressions. Result shows that only banks with Low level of market power is negatively associated with banking stability. Source: RBI and WDI. Coverage: 1992-2012.

	Z-score [(ROA+EQA)/(sd(ROA)]						Return volatility [-log(sd(ROA))]					
VARIABLES	1	2	3	4	5	6	7	8	9	10	11	12
High C-Lerner	1.064***						0.218**					
	[0.324]						[0.105]					
Average C-Lerner		0.990***						0.977***				
		[0.220]						[0.211]				
Low C-Lerner			-1.626***						-1.305***			
			[0.238]						[0.217]			
High E-Lerner				0.722**						0.074		
				[0.284]						[0.076]		
Average E-Lerner					0.451**						0.306*	
					[0.200]						[0.180]	
Low E-Lerner						-1.068***						-0.600***
						[0.250]						[0.228]
Deregulation	2.167**	3.006***	3.481***	1.312	2.676**	2.015*	2.066**	2.888**	3.124***	1.979*	2.390**	1.968*
	[1.029]	[1.150]	[1.247]	[1.113]	[1.081]	[1.089]	[1.025]	[1.149]	[1.184]	[1.034]	[1.050]	[1.043]
Diagnostic Test												
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	OLS	GMM	GMM	OLS	GMM	GMM
Bank controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Macro controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
First Stage F-test	24.89***	47.90***	57.70***	27.89***	60.79***	57.93***		47.70***	58.62***		60.73***	57.78***
Hansen's J Chi2	0.36	0.378	0.126	0.64	0.129	0.00168		1.154	0.65		0.962	0.619
Hansen's J [p-value]	0.548	0.538	0.722	0.424	0.72	0.967		0.283	0.42		0.327	0.431
Second Stage F-test	12.87***	11.80***	13.45***	12.43***	11.85***	12.37***	8.524***	8.530***	9.515***	8.390***	8.912***	9.209***
Adj. r2	0.136	0.083	0.078	0.134	0.134	0.092	0.113	0.014	0.046	0.110	0.095	0.080
No. of Obs.	1,561	1,561	1,561	1,561	1,561	1,561	1,569	1,566	1,566	1,569	1,566	1,566
No. of banks	106	106	106	106	106	106	106	106	106	106	106	106

Table 6: Sensitivity analysis of the impact of CDR using matching techniques

VARIABLES	Z-score [(ROA+EQA)/(sd(ROA)]			Return volatility [-log(sd(ROA))]		
Matching	Kernel	Stratified	Abadie and	Kernel	Stratified	Abadie and
ATT	0.58***	0.48***	0.84***	0.57***	0.45***	0.70***
SE	[0.08]	[0.09]	[0.13]	[0.09]	[0.09]	[0.13]
t-statistics	7.04	5.13	6.59	6.18	4.94	5.19
Observations	1,403	1,403	1,240	1,403	1,403	1,241
Common support condition	√	√	√	√	√	√

Note: Three matching methods are used include Kernel matching, Stratified matching and the nearest-neighbour bias-corrected matching estimators proposed by Abadie and Imbens (2006). Abadie and Imbens method adjusts the differences within the matches for the differences in covariate values. Following Abadie et al. (2004), we use four matches per observation. The variables that are used for the matching (or bias-adjusted variables) include the age of the bank, listed bank dummy (equal to one if a bank is listed in the stock market, or else zero), the number of employee, the number of branches and the logarithm of total assets. ATT is the average treatment effect for the treated. The standard errors in Abadie and Imbens are heteroskedasticity-consistent, and *Z*-stats are reported. For the rest, we report absolute values of bootstrapped *t*-stats in bracket. Observation size is reduced as we do not have information on the number of employee for all banks prior to 1997. The number of observation also differs due to the difference in the underlying matching approaches. We run balancing test on all the independent variables included in the logit regression, which has been satisfied. Hosmer–Lemeshow test confirmed goodness-of-fit of logit model (unreported but available upon request).

Table A1: Correlation table

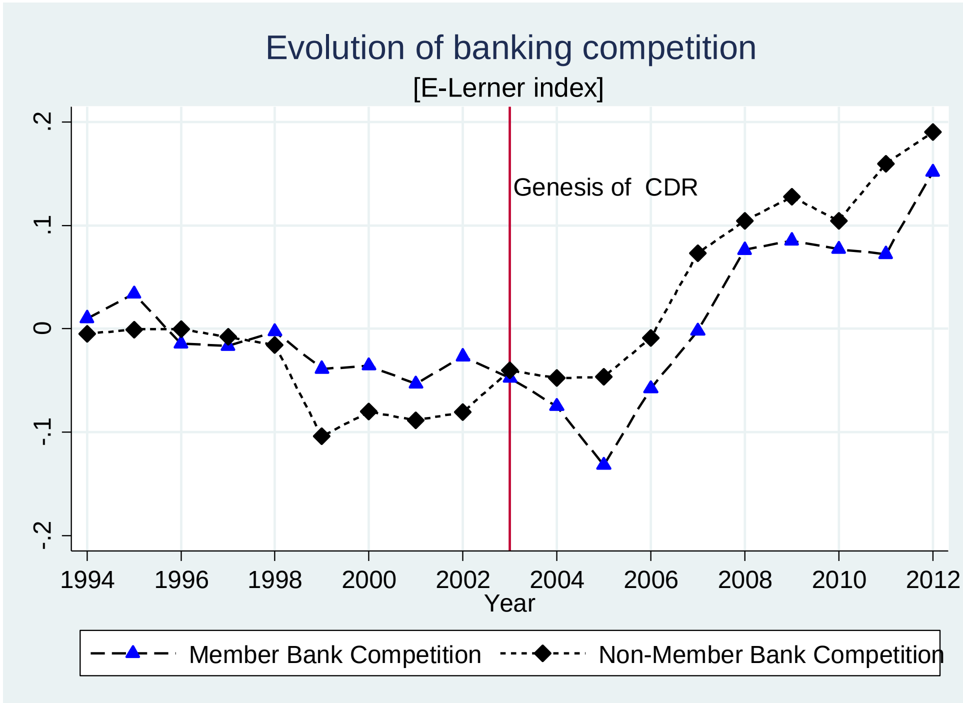
This table provides information on the correlation between the market power, bank-specific and macroeconomic variables used throughout the paper. It contains pairwise correlation coefficients and the indication of their significance of the correlation.

		1	2	3	4	5	6	7	8	9	10	11
C-Lerner	1	1										
E-Lerner	2	0.56***	1									
Size	3	-0.32***	-0.22***	1								
Loan ratio	4	-0.13***	0.12***	0.35***	1							
LLP ratio	5	0.28***	0.19***	-0.20***	-0.08***	1						
NIM	6	0.42***	0.32***	-0.42***	-0.26***	0.22***	1					
Diversification	7	0.54***	0.30***	-0.21***	-0.20***	0.10***	0.10***	1				
Equity ratio	8	0.35***	0.37***	-0.53***	-0.24***	0.13***	0.52***	0.31***	1			
Per Cap. GDP	9	0.10***	0.13***	0.28***	0.27***	-0.12***	-0.15***	0.19***	0.20***	1		
GDP Volatility	10	0.08**	0.13***	0.12***	0.15***	-0.02	-0.06*	0.03	-0.01	0.28***	1	
Inflation	11	0.02	0.19***	0.03	0.16***	-0.01	0.03	-0.06*	-0.04	0	0.26***	1

Table A2: Competition-Fragility: Fund-adjusted Lerner with 1% outlier correction

The dependent variable is the Z-score, reported in columns 1, 2 and 3; standard deviation of return on assets, reported in columns 3, 4 and 5; and nonperforming loans is reported in 7, 8 and 9. Bank competition is proxied by three variants of the Lerner indices i.e., conventional Lerner (C-Lerner), efficiency-adjusted Lerner (E-Lerner) and funding-adjusted Lerner (F-Lerner). De-regulation dummy takes one for the year 1998 and thereafter and otherwise zero. Bank size is the logarithm of total assets valued in million rupees. Bank's liquidity is proxied by the ratio of net loan over assets. LLP ratio is measured as loan loss provision as a percentage of total assets, where income diversification is the ratio of non-interest income over total income. The profitability measure NIM is measured as the net interest income over total earning assets. Banks' equity is the bank total equity to asset ratio. To control for economic development, logarithm of GDP per capita is used, and volatility of GDP growth rate, measured as the standard deviation of GDP growth rate using 5-year rolling window, is used to account for precariousness of business cycle for the last two decades. Inflation is used to capture the economic uncertainty. Before deciding which estimator to apply, we run an endogeneity test for the Lerner indices, if we reject the null hypothesis of exogeneity, we use GMM estimator, or else use OLS fixed effects estimator. In both cases, we consider heteroskedasticity-autocorrelation robust standard errors (HAC). ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels respectively. Source: RBI and WDI. Coverage: 1992-2012.

	1	2	3	4	5	6	7	8	9
VARIABLES	Z-score [(ROA+EQA)/(sd(ROA)]			Return volatility [-log(sd(ROA))]			NPL [log(NPL)]		
C-Lerner	6.195***			4.247***			-2.276***		
	[0.735]			[0.663]			[0.517]		
E-Lerner		2.905***			1.663***			-0.384	
		[0.546]			[0.478]			[0.247]	
F-Lerner			6.256***			4.396***			-1.836***
			[0.675]			[0.621]			[0.478]
Deregulation	3.571***	1.576	2.690***	3.075***	1.755*	2.490**	-1.685***	-1.567***	-1.590***
	[1.025]	[1.090]	[0.982]	[1.022]	[1.048]	[0.987]	[0.427]	[0.433]	[0.424]
Diagnostic Test									
Estimator	GMM	GMM	GMM	GMM	GMM	GMM	FE	FE	FE
First Stage F-test	84.95***	45.65***	85.87***	84.64***	46.37***	84.59***	-	-	-
Hansen's J Chi2	0.661	0.0591	1.530	0.964	0.539	1.666	-	-	-
Hansen's J [p-value]	0.416	0.808	0.216	0.326	0.463	0.197	-	-	-
Second Stage F-test	16.42***	13.68***	17.32***	10.56***	9.848***	11.29***	54.32***	51.80***	54.62***
Adj. r2	0.218	0.142	0.237	0.148	0.107	0.160	0.469	0.454	0.465
No. of Obs.	1,561	1,561	1,561	1,566	1,566	1,566	1,567	1,567	1,567
No. of banks	106	106	106	106	106	106	105	105	105



Note: Figure A1. **Evolution of bank competition**. Following Vig (2013), de-meaning of efficiency-adjusted Lerner indices is done for each groups (Member and Non-Member), and then we plot the time series of de-meaned values of Lerner indices. It clearly shows that during treatment period, member banks could increase market power substantially may be because member banks could exploit CDR mechanism to ***“hide NPLs and hike profitability”***, enhancing margins and subsequently market power.

Table A3: Propensity to participate into CDR- Logit model and descriptive statistics

Panel A: Logit model			Panel B: Descriptive statistics of matched sample			
Dependent variable: CDR	**Coefficient**	**S.E.**	**Member banks**	**Non-member banks**	**p-value**	**t-stats**
Log of Age	0.887***	[0.343]	4.23	4.16	0.28	1.08
Log of number of employee	-2.434***	[0.713]	9.18	9.28	0.50	-0.67
Log of number of branches	1.272**	[0.519]	6.54	6.65	0.42	-0.80
Listed bank dummy	1.879*	[0.963]	0.89	0.92	0.35	-0.94
Bank size (log total assets)	2.265***	[0.368]	12.10	12.15	0.65	-0.46
Observation	1,340					

Note: In Panel A, the dependent variable CDR is an indicator variable that takes value 1 for banks which participate into Corporate Debt Restructuring Mechanism in 2003 and thereafter or else zero. We use the logarithm of total age of individual banks, the number of employees, branches, listed dummy and banks size of each banks in the Logit model in order to measure the propensity score where standard errors are clustered at the bank level and reported on brackets. Since information on bank employees are missing prior to 1997, our total number of observations is reduced to 1340. The Hosmer–Lemeshow test (p-value = 0.62) confirms the goodness-of fit of Logit model. In Panel B, we shows the descriptive statistics of the matched sample for which p-values are reported.

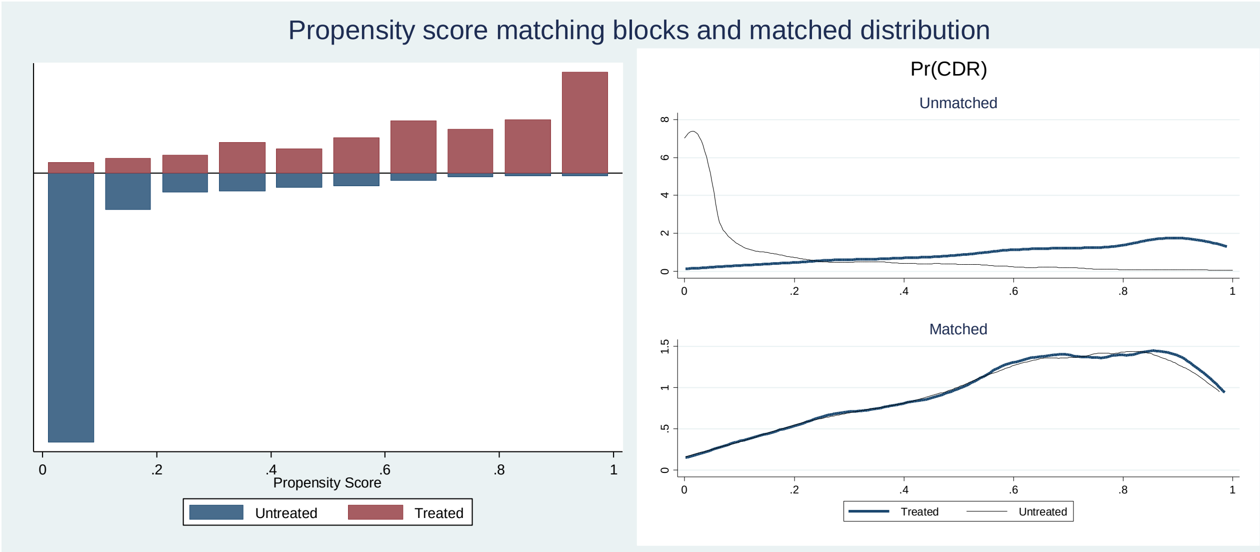


Figure A2: Graph on the left shows how several blocks where member and non-member banks were matched. Graphs on the right show the Kernel distribution of the matched and unmatched banks.

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