The Enforcement Bottleneck: Judicial Capacity and the Limits of Bankruptcy Reform

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Abstract

The efficacy of bankruptcy reforms in strengthening lender rights and credit markets often depends on local enforcement capacity through courts. I analyze India's national bankruptcy reform in 2016 using a triple difference research design, exploiting variation in time, baseline district-level judge-to-population ratios, and firm-level default risk or capital efficiency (marginal revenue product of capital or MRPK). The reform reduced borrowing by high-default-risk firms but did not increase borrowing by high MRPK firms in districts with better judicial capacity. Furthermore, I find negative economic effects among high-default-risk firms and limited positive effects among high MRPK firms, suggesting that such reforms fall short of achieving allocative efficiency.

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1 Introduction

A large and influential literature has focused on the role of institutions in explaining current differences in economic growth across countries (La Porta et al. 1998; Acemoglu and Johnson 2005; Djankov et al. 2007). Many have paid specific attention to variation in legal and regulatory institutions as causes of economic development and misallocation of capital (Cantoni and Yuchtman 2014; Chemin 2020; Bazzi et al. 2023; Bau and Matray 2023). However, we know little about the details of these institutions, which are often treated as a black box, and thus have limited evidence on the types of policy reforms required. For example, is it the courts, the legal profession (bar associations, quality of lawyers, etc.), or laws governing access to finance that drive the productivity differences? Perhaps, rather than a horserace, these different institutions complement each other so that reforming one without the other will not lead to productivity gains.

In this paper, I estimate the consequences of a large-scale national-level bankruptcy reform in India (Insolvency and Bankruptcy Code, 2016 or IBC) on firm-level borrowing and productivity using pre-determined variations in local enforcement capacity through district courts, and firm-level default risk and capital efficiency or MRPK in a triple difference (DDD) research design.[1] I find that this interaction between local enforcement and the legal reform is significant but falls short of improving allocative efficiency. Borrowing and economic outcomes fall for high-default risk firms in districts with better enforcement capacity after the reform whereas I see no significant impact on high-MRPK firms. All firms increase their liquidity holding.

A well-functioning bankruptcy process enables producers to take risk by providing an exit route in the event of failure, thus easing firm entry and exit in creating competitive markets (La Porta et al. 1998). However, there is wide variation in the design and implementation of bankruptcy process, particularly with regard to the rights of lenders in the recovery of capital (Giné and Love 2010; Vig 2013; Alok et al. 2022; Closset et al. 2023). The strength of such rights and its enforcement through judicial institutions determine the nature of production across countries, including the ownership structure of firms (Glaeser and Shleifer 2003), input use (Alok et al. 2022), and competition in the credit markets (Gormley et al. 2018).

In the particular context of India, local district courts played a direct role in bankruptcy

[1] MRPK is a standard measure of firm's capital efficiency in the literature, for example, Bau and Matray (2023). Ideally, one would use marginal product of capital (MPK) but because data is mainly available for sales revenue instead of production, MRPK is used as a close proxy.

process under the Provincial Insolvency Act, 1920, which the 2016 reform superseded. The reform strengthened lender rights in both asset restructuring (Chapter 11) and liquidation (Chapter 7) processes on paper. However, in practice, many aspects of the reform are yet to be notified and implemented on the ground even as of 2025. As a result, local courts continue to play a complementary role in the bankruptcy process. Thus, local judicial capacity could have implications for the extent of frictions in financial markets, which could, in turn, introduce misallocation of capital if lenders take institutional quality into account in their lending decisions (Djankov et al. 2007; Gopalan et al. 2007; Ponticelli and Alencar 2016; Gormley et al. 2018; Müller 2022).

I exploit cross-sectional variation in pre-reform district-level judicial capacity (frontline judiciary in India), measured as judge to population ratio using the full universe of legal records data from Ash et al. (2025), and variation in firm-level default risk (or MRPK) among firms located in the corresponding court jurisdiction in a triple difference research design. I focus on the capacity within the frontline judiciary due to the imperfect hand-over of bankruptcy process from district courts, making them continue to be a relevant judicial body even under the new regime. Furthermore, district courts are the main institutions responsible for the final execution of any judicial order, including those from specialized bankruptcy courts created by the reform, as well as to file counter suits by borrowers.[2]

I measure judicial capacity using judge to population ratio to reflect the underlying bureaucratic capacity to resolve legal cases, where the national average is 20 judges per million compared to over 100 in advanced economies like the United States. Number of judges per capita is a commonly used metric to measure judicial capacity, including for cross-country comparison (Wittrup 2024). Judges provide legal human capital, which is a central input to a court's production function - the findings of Cantoni and Yuchtman (2014) provide evidence in the historical context of commercial revolution in medieval Europe. In the context of frontline judiciary in India, Rao (2025) shows that resolving judge vacancy substantively reduces pending case backlog in district courts. Since vacancy varies over time, I use total number of judge seats (positions) per court prior to the reform in calculating the judge to population ratio as a measure of local judicial capacity.[3]

[2]For example, I note over 100 cases pertaining to a specific bankruptcy law (from prior to the 2016 reform) in district courts using the Ash et al. (2025) dataset. These cases invoke Section 17A of the SARFAESI Act, 2002, which allows firms or individuals to challenge liquidation of their assets by financial institutions in their local court. Additionally, over 1 million legal cases in district courts pertain to execution of past judgements/orders.

[3]This is conservative considering that not all judge positions are filled and many continue to be vacant even in the long run.

Variations in the capacities of courts in enforcing the bankruptcy process could generate differences in de facto lender rights. Empirical evidence on this interaction is relatively mixed - on the one hand, Visaria 2009; Ponticelli and Alencar 2016; Müller 2022 suggest that better judicial capacity improves the functioning of bankruptcy process and relaxes capital constraints faced by firms to enable growth. On the other hand, Vig 2013; Closset et al. 2023 document that strengthening creditor rights through better bankruptcy implementation could have negative implications for firms by increasing liquidity hoarding to overcome costly expectations of bankruptcy or increased concentration in debt structure, generating negative welfare consequences.

This paper addresses this dichotomy by examining firm-level borrowing based on their ex-ante default risk or ex-ante capital efficiency to test whether local court capacity affects credit allocation after the bankruptcy reform. I classify firms based on their pre-determined default risk measured in terms of low credit rating as well as by their estimated MRPK using balance sheet data from a representative sample of formal sector firms in the CMIE Prowessdx database (following Bau and Matray 2023). I mainly focus on these two firm-level characteristics to test a standard hypothesis on allocative efficiency: is the marginal dollar allocated to firms with higher marginal returns. While allocation based on MRPK assumes that this feature is observable and incentive-compatible with the lender's agent, I also use default-risk to examine allocations, particularly if lending agent's career incentives are not aligned with maximizing capital efficiency but rather minimizing defaults.

I develop a simple model of credit allocation in the presence of varying institutional quality and incentives faced by lending agents (bank or loan officials), who act on behalf of lenders. Typically, bank officers have lower incentives to declare a default and often provide additional loans to refinance older, delinquent debt. This phenomenon is referred to as "ever-greening" and is prevalent not only in India (Kulkarni et al. 2025) but also globally (Jordà et al. 2022; Li and Ponticelli 2022; Faria-e-Castro et al. 2024). As lender rights improve, these incentives could change as defaulters undergo asset restructuring or liquidation, enabling lenders to recover their capital. However, if lenders prioritize default risk that is easily observable based on credit ratings, which may only be an imperfect proxy for capital efficiency, we may only expect changes along one margin and not the other. Consequently, the reform may result in relative and not absolute improvement in allocative efficiency if lending decisions based on capital efficiency remain unchanged.

The assumption for causal identification is that the outcomes of firms by default risk (or

MRPK) trend similarly within subgroups of districts with higher or lower judicial capacities in the absence of the bankruptcy reform. The research design relaxes the more stringent parallel trends assumptions by requiring that high and low-default risk firms (or high and low MRPK firms) trend similarly within high or low judicial capacity districts even if they do not trend similarly on average. This however requires that any deviation in parallel trends be limited to comparisons across high and low judicial capacity district groups. The bankruptcy reform was a one-time national-level reform, applicable to all districts at the same time, which allays any concerns arising from staggered rollout designs. I use firm-level balanced panel data on economic and financial outcomes to implement my research design. The balanced panel nature of the data allows me to include firm fixed effect to account for firm-level time invariant unobserved characteristics. I also include district-year and industry-year fixed effects to capture any unobserved trends at the district (to incorporate any time variation in district environment, including, for example, changes in judge vacancies) and industry levels (for example, to incorporate secular changes in industry-specific market supply and demand). I do not condition these specifications on any other covariates beyond the fixed effects, which could otherwise raise concerns of bias (Ortiz-Villavicencio and Sant'Anna 2025).

I note three main findings. First, I find that borrowing decreases but net short-term liquidity increases among high-default-risk firms in better judicial capacity districts following the reform. On the other hand, I do not find any clear effects on borrowing among high-MRPK firms in similar districts but I find some positive effects on their short-term liquidity position. I note that a firm's classification of default risk is not strongly (negatively) correlated with its estimated MRPK even after accounting for industry and location of the firms, making these relatively independent metrics. As a result, I rationalize these results on borrowing and liquidity by acknowledging that firms classified as high default risk are different from low-MRPK firms and that I see borrowing effects only by default risk and not capital efficiency. I interpret increased liquidity as suggesting that all firms hold more cash at hand in districts with better enforcement after the reform. This result is consistent with the findings of Vig 2013; Closset et al. 2023, who find that strengthening creditor rights increased liquidity hoarding among firms in a similar context with multiple market failures.

Second, I note significant negative effects on economic outcomes, including legal and interest expenditures, investment, and sales revenue of high-default-risk firms in high judicial capacity districts following the reform. I find no effects on expenditures or sales revenue among high-MRPK firms but note increasing investment over time. These results are not inconsistent with the results on financial outcomes, where high risk firms experiencing lower rates of borrowing also experience correspondingly lower interest expenditures. Furthermore, they also lower investments and incur fewer legal expenses, which include accounting and legal compliance costs. High MRPK firms experience no change in their borrowing and correspondingly I observe no differences in their interest or legal expenditures, or sales. The observed increase in investments by high MRPK firms could indicate their ability to reap financial gains in the future, reflecting their long-run cash-flow planning through investments in financial instruments rather than in their productive capacities.

In our third result, I examine judicial filings, resolutions, and pending backlog of firm-level legal cases in district courts using the same variation as before. I use detailed case-level data merged with litigant identity from Rao (2025). I also examine judicial outcomes of cases involving banks. Overall, I find increased resolution of firm-level cases in district courts with better judicial capacity, particularly in cases involving high-default-risk firms as defendants. I find suggestive evidence of increased resolution of bank-level cases when banks appear as plaintiff although this result is not significant at conventional levels. The extent of pending cases also reduce for high-MRPK firms, consistent with improved functioning of courts in better judicial capacity districts.

Taking the results together, I find that bankruptcy reforms differentially impact credit allocation based on local institutional quality. However, I cannot conclude that this reduced misallocation as high-MRPK firms experienced no change in borrowing nor did they experience any significant production effects. However, credit allocation and subsequently production outcomes decline for high-default-risk firms, suggesting some credit disciplining effects of the reform in districts with better judicial capacity.

This paper contributes to two main strands of the academic literature. First, it provides evidence on the importance of local court capacity in complementing bankruptcy reforms. Literature has documented mixed evidence of impact of legal reforms protecting lender and investors' interests in creating a diverse and competitive credit markets (La Porta et al. 1998; Rajan and Zingales 1998), credit availability for firms (Giné and Love 2010; Vig 2013; Closset et al. 2023) and subsequent implications for real firm-level decisions (Ponticelli and Alencar 2016; Amirapu 2021; Alok et al. 2022) and trade (Paravisini et al. 2015). However, timely enforcement could be important for debt recovery (Visaria 2009; Rao 2025) or bankruptcy (Ponticelli and Alencar 2016; Müller 2022; Li and Ponticelli 2022). This paper provides evidence that local courts matter by complementing bankruptcy courts through increased resolution of civil lawsuits filed against high-default-risk firms. Consequently, I find evidence in support of lower allocation of capital and financial outcomes among such firms.

Second, I contribute to the literature on credit misallocation by focusing on institutional factors of misallocation. Regulatory state lending and bailout policies (Banerjee and Duflo 2014; Giné and Kanz 2018; Bau and Matray 2023), and incentives faced by banking officials (Cole et al. 2015; Fisman et al. 2017; Faria-e-Castro et al. 2024; Naaraayanan and Wolfenzon 2024; Kulkarni et al. 2025), could ignore allocative efficiency (Müller and Verner 2023) and focus more on political or individual incentives. For example, literature has documented that banks allocate more loans to larger or politically connected borrowers when faced with negative shocks (Khwaja and Mian 2008) in weaker bankruptcy regimes (Lilienfeld-Toal and Mookherjee 2016). This paper demonstrates that while a strong bankruptcy regime requires complementary investment in judicial capacity to reduce lending towards high-default-risk firms, it isn't enough for increasing allocation towards more productive firms that would signal improved allocative efficiency. This could be due to fact that there is very little overlap between default-risk and capital efficiency and that reforms do not significantly affect bank officials' incentives to increase lending to productive firms even though they may decline lending to high-default-risk firms. Emphasizing the importance of marginal product of capital is important and requires additional research to examine the role of informational frictions in assessing capital efficiency in addition to predicting default risk.

Rest of the paper is structured as follows. Section 2 describes the banking sector, lender rights and enforcement mechanism in India under pre-reform and post-reform regimes. Section 3 presents a simple conceptual framework of credit allocation to draw testable hypotheses on credit allocation as a function of bankruptcy regime and local enforcement capacity. Section 5 describes the datasets and variables used in the analysis. I estimate our central hypothesis on credit allocation using the empirical strategy laid out in Section 4. I report our results in Section 6 and conclude in Section 7.

2 Context: Banking in India

The banking sector in India is characterized by a dominant share of public sector banks and a small share of private banks, together known as Scheduled Commercial Banks or SCBs, which are regulated by the central bank, Reserve Bank of India (RBI). The state has always played a key role in the evolution of this sector through varying systems of controls on the sector's operation including nationalization or the dominant public ownership but also controls over lending operations through priority sector lending norms as well as liquidity and cash reserves requirement (Demetriades and Luintel 1996).

Despite economic liberalization of the 1990s, lending controls in the form of priority sector lending continues even till this date. These norms are not limited to public sector banks but also apply to any bank registered for operations in India including private sector and foreign banks. Borrowers, particularly agricultural and small firms, are also frequently bailed-out by the government prior to elections, eroding timely repayment behavior (Giné and Kanz 2018). As a consequence, the incentives facing a lender need not necessarily mean profit maximization but rather default minimization.

Defaults occur when a borrower faces significant negative shocks (distressed default) or strategically avoids repaying if they think that enforcement is weak. Defaulted loans are eventually classified as non-performing assets (NPAs), which measure the extent of capital that the credit market is unable to recover to recirculate. In developed countries such as the Unites States, the percentage of total lending that is deemed as a NPA is typically under 1% as per the Federal Reserve. Even during the height of the 2008-2010 financial crisis, the total NPA was just above 3% in the US. In contrast, the NPAs in India have historically been over 2% and steadily increasing since 2012, peaking to slightly above 11% (Figure 1). The peak roughly corresponds to the timing of bankruptcy reform and other regulatory changes intended to address this problem of growing NPA.

2.1 Bankruptcy Process

The bankruptcy process in India until 2016 favored promoters/founders and shareholder rights over lender rights during restructuring or liquidation proceedings. The 2016 Insolvency and Bankruptcy Code (IBC 2016) is a new consolidated law on bankruptcy process that provides for a market-based mechanism for time-bound resolution, either through restructuring or liquidation, and at the same time prioritizing the rights of financial lenders such as banks in the recovery of unpaid debt from the borrower.

Figure 2 provides the timeline of the reform. Up until 2016, codes governing bankruptcy proceedings were fragmented across many statutes. Company Law, which lays down the rules governing incorporated entities, was amended in 2013 in an attempt to streamline the process. An all encompassing bankruptcy statute under IBC was tabled in the Parliament in the winter session of 2015, passed and became a law by May 2016. The first set of bankruptcy resolutions were passed in 2017 that changed borrower-lender relationships. I use the year of the law (2016) to divide the time period into pre-reform period when the rights of financial lenders were weak and post-reform when the lenders were made key stakeholders in resolving debt defaults, particularly large scale corporate debt defaults, to decide on restructuring or liquidation as the appropriate next step.

2.2 Role of the Judiciary in Bankruptcy

Regular courts and a specific bankruptcy institution - National Company Law Tribunal or NCLT - that was set up under IBC 2016, are together responsible for implementing the law and for providing clarity over both the process and outcomes for borrowers and lenders. In addition to providing interpretation of the law, the judiciary, especially frontline district courts, are important in the process of recognizing a loan as a non-performing asset and in the subsequent recovery or pre-bankruptcy proceedings against the defaulter. This role of local courts is particularly important as many aspects of the new bankruptcy regime are yet to be implemented in practice. Furthermore, district courts are the final enforcement authority responsible to *execute* any orders following the bankruptcy proceedings. These courts are general courts of law that resolve cases pertaining many different aspects of legal disputes including civil disputes (contractual, property, or debt) as well as criminal disputes (such as thefts, arson, as well as major crimes like homicide).

Specific debt recovery related cases are filed in local district courts with jurisdiction over defaulting firm location or in specialized Debt Recovery Tribunals (DRT) depending on the monetary limit of the debt claim. Which court a suit should be filed is defined in the Code of Civil Procedure, 1908. Neither the lender nor the defaulting borrower has any choice over where they can file their lawsuit. The bankruptcy process itself is adjudicated by the NCLT (a centralized tribunal), where the suit can either be filed by the lender or initiated by *corporate* borrowers either through liquidation or asset restructuring. However, bankruptcy proceedings related to individual borrowers, or liabilities from criminal offense, fraud and family disputes, personal insolvency, anti-trust and intellectual property, and property related disputes such as tenancy and eviction continue to be litigated within the district courts under the Provincial Insolvency Act, 1920. District courts are also the relevant institutions where lenders can claim their ownership of securitized assets during liquidation process by filing claims under laws such as SARFAESI Act, 2002 (Vig 2013). As a result, these courts play a complementary role in the enforcement of lender rights under the new bankruptcy regime and their capacity could matter for the subsequent impact of the reform.

How well the district courts function depend on the staffing levels in such courts (Rao 2025). While there is active debate and discussion on how best to arrive at the "optimal" number of judges per court (*Imtiyaz Ahmed v. State of U.P. , 2012*), the method of allocating number of judges per court during the study period followed a rule of thumb approach of 50 judges per million people (*All India Judges' Association case, 2002*). In practice, many courts fall short of this number and there is wide variation in the realized number of judges per capita across districts in India. Among the main reasons include: (a) financial constraints and differing state priorities (limited budget to be allocated across various needs including infrastructure, health, education, etc. See India Justice Report 2025 for details) , (b) inadequate infrastructure, i.e. courtrooms and buildings (Rajya Sabha Unstarred Question No. 3950, 2023), (c) slow and difficult recruitment process due to frequent litigation (*Malik Mazhar Sultan & Anr. vs. U.P. Public Service Commission, 2006*). Thus, the staffing levels per capita could dramatically vary across district courts, which could also be correlated with the characteristics of the underlying district/region. I explain why this is unlikely to be a problem for causal inference later in Section 4.

2.3 Bank Officers' Incentives

In addition to institutional constraints, credit misallocation could also arise from poor monitoring and incentives of bank officials. Since employees of public sector banks are tenured officials, who are subject to frequent transfers to different branch locations, their incentives to sanction loans may not align with the objective for efficient credit allocation but rather to maximize their own personal incentives such as enforceability of repayment irrespective of capital efficiency (Fisman et al. 2017). Furthermore, initiating bankruptcy process requires lenders to make provisions for any expected losses, which may be at odds with the incentives of the bank official that depends on the extent of surplus on the bank's balance sheet (Kulkarni et al. 2025). Acknowledging that such incentives could limit the impact of the reforms, India's central bank, the RBI, circulated guidelines to all banks to tighten supervision and reporting of defaulted loans in a timely fashion, within a few months following the first set of bankruptcy resolution (Kulkarni et al. 2025). However, these guidelines did not change lenders' incentives to lend more to entities with higher marginal product of capital and thus, the impact of the reform on efficient credit allocation is not apriori clear.

3 A Conceptual Framework on Credit Allocation

In this section, I sketch a simple two-period model on credit allocation in an environment dominated by the presence of the public sector in the banking system. The system creates an incentive against detection and reporting of loan defaults for the bank officials, who continue to provide fresh loans to the potential defaulter to prevent labeling the past loan as default ("ever-greening"). This extends the model in Banerjee and Duflo (2014) by making the incentive of bailout by the bank official (default avoidance) as a function of institutional quality.

Consider a representative bank official, who has L units of credit to allocate to borrowers in each period. Borrowers are of two types in the population - a type H with a share ϕ in the population and a type L constituting the remaining $1-\phi$. The type H borrower has a deterministic production function with probability of success, $s_H = 1$ whereas the type L face a non-zero probability of production failure $1-s$ such that $s_L = s < 1$. The borrower type is unknown to both bank official and borrower in the initial period, which gets revealed with the outcome of production. So in the first round of allocation, the official equally distributes total credit L equally among the borrowers such that each borrower gets l units of credit.

At the end of period 1, the official receives a signal that the borrower is of type H conditional on observed production success. This signal probability is $S_H = \frac{\phi}{\phi+(1-\phi)s}$. Among type L borrowers, $(1-\phi)(1-s)$ fail. In period 2, the official can either declare loan provided to type L as default and face a penalty $P_1(l,\Gamma)$ or provide fresh loan to type L borrower to continue production, which would lead to a bigger default at the end of period 2 with probability $1-s$. Penalty in period 1 is a function of loan size, l, and local court quality Γ, such that $\frac{\partial P_1}{\partial \Gamma} > 0$, i.e. well-functioning courts generate a larger penalty, and $\frac{\partial P_1}{\partial l} > 0$. The official will bail out type L borrower by lending l_L in period 2 if $sf(l_L - l) \geq l_L$, where l due from period 1 is paid out of l_L and the rest put into production. Rationality implies that $l_L^* = sf(l_L^* - l)$, that is, the official lends the minimum amount to type L borrower to hedge the risk of default at the end of period 2. Therefore, the official compares the option of bailing in period 1 by declaring a default earlier, which costs him $P_1(l,\Gamma)$. So, bailing will be the dominant strategy if the penalty from default at the end of period 2 is less than the penalty from default at the end of period 1. Penalty in period 2 has an additional institutional parameter, Θ - a measure of creditor (bank's) rights in the form of redressal through bankruptcy process. I assume that $\frac{\partial P_2}{\partial \Gamma} > 0$, $\frac{\partial P_2}{\partial \Theta} > 0$ and $\frac{\partial^2 P_2}{\partial \Gamma \partial \Theta} > 0$. That is, penalty in period 2 is higher due to the complementary effects of default detection through courts as well as protection of creditor rights under bankruptcy reform. Thus, bailing a defaulter will be the optimal response if the following holds:

$$(1-s)P_2(l_L^*, \Theta, \Gamma) \leq P_1(l,\Gamma)$$
$$P_2(l_L^*, \Theta, \Gamma) \leq \frac{P_1(l,\Gamma)}{1-s}$$

Assuming that the penalty can be expressed as a share of the loan amount, $P_1(l,\Gamma) =$

$lP_1(\Gamma)$ and $P_2(l_L^*, \Theta, \Gamma) = l_L^* P_2(\Theta, \Gamma)$. Therefore, the bailout loan can be expressed as:

$$l_L^* \leq \frac{lP_1(\Gamma)}{(1-s)P_2(\Theta, \Gamma)}$$

The right hand side of the above expression for period 2 bailout loan varies by both the quality of local courts, Γ, as well as the overall environment of creditor rights Θ. The bankruptcy reform increases Θ whereas higher judicial capacity (higher judge to population ratio) increases Γ. From this set-up, I get the following results with corresponding hypotheses to test with data.

Result 1: Bailout loan, l_L^*, decreases as both institutional parameters Θ and Γ increase, i.e. $\frac{\partial l_L^*}{\partial \Theta \partial \Gamma} < 0$. That is, bailout lending is lower to type L borrowers in credit markets (districts) with higher judicial capacity after the bankruptcy reform.

Proof

$$\frac{\partial l_L^*}{\partial \Theta \partial \Gamma} = \frac{l}{1-s}\left(\frac{-1}{P_2^2}\frac{\partial P_1}{\partial \Gamma}\frac{\partial P_2}{\partial \Theta} - \frac{P_1}{P_2^2}\frac{\partial^2 P_2}{\partial \Theta \partial \Gamma} + \underbrace{\frac{2P_1}{P_2^3}}_{\to 0}\frac{\partial P_2}{\partial \Gamma}\frac{\partial P_2}{\partial \Theta} \right) < 0$$

Result 2: In the absence of strong creditor rights through the bankruptcy reform, the effect of higher judicial capacity on bailout loan is ambiguous or likely positive.

Proof

$$\frac{\partial l_L^*}{\partial \Gamma} = \frac{l}{1-s}\left(\frac{1}{P_2}\frac{\partial P_1}{\partial \Gamma} - \frac{P_1}{P_2^2}\frac{\partial P_2}{\partial \Gamma} \right) > \text{ or } < 0$$

Implication Given this framework, the following section presents the empirical strategy to test the hypotheses on credit allocation generated by the above results. Specifically, from result 1, I examine whether lending to "riskier" borrowers (from the perspective of default probability) diminishes after the bankruptcy reform in districts with better judicial capacity. Result 2 suggests plausible "parallel trends" prior to the reform since lending decisions to specific type of borrower are more likely to be driven by interaction with bank official's incentives rather than institutional quality alone.

4 Empirical Strategy

4.1 Effect on Firm-level Outcomes

I follow a triple difference (DDD) research design to test the hypothesis from Result 1 from the framework above that local judicial capacity plays a complementary role to bankruptcy reforms in reducing lending to risky borrowers and improve efficiency of credit allocation. To see this, I estimate the following specification using pre-reform variation in firms' default risk and variation in local judicial capacity measured as judge to population ratio in a triple difference design. To analyze the impact on the efficiency of credit allocation, I estimate a similar specification but using pre-reform variation in firms' estimated MRPK.

$$\begin{aligned} Y_{fidt} &= \beta_1 \text{Hi Risk/MRPK}_f \text{ x Hi-Jdg-Pop}_d \text{ x } Post_t + \beta_2 \text{Hi Risk/MRPK}_f \text{ x } Post_t \\ &+ \delta_f + \delta_{it} + \delta_{dt} + \epsilon_{fidt} \end{aligned} \tag{1}$$

where Y_{fidt} represents relevant outcomes (borrowing or productivity) of firm f, in industry i, registered in district d in year t. Firms are classified as high-default-risk or high-MRPK as defined in Section 5, where Hi Risk_f is a dummy variable taking value 1 if their credit rating falls in any of the 3 risk categories at least once in the pre-reform period. Similarly, Hi MRPK_f is a binary variable based on categorization of firms as above median in the distribution of estimated pre-reform MRPK across the sample firms (coded as 1 and below median coded as 0). Districts are classified as high judicial capacity, which is denoted by dummy variable High Jdg Pop_d that takes value 1 if the judge-to-population ratio in the pre-reform period is above the average ratio across all sample districts, and 0 otherwise. $Post_t$ is a dummy indicating whether year $t > 2016$ (i.e. period after the reform), defined as $Post_t = 1$, for $t > 2016$ and 0 otherwise. Since the data follows a panel structure, I include firm fixed effects denoted by δ_f to account for all time invariant unobserved potential confounders. In addition, I flexibly account for time-series variation using industry-year interactions (with industry measured as 2 digit NIC product code associated with each firm) and district-year interactions (to account for any unobserved changes in district institutional environment and other potential confounders). These are denoted by terms δ_{it} and δ_{dt}, respectively. ϵ_{fidt} is the idiosyncratic error term. Since the "treatment" varies at the district level, I cluster standard errors by district.

The main null hypothesis of interest is whether the coefficient $\beta_1 = 0$ in Equation 1 above. A negative and significant coefficient would imply that the outcome declines in the post reform period in districts with better judicial capacity for a firm belonging to the specific category. Similarly, a positive coefficient would imply that the outcome increases in the post reform period in district with better judicial capacity for firms of a specific type. Result 1 from Section 3 implies that $\beta_1 < 0$ for high-default-risk firms. Moreover, if we expect allocative efficiency to improve (which is not explicitly modeled), then we expect $\beta_1 > 0$ for high MRPK firms.

To interpret β_1 as a causal parameter, the assumption is that borrowing (and any other outcomes, Y_{fidt}) by hi-default-risk (high MRPK) trends in parallel to those by low risk firms (low MRPK) within high judicial capacity or low judicial capacity districts, even if, on average, they don't trend in parallel to each other. That is, the design relaxes the assumption that high-risk firms trend similarly to low-risk firms everywhere. For example, it is plausible that high-risk firms could experience more unobserved shocks over time due to their behavior, which could put them on a different trend than low-risk firms. While this would be problematic in a difference in differences (DiD) design, the DDD design allows such differential trends as long as the same trends are observed in high and low judicial capacity districts. Furthermore, I include industry-year and district-year fixed effects in order to control for any unobserved time-varying confounders by industry or geography. Finally, because the bankruptcy reform was a one time, pan-India reform with no staggering of treatment, I do not impose additional restrictions of homogenous treatment effects across space and over time.

I implement Equation 1 using two-way fixed effect specification (firm and year fixed effects) with industry-year and district-year interactions, clubbing annual outcomes into pre and post reform periods. I also implement the design using an event study specification, presenting β_1 for each year-bin prior to and post reform. The event study implementation allows us to examine the dynamic effects of the reform across varying judicial capacity by firm type and also test for the parallel trends assumption within district groups by judicial capacity.

4.2 Testing Identifying Assumptions for Causal Inference

Since the reform was a one-time, pan-India reform, all districts and firms experienced the regime change at the same time. This allays any concern arising from staggered roll-out research designs that require strong assumptions for causal identification. Furthermore, it is also plausible that local actors such as banks could lobby to improve their respective courts' judicial capacity by asking for more judges in areas with more efficient or high risk firms in order to initiate bankruptcy processes. This would make judicial capacity endogenous to the bankruptcy regime. I address this concern by using pre-reform judge to population ratio as a pre-determined measure of local institutional capacity to test my main hypotheses.

I test for the assumptions for causal inference in two ways. First, I examine whether there are any differential trends in outcomes between high risk/MRPK firms and low risk/MRPK firms across districts with varying judicial capacities before the reform (i.e., look for any "pre-trends" in the pre-reform period in the DDD set up). Second, I estimate and examine the prior-period trends in a simple DiD framework by examining outcomes across all firms between high and low judicial capacity districts before the reform. This is to test whether the composition of firms and their dynamics prior to reform could confound the post reform effects in the DDD specification.

Lastly, one may be concerned about contemporaneous expansion of bankruptcy courts (NCLT and its regional benches) following the 2016 reform, which could confound whether the results are driven by local district court capacity. This concern is effectively addressed due to the specific context of this study as the newly introduced bankruptcy courts had a more aggregate jurisdiction than that of a district court (it was even larger than a state). At the time of the reform in 2016, the federal government introduced 10 regional benches and one principal bench (New Delhi), which was slowly expanded to 15 benches in total as of 2025. Since the geographic scale of these benches is much larger than a district, the empirical specification Equation 1 exactly accounts for such concerns through the district-year fixed effects. Consequently, the observed estimates are to be inferred as additional effects of local court capacity over and above any simultaneous effects of new bankruptcy courts.

4.3 Effect on Litigation Outcomes

Since one of the key assumptions in our model in Section 3 is that institutional quality Γ matters in credit allocation, I use legal case-level data, merged with firms' identity to examine how local courts resolve cases pertaining to firms of specific type (high-default-risk or high-MRPK) or those pertaining lenders (banks) before and after the reform. Finally, as the case records allow me to identify the litigant type of firm involved in the case - as plaintiff or defendant, I estimate the following specification to examine firm-specific litigation outcome L_{fdt} - number of cases filed, resolved, or pending - separately by litigant-type. All subscripts and RHS variables are as defined before.

$$
\begin{aligned}
L_{fidt} &= \gamma_1 \text{Hi Risk/MRPK}_f \text{ x Hi-Jdg-Pop}_d \text{ x } Post_t + \gamma_2 \text{Hi Risk/MRPK}_f \text{ x } Post_t \\
&+ \delta_f + \delta_{dt} + \delta_{it} + \epsilon_{fidt}
\end{aligned} \tag{2}
$$

For banks, I estimate a DiD specification instead of a DDD to examine bank-specific litigation outcomes, separated by litigant-type (for cases where banks appear as a plaintiff or as defendant), to examine how debt recovery cases are handled by courts of differing capacities before and after the bankruptcy reform. This slightly different approach is required since the same classification of firms as high risk or high MRPK does not apply to banks. Moreover, banks are special types of firms that operate through their location-specific branch offices to make lending decisions. So, even for a national bank, local institutional quality would matter because their lending decisions are made by their local branch offices. Not surprisingly, banks have multiple cases against different types of defaulters across multiple districts from their lending operations. Using the specification below, I examine the effect of high judge-to-population ratio of a district's judiciary Hi Jdg Pop_d on banks' b litigation outcomes L_{bdt} - number filed, number resolved, number pending - in district d in year t, before and after the bankruptcy reform after accounting for bank fixed effect δ_b and district-year interaction δ_{dt}.

$$
L_{bdt} = \gamma \text{Hi Jdg Pop}_d \text{ x } Post_t + \delta_b + \delta_{dt} + \varepsilon_{bdt} \tag{3}
$$

As before, I implement Equation 2 and Equation 3 using two-way fixed effect specification pooling all the post-reform period as well as using an event study design to present the dynamic effects of the reform.

5 Data

I use two main datasets for implementing the research design above. The first pertains to measuring judicial capacity and judicial outcomes, for which I use Ash et al. (2025) and Rao (2025) datasets, respectively. The second pertains to measuring firm-level characteristics to study allocation and primary outcomes of interest - borrowing, short-run liquidity, and production outcomes, for which I use CMIE Prowess dx dataset. I describe both the data and variables constructed for analysis in greater detail below.

5.1 Judicial Capacity and Judicial Outcomes

Judge to population ratio is a standard measure of judicial capacity used in the literature (see Wittrup 2024; India Justice Report 2025). More broadly, staff-per-capita is a commonly used metric to reflect underlying state capacity in the absence of data on service quality or efficiency metrics. For example, Chalfin and McCrary (2018) show that number of police officers per capita is a strong determinant of crime reduction in large cities in the United States. Needleman et al. (2002) discuss how shortage of nurses affects health outcomes and mortality of patients. In the context of India, Dhaliwal and Hanna (2017) show that increased attendance of nurses in primary health centers reduced children born with low birth weight. More directly related to the context of this paper, Rao (2025) shows that backlog in district courts reduces when more judge are added to a court.

I use the universe of legal case data from Ash et al. (2025) to calculate district-level judicial capacity measured as judge-to-population ratio. I use the judge data table to compute total number of judges observed prior to the reform using judge tenure start and end dates. The data table includes the following variables: state, district, court establishment (or simply the court), and the judge position. For each judge position within a court, the data also contain the start date and the end date of the judge assigned to the position.[4] Next, I create a dummy variable assigning a value 1 for every calendar year between the start and end years for the assigned judge, and 0 for calendar years outside this range. I do this for all of state-district-court-judge position-start year-end year tuples over a calendar year range 2010-2018 available in the judicial data. I collapse the data at district-court-year level to estimate the total number of judges per year. Lastly, I identify the maximum of this total number of judges for a district in the pre-reform period to calculate the district-level judge-to-population ratio using the the 2011 district population census estimates.[5]

To measure litigation-specific outcomes such as filing rates, resolution rates, and pending cases at firm-level, I use data from Rao (2025) containing all meta-data and identifying information from the universe of legal case records from a sub-sample of 195 districts over the same time period. I match firm-level identifiers with the legal case-level data from this dataset using firm name and place of registration, followed by manual verification of the resulting match. I identify over 3500 unique non-financial firms with cases across these

[4] The public version of the data does not contain any identifiers such as judge or litigant names.

[5] I also calculate the number of judges for years after the bankruptcy reform but I exclude using this on the right-hand-side of our estimating equations if judicial capacity endogeneously responds to the reform. The average judge to population ratio based on this approach is 18.6 judges per million, which is very close to the aggregate number of 20 reported by the Supreme Court of India.

courts with different baseline levels of judge-to-population ratios. The metadata allows me to tag each firm-case record to identify whether the firm appears as a plaintiff or as a defendant. For each combination of firm-court-litigant type, I calculate number of new cases filed, number of cases resolved, and total pending backlog using filing and decision time stamps in the meta-data. I follow similar algorithm for cases involving banks and financial institutions.

Lastly, I construct measures of high judicial capacity as a dummy variable if a district's pre-reform judge-to-population ratio is higher than the average judge-to-population ratio across all districts that merge with the firm-level data. I note that this average number is higher (51.4 per million) than the overall average judge-to-population ratio (18.6 per million) across all districts in India. This difference arises due to clustering of firms in more urbanized districts.[6]

5.2 Firm-level Default Risk and Capital Productivity

I use CMIE Prowess dx dataset that contains a representative sample panel data of corporate entities (registered formal sector firms) in India with annual financial and production data since 1990s. This dataset offers the advantage of a large-scale firm-level panel data for India, which includes company name, registration details in addition to annual financial and production information. It represents multiple sectors including manufacturing, trade, and services, and thus suitable for research questions requiring firm-level information and their fine-geographic footprint. I am interested in non-financial sector firms, which form the main sampling frame for our analysis.[7]

I focus on firms that were incorporated prior to 2010 and continue to exist through the study period. This allows me to construct a balanced panel of firms and at the same time minimize concerns about endogenous entry and exit decisions.

In order to examine credit allocation across firms, I classify firms based on their default risk and capital productivity, estimated using their credit ratings and MRPK, respectively, from the pre-reform period. Each year, firms are rated based on their past performance on credit contracts by credit bureaus. There are five credit bureaus - CRISIL, ICRA, CARE, IND-RA, and BRICKWORK. These are similar to global agencies like Moody's and Standard

[6] Results from the classification of a district court as high or low judicial capacity is robust to using other cut-offs such as the median instead of average.

[7] Other firm-related datasets from India are the Annual Survey of Industry (ASI) and the Micro-Small- and Medium Enterprise (MSME) datasets, neither of which provide firm-level identity and their specific geographic location. However, the key trade-off in using Prowess is that it excludes smaller firms and those in the informal sector. Information from these can mainly be collected through primary enterprise surveys, often requiring large funding for data collection.

& Poor's. Ratings like {PR 1+, A1+, A1, PR2, A+, A, A-, ... }, which map to specific credit safety measures are classified into 8 bins as in decreasing order as "Highest Safety, High Safety, Moderate Safety, Adequate Safety, Inadequate Safety, High Risk, Substantial Risk, and Default". I classify firms as high-default-risk if their credit rating in any of the pre-reform period is marked "High Risk" or worse (i.e., High Risk, Substantial Risk, or Default).

I estimate firm-level MRPK by assuming Cobb-Douglas production function as in the literature (for example, Bau and Matray 2023). This is a two-step approach where in the first step, I estimate the input shares in the production function using panel-data structure from the pre-reform period in a log-log specification. I regress firm-level log sales revenue on log value of plant and machinery (capital) and log wage bill, controlling for firm and year fixed effects. Next, I scale the average products (sales revenue per unit capital or per unit wage bill) using these input shares to obtain the marginal revenue products of capital and labor, respectively. I mainly focus on MRPK to test efficiency of credit allocation by lenders. Since MRPK is a continuous measure, I classify firms as high-MRPK if their pre-reform estimated MRPK is above the median value across all sample firms.

5.3 Outcome Variables

I focus on 2010-2024 as the study period after merging CMIE data with firm-specific pre-reform characteristics and annual balance sheet data with district-specific judicial data. I focus on these years to include multiple observations prior to the reform but after the global financial crisis of 2007-09 as well as a long post-period. CMIE provides the district of firms' location of registration, which I use to merge the firm-level data with the judicial data. The analysis sample contains a balanced panel of 3500 firms located across India. I impute any missing values of the outcome measures using the firm-specific average during the study period.

I focus on two sets of outcomes. The first set of outcomes include borrowing and short-run liquidity (net working capital) to test our specific hypotheses on credit allocation. The second set of outcomes include economic outcomes measured as legal and interest expenditures, investments, and sales revenue to examine productivity implications of the reform and judicial capacity.

5.4 Summary Statistics

Table 1 presents a summary of the main dataset used in the analysis. First thing to note is that the judge to population ratio is higher in the analysis sample than the national average because the districts with formal sector firms are not necessarily representative of a typical district in India, which is more rural. The average judge to population ratio is around 52 judges per million population. Second, firms are large, formal sector firms, where 80% of the sample are publicly listed on various stock exchanges. These firms exhibit a large variation in their default risk (average rating close to 6) and capital efficiency estimated as MRPK (average marginal return of 9 for every additional rupee of capital). Most firms are between 20-60 years old, 60% engaged in manufacturing, 19% in trade, 11% in construction, 2% in services and remaining 8% in unclassified, non-financial sectors. The average sales revenue and assets are 4.6 and around 6 billion Indian Rupees (US $54 and $ 70 million, respectively).

6 Results

I begin by examining firm-level balance sheet data using borrowing and short-term liquidity (net working capital) outcomes among sample firms by their characterization of default-risk and capital productivity. Next, I estimate the effects on economic productivity focusing on sales revenue, expenditures on compliance/legal, and long run investment. To shed light on last-mile enforcement as mechanism, I examine firm-level litigation outcomes using legal case-level data in a subset of the sample districts for which firm-specific litigation data was available.

6.1 Borrowing and Liquidity

I start my analysis with borrowing and short-run liquidity outcomes to examine credit discipline - how default risk is handled - and allocative efficiency in response to complementary investments in lender rights through a change in bankruptcy regime and local enforcement capacity through district courts. Since default risk is typically observable to economic agents and the econometrician through corporate credit ratings, I first estimate Equation 1 to examine the effect of reform and judicial capacity on borrowing and liquidity outcomes of high-default-risk firms relative to low risk firms. Panel A Figure 3 (left) presents the event study estimates and Col 1 Table 3 presents the DDD estimates. I find a reduction in borrowing by high risk firms in better judicial capacity districts, which is mainly evident in the long run (about 30% reduction in the long-run). The post-reform average treatment effects on the treated (ATT) is -11.4% (Col 1 Table 3), which loses statistically significance due to dynamics that plays out over a longer term but is economically meaningful.

Panel A Figure 3 (right) and Col 2 Table 3 present the event study and DDD estimates using net working capital (indicating short term liquidity position) as the dependent variable, respectively. I find a persistent increase in short term liquidity by over 50% among high-default-risk firms in better judicial capacity districts post reform. The DDD estimates in Col 2 Table 3 shows an average, post-reform increase in short term liquidity by 77%. Interpreting the results on borrowing along with short term liquidity, I note that high-default-risk firms reduce overall borrowing and increase their cash holdings plausibly to pay back any outstanding dues to avoid initiation of bankruptcy proceedings.

Next, I examine these outcomes by firms' pre-reform MRPK. An increase in allocative efficiency would suggest that lenders should prioritize firms with higher marginal product of capital (or its proxy MRPK). However, I don't find evidence in support of this and I am unable to reject the null hypothesis of no effect on borrowing by firms' MRPK in better judicial capacity districts after the reform. Panel B Figure 3 and Col 3-4 Table 3 present the estimates on borrowing and net working capital by high-MRPK in better judicial capacity districts before and after the reform. Both event study and DDD estimates suggest a muted effect on borrowing by high-MRPK firms. In contrast, I find large, positive effects on short-run liquidity position (a 45% increase) among high-MRPK firms in better judicial capacity districts.

I interpret these results keeping in mind the fact that these characteristics of a firm - default-risk and MRPK - are potentially non-overlapping and that easily observable characteristics such as credit rating fails to provide information on capital productivity. Specifically, I find weak negative correlation between a firm's classification as high-default-risk and its classification as high-MRPK. Without any fixed effects, a high-default-risk firm is 9% less likely to be classified as a high-MRPK firm (Col 1 Table 2). After adjusting for industry or location or both, this correlation coefficient halves and loses statistical significance. As a result, any information on default risk, such as that provided by credit rating, is less informative about a firm's capital efficiency or MRPK. This would be surprising in a world with perfect information where we would expect that high-MRPK firms should be more profitable and thus less likely to default. Since this weak correlation is observed despite including industry fixed effects (i.e., comparing MRPK and default risk among firms within a specific industry) and in a context with multiple market failures and frictions, this isn't surprisingly at all. For example, consider firms that have made huge, upfront investment and that expected future productivity includes some risk. Such firms are susceptible to business cycle shocks, which could lead them to default given their relatively weak cash position. Another exactly opposite example would be incumbent firms with moderate or even low MRPK but with consistent cash flow such that they are less likely to default. Both these examples illustrate hidden type and hidden action mechanisms that are not currently accounted in the computation of credit ratings, which is mainly based on observable and backward-looking measures such as leverage and past payment history.

I rationalize these results by inferring that firms may have become risk averse by holding more cash at hand in areas with better court capacity after the reform. I observe only some improvement in credit allocation - borrowing by high-default-risk firms decline, indicating a plausible reduction in "ever-greening" phenomenon but only in specific areas with better courts. The reform also falls short of improving overall allocative efficiency.

6.2 Economic Outcomes

I examine four relevant economic outcomes to measure the combined effects of the reform and local enforcement capacity. These include legal expenditure, interest expenditure, investments, and sales revenue. Legal expenditure includes costs towards legal advisors, including lawyers and law firms, on matters related not just to litigation but also advice on matters pertaining to legal compliance of various laws and orders. Interest expenditure includes interest payments on all types of borrowing - either for working or investment capital - from multiple lenders. Investments are those made by the firm with return expected to accrue after a year ($>$ 12 months), and thus considered long-run. These include investments in financial (such as shares/bonds, etc.) and non-financial assets (such as property, joint ventures, etc.). Sales revenue includes all income generated from sale of goods and non-financial services.

Figure 4 and Table 4 presents the estimates from the DDD design both as event study and two-way fixed effects specification, respectively, comparing firms' by their baseline default-risk across districts with varying judicial capacities. I find significant decline in such firms' legal (17%, $p < 0.01$) and interest expenditures (33%, $p < 0.01$) in districts with better judicial capacity. I also find reduced investment by such firms, at least in the initial years following the reform, and a negative but noisy effects on their sales revenue.

Figure 5 and Table 5 presents the results using firms's baseline MRPK across districts with better or worse judicial capacities. I find a significant increase in investment by such firms after the reform in better capacity districts, which I observe both over time (event study) as well as ATT effects (40%, $p < 0.01$). On the other hand, I find almost no effects on legal or interest expenditures or on sales revenue.

I interpret these findings as suggesting that worse firms, like those characterized by high default risk are more likely to shrink by lowering their legal expenditure and investments. Moreover, the result on interest expenditure is consistent with the reduced borrowing over the same time period, indicating a decline in interest costs from lower borrowing. While I don't observe their complete exit or liquidation in the data, it is likely that such firms may eventually file for bankruptcy to seek liquidation or restructuring. At the same time, better firms characterized by high baseline MRPK are likely to increase investment in the post reform period, potentially to improve their liquidity position in the future. Since there were no effects on borrowing for such firms, I correspondingly find no effects on interest or legal expenditures. I also find no productivity improvements among such firms, suggesting no stark positive impact among high capital efficiency firms.

6.3 Threats to Identification

Since the dataset is a balanced panel, the main threat to identification is from time varying firm-level confounders. A lack of pre-trends in the triple difference (DDD) specifications by firm characteristic (default risk or MRPK) is reassuring that observed effects are unlikely to be driven by any unobserved, time varying confounders at the firm-level.[8] Any concerns such as industry lobbies to delay bankruptcy proceedings or intervening with local judicial capacity are likely addressed by including industry-year and district-year fixed effects.

To address concerns about differential composition of firms by their borrowing, liquidity, or production outcomes, I examine the effects of the bankruptcy reform on these same outcomes across all firms (without differentiating their characteristic by default-risk or MRPK) by underlying judicial capacity of the districts using a DiD design. I do not find any differential trends in borrowing across all firms in the pre-reform period by district judicial capacity (see Figure A.1). The post reform results suggest that in fact, borrowing by the average firm increases in the long run in better judicial capacity districts. While I find an increasing trend in short run liquidity among firms in better judicial capacity districts prior to the reform, this trend actually reverses post reform, where the average firm holds less cash at hand.

[8] Recall that all specifications have firm fixed effect in addition to district-year and industry-year fixed effects. Thus, any confounder must vary at the firm-level over time along with the primary outcomes.

On balance sheet and production outcomes (Figure A.2), I do not notice strong pre-trends in the period prior to the reform. However, the effect of the reform on the average firm in better judicial capacity district indicates higher legal and interest expenditures, and plausibly lower long-run investment and sales, respectively (see Table A.1 for the DD estimates). These are not inconsistent with the main finding that the effects of bankruptcy reforms are not unequivocally positive due to other frictions in the credit market.

6.4 Robustness to Alternate Definitions of Judicial Capacity

These results are not driven by how I define judicial capacity. I find similar results if I use median value of judge to population ratio to classify as high or low judicial capacity instead of the average. See Table A.2, Table A.3, Table A.4. I also use pre-reform vacancy rates among district judge positions as another way to measure judicial capacity. I find qualitatively similar effects of the bankruptcy reform in high judicial capacity districts (defined as below median vacancy rates in the pre-reform period) on firm-level outcomes including borrowing, liquidity, and production outcomes (see Table A.5, Table A.6, and Table A.7).

6.5 Mechanism: Last Mile Enforcement by District Courts

In order to understand why I see the results I see among firms in districts with better judicial capacity, I use legal case data matched to firm identifiers from Rao (2025). I examine three main judicial outcomes specific to the matched firms - number of cases filed in the district courts, number of cases resolved, and number of pending cases - for each firm in the analysis sample during the study period. Next, I estimate the main identifying specification Equation 2 using these firm-level judicial outcomes as the dependent variables, separately when the sample firm appears as a plaintiff and a defendant. These set of analyses tests the role of the local court in accepting and resolving litigation against firms, based on their baseline characteristics, to show how local enforcement could matter.

Figure 6 and Table 6 presents the results for high-default-risk firms when they either appear as plaintiff (Panel A Figure 6 or Col 4-6 Table 6) and when they appear as defendant (Panel B Figure 6 or Col 1-3 Table 6). Since the outcome data is at the district court-firm-case-level and that the same firm could have cases in multiple courts, I can identify the coefficient on high judge-population districts interacted with post-reform dummy variable (which would otherwise be collinear with district-year fixed effects). The coefficient on Hi-Jdg-Pop x Post suggests that better district courts have higher rates of resolution and lower pending backlog per defending firm in the post reform period. These court-level effects are muted for plaintiff firms in the post reform period. The DDD event study parameters (Panel B Figure 6) are noisy but suggest that more cases are filed against high default-risk firms (i.e. as defendants) and there is increased resolution of cases against such firms in courts with better judicial capacity. On the other hand, there is no conclusive evidence on judicial outcomes for cases involving high-default-risk firms as plaintiff. The point estimates suggest that such firms are less likely to file complaints in better courts, and if they do, they are less likely to be resolved.

Figure 7 and Table 7 presents the results for high-MRPK firms litigating in the sample courts. The coefficients on high judge-population ratio in the post reform period suggests higher rates of resolution and lower pending backlog per firm against all defending firms. The event study and DDD estimation suggests a higher rates of resolution and lower filing rates among high-MRPK plaintiff firms.

I rationalize these results as follows: high-default-risk firms are more likely to default on credit contracts, which results in cases being filed *against* such firms (who then appear as defendants). Our results suggest that the local courts with better capacity are more likely to resolve such cases when high-default-risk firms are defending, enforcing contracts. In contrast, when high-MRPK firms file cases against other economic agents as plaintiff, better local courts enable faster resolution of such cases.

Lastly, I estimate Equation 3 using legal case data involving banks, separated by whether cases are filed by them (banks as plaintiff) or against them (for example, a defaulter could preemptively file a suit against their lender to delay debt recovery where banks appear as defendants). I find that better courts are less likely to resolve cases against banks (when banks are defendants, see Table 8). While the results are noisy, the DiD coefficients when banks appear as plaintiffs suggest increased resolution of cases per bank. I read these results together to infer that better courts are able to discern the reasons behind contract failures and either correctly enforce them or preempt when they are potentially frivolous.

7 Conclusion

This paper provides evidence in support of the complementary role local courts play in enforcing creditor rights affected by the bankruptcy regime change on credit allocation and subsequent production implication among formal sector firms. To show this, I exploit cross-sectional variation in district judicial capacity, measured as average judge to population ratio in district courts prior to the 2016 national-level reform. The reform strengthened creditor rights, which prioritized creditors over all other stakeholders in bankruptcy proceedings. To answer the question on credit allocation specifically, I leverage variation between local firms in their baseline default-risk (as measured based on their pre-reform credit scores) or capital productivity (MRPK) in a triple difference (DDD) design by comparing high-default-risk (high MRPK) firms with low-default-risk firms (low MRPK) across districts with high or low judge-to-population ratios. I find that high-default-risk firms reduce borrowing after the reform in districts with better judicial capacity and increase their short-term liquidity. In contrast, I find no effects on borrowing among high-MRPK firms although I find some increase in short-term liquidity among such firms as well. I find a corresponding decrease in economic outcomes - legal and interest expenditures, investment, and sales revenue - among high-default-risk firms in districts with better judicial capacity after the reform. I find an increase in investment by high MRPK firms but no changes in other indicators.

To understand the role of local courts, I test whether the case-level outcomes of the sample firms vary by the capacity of their corresponding district court after the reform. I find suggestive evidence of overall reduction in pending backlog of cases per firm in better capacity courts, increased resolution of cases filed against high-default-risk firm (when they appear as defendants), increased resolution of cases filed by high-MRPK firms (as plaintiff), and lower resolution of cases filed against banks (as defendants). These indicate that local courts facilitate contract enforcement by increasing filing and resolution of cases against high-default-risk firms, and at the same time, handling frivolous cases filed against banks.

While these efforts along with the bankruptcy reform could reduce allocation of capital towards high-default-risk firms, it is insufficient to increase allocation of credit towards high-MRPK firms. Perhaps lenders and institutions aren't fully able to discern high capital efficiency firms to increase allocative efficiency. This is evident in the weak correlation between observed firm-level default risk (credit ratings) and capital efficiency (MRPK) indicators.

Using recent data and institutional reforms, this paper presents evidence to enable discussion surrounding the direction of reforms focusing on local judiciary in the economic development process. Given the timing of the reform in 2016, this paper provides short and medium run effects on credit and firm-level economic outcomes. As the law takes full effect over time, the long run and general equilibrium effects may be different. These could have ramifications on what types of firms are liquidated and what types are restructured through re-investment, and therefore left for further research as and when such data becomes available. Furthermore, what this paper examines is capacity measured in terms of judge-to-population ratios, which is one specific aspect of judicial capacity. Other investments in the local enforcement environment, such as better triage through alternate dispute resolution and conciliation for enforcing any liquidation or asset transfers may have different impact, which remain as open questions for future research.

References

Acemoglu, Daron and Simon Johnson, "Unbundling Institutions," *Journal of Political Economy*, 2005, *113* (5), 949–995. Publisher: The University of Chicago Press.

Alok, Shashwat, Ritam Chaurey, and Vasudha Nukala, "Creditors' Rights, Threat of Liquidation, and the Labor and Capital Choices of Firms," *The Journal of Law and Economics*, 2022, *65* (4), 687–714.

Amirapu, Amrit, "Justice Delayed Is Growth Denied: The Effect of Slow Courts on Relationship-Specific Industries in India," *Economic Development and Cultural Change*, October 2021, *70* (1), 415–451. Publisher: The University of Chicago Press.

Ash, Elliott, Sam Asher, Aditi Bhowmick, Sandeep Bhupatiraju, Daniel Chen, Tanaya Devi, Christoph Goessmann, Paul Novosad, and Bilal Siddiqi, "In-Group Bias in the Indian Judiciary: Evidence from 5 Million Criminal Cases," *The Review of Economics and Statistics*, 2025.

Banerjee, Abhijit V. and Esther Duflo, "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program," *The Review of Economic Studies*, April 2014, *81* (2), 572–607.

Bau, Natalie and Adrien Matray, "Misallocation and Capital Market Integration: Evidence From India," *Econometrica*, 2023, *91* (1), 67–106.

Bazzi, Samuel, Marc-Andreas Muendler, Raquel F. Oliveira, and James E. Rauch, "Credit Supply Shocks and Firm Dynamics: Evidence from Brazil," Working Paper September 2023.

Cantoni, Davide and Noam Yuchtman, "Medieval Universities, Legal Institutions, and the Commercial Revolution *," *The Quarterly Journal of Economics*, May 2014, *129* (2), 823–887.

Chalfin, Aaron and Justin McCrary, "Are U.S. Cities Underpoliced? Theory and Evidence," *The Review of Economics and Statistics*, March 2018, *100* (1), 167–186.

Chemin, Matthieu, "Judicial Efficiency and Firm Productivity: Evidence from a World Database of Judicial Reforms," *The Review of Economics and Statistics*, March 2020, *102* (1), 49–64.

Closset, Frédéric, Christoph Großmann, Christoph Kaserer, and Daniel Urban, "Corporate restructuring and creditor power: Evidence from European insolvency law reforms," *Journal of Banking & Finance*, April 2023, *149*, 106756.

Cole, Shawn, Martin Kanz, and Leora Klapper, "Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers," *The Journal of Finance*, 2015, *70* (2), 537–575. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12233.

Demetriades, Panicos O. and Kul B. Luintel, "Financial Development, Economic Growth and Banking Sector Controls: Evidence from India," *The Economic Journal*, March 1996, *106* (435), 359–374. Publisher: Oxford Academic.

Dhaliwal, Iqbal and Rema Hanna, "The devil is in the details: The successes and limitations of bureaucratic reform in India," *Journal of Development Economics*, January 2017, *124*, 1–21.

Djankov, S, C Mcliesh, and A Shleifer, "Private credit in 129 countries," *Journal of Financial Economics*, May 2007, *84* (2), 299–329.

Faria-e-Castro, Miguel, Pascal Paul, and Juan M. Sánchez, "Evergreening," *Journal of Financial Economics*, 2024, *153*, 103778.

Fisman, Raymond, Daniel Paravisini, and Vikrant Vig, "Cultural Proximity and Loan Outcomes," *American Economic Review*, February 2017, *107* (2), 457–492.

Giné, Xavier and Inessa Love, "Do Reorganization Costs Matter for Efficiency? Evidence from a Bankruptcy Reform in Colombia," *The Journal of Law and Economics*, November 2010, *53* (4), 833–864. Publisher: The University of Chicago Press.

_ **and Martin Kanz**, "The Economic Effects of a Borrower Bailout: Evidence from an Emerging Market," *The Review of Financial Studies*, May 2018, *31* (5), 1752–1783. Publisher: Oxford Academic.

Glaeser, Edward L. and Andrei Shleifer, "The Rise of the Regulatory State," *Journal of Economic Literature*, June 2003, *41* (2), 401–425.

Gopalan, Radhakrishnan, Vikram Nanda, and Amit Seru, "Affiliated firms and financial support: Evidence from Indian business groups," *Journal of Financial Economics*, December 2007, *86* (3), 759–795.

Gormley, Todd, Nandini Gupta, and Anand Jha, "Quiet Life No More? Corporate Bankruptcy and Bank Competition," *The Journal of Financial and Quantitative Analysis*, 2018, *53* (2), 581–611. Publisher: [Cambridge University Press, University of Washington School of Business Administration].

India Justice Report , "India Justice Report: Ranking States on the Capacity of Police, Judiciary, Prisons, and Legal Aid," Technical Report 2025.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, September 2008, *98* (4), 1413–1442.

Kulkarni, Nirupama, S. K. Ritadhi, Siddharth Vij, and Katherine Waldock, "Unearthing Zombies," *Management Science*, January 2025. Publisher: INFORMS.

Li, Bo and Jacopo Ponticelli, "Going Bankrupt in China," *Review of Finance*, May 2022, *26* (3), 449–486.

Müller, Karsten, "Busy bankruptcy courts and the cost of credit," *Journal of Financial Economics*, 2022, *143* (2), 824–845.

_ **and Emil Verner**, "Credit Allocation and Macroeconomic Fluctuations," *The Review of Economic Studies*, 12 2023, *91* (6), 3645–3676.

Naaraayanan, S Lakshmi and Daniel Wolfenzon, "Business Group Spillovers," *The Review of Financial Studies*, January 2024, *37* (1), 231–264.

Needleman, Jack, Peter Buerhaus, Soeren Mattke, Maureen Stewart, and Katya Zelevinsky, "Nurse-Staffing Levels and the Quality of Care in Hospitals," *New England Journal of Medicine*, May 2002, *346* (22), 1715–1722. Publisher: Massachusetts Medical Society _eprint: https://www.nejm.org/doi/pdf/10.1056/NEJMsa012247.

Ortiz-Villavicencio, Marcelo and Pedro H. C. Sant'Anna, "Better Understanding Triple Differences Estimators," May 2025. arXiv:2505.09942 [econ].

Paravisini, Daniel, Veronica Rappoport, Philipp Schnabl, and Daniel Wolfenzon, "Dissecting the Effect of Credit Supply on Trade: Evidence from Matched Credit-Export

Data," *Review of Economic Studies*, 2015, *82* (1), 333–359. Publisher: Oxford University Press.

Ponticelli, Jacopo and Leonardo S. Alencar, "Court Enforcement, Bank Loans, and Firm Investment: Evidence from a Bankruptcy Reform in Brazil," *The Quarterly Journal of Economics*, August 2016, *131* (3), 1365–1413.

Porta, Rafael La, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny, "Law and Finance," *Journal of Political Economy*, December 1998, *106* (6), 1113–1155.

Rajan, Raghuram G. and Luigi Zingales, "Financial Dependence and Growth," *The American Economic Review*, 1998, *88* (3), 559–586.

Rao, Manaswini, "Front-line Courts As State Capacity: Evidence From India," *Working Paper*, 2025.

Vig, Vikrant, "Access to Collateral and Corporate Debt Structure: Evidence from a Natural Experiment," *The Journal of Finance*, 2013, *68* (3), 881–928.

Visaria, Sujata, "Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India," *American Economic Journal: Applied Economics*, 2009, *1* (3), 59–81.

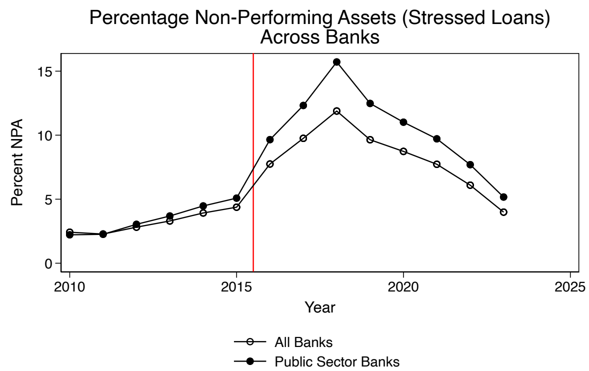
von Lilienfeld-Toal, Ulf and Dilip Mookherjee, "A General Equilibrium Analysis of Personal Bankruptcy Law," *Economica*, 2016, *83* (329), 31–58.

Wittrup, Jesper, "Explaining Cross-Country Differences in the Number of Judges per Capita | International Journal for Court Administration," *International Journal for Court Administration*, June 2024.

Òscar Jordà, Martin Kornejew, Moritz Schularick, and Alan M Taylor, "Zombies at Large? Corporate Debt Overhang and the Macroeconomy," *The Review of Financial Studies*, October 2022, *35* (10), 4561–4586.

8 Figures

Figure 1: NPA Across Banks in India



Notes: The figure above graphs the percentage of total lending declared as a non-performing asset (NPA) aggregated across all commercial banks in India and by public sector banks, as reported by the central bank, Reserve Bank of India. The red vertical line indicates when the bankruptcy bill was first tabled in the national parliament. I present the timeline of the reform below.

Figure 2: Timeline of Bankruptcy Reform

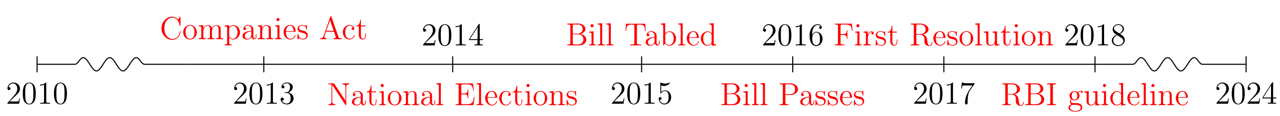
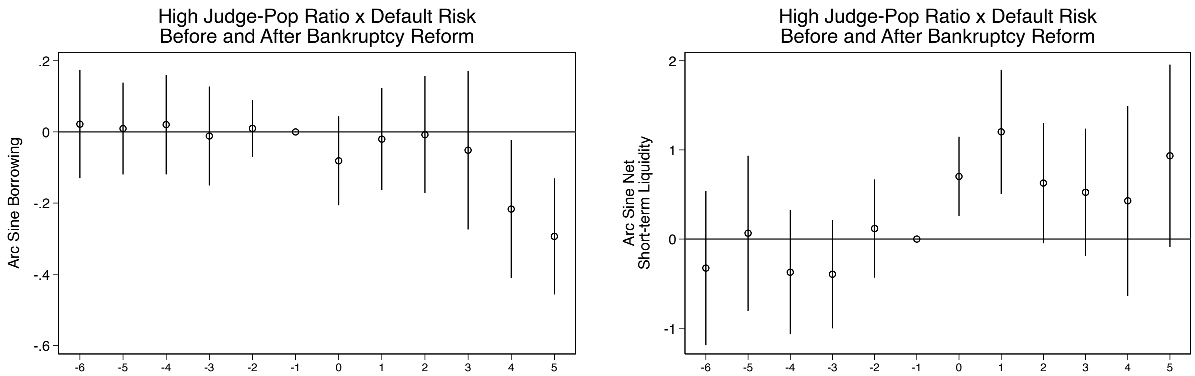
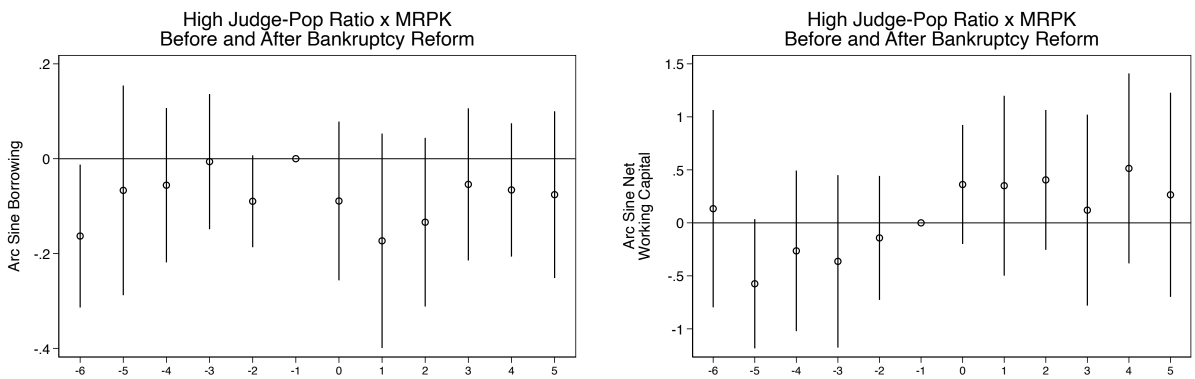


Figure 3: Borrowing and Liquidity Outcomes

Panel A: By Baseline Default Risk

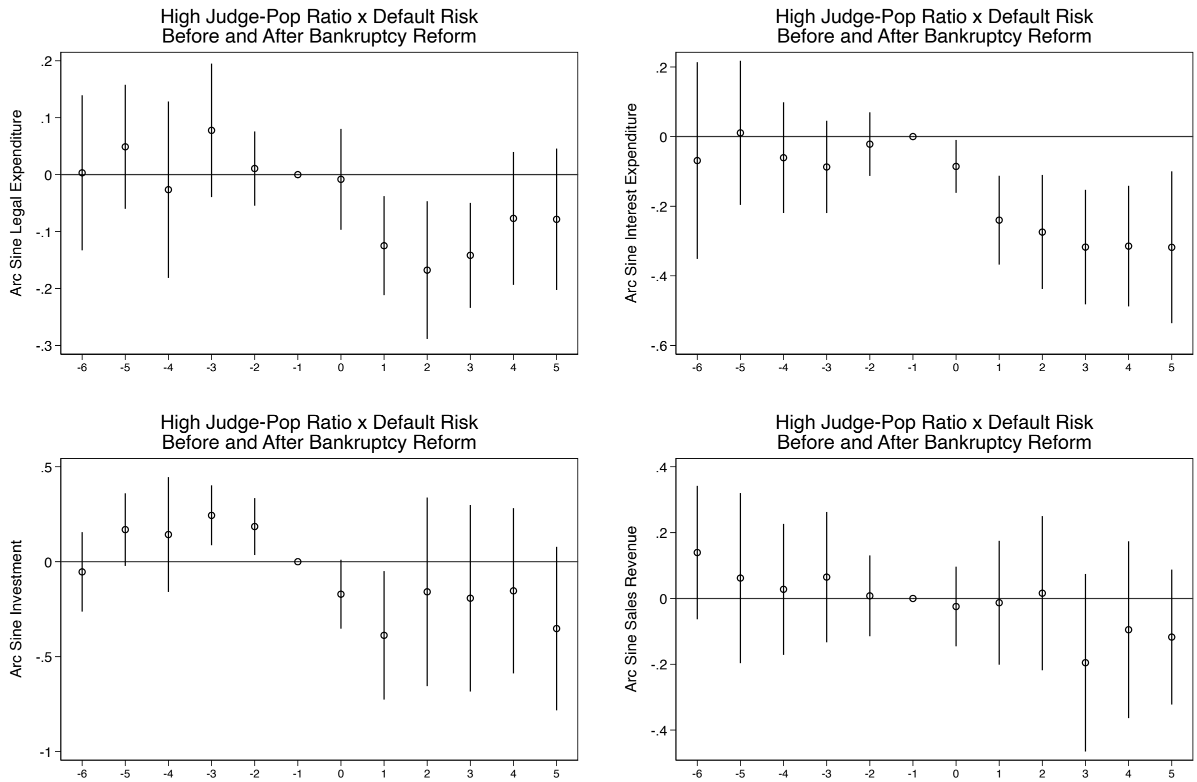


Panel B: By Baseline MRPK



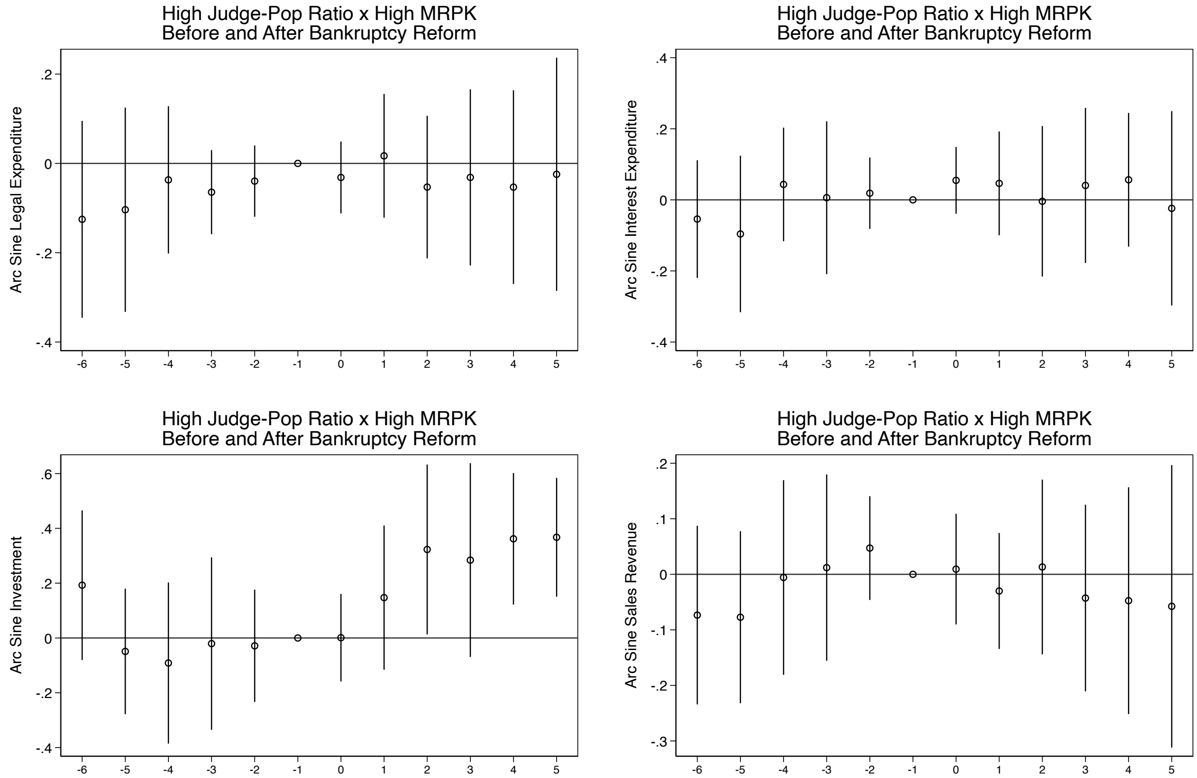
Notes: Panels A and B above present the estimates of event study implementation of Equation 1 using borrowing and short-term liquidity outcomes as dependent variables for high-default-risk (Panel A) and high-MRPK (Panel B) interactions, respectively. The reference year is 2015, a year before the bankruptcy bill becomes an act of the Indian Parliament. The coefficients are all relative to the reference year. High judge to population ratio districts are those with the ratio above the sample average. High default risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Error bars present 95% confidence interval. Standard errors are clustered by district. The DDD estimates are reported in Table 3.

Figure 4: Economic Outcomes: By Baseline Default Risk



Notes: The figures above present the triple interaction estimates of event study implementation of Equation 1 using financial and economic outcomes as dependent variables for firms classified as high-default risk in high judge-population ratio districts. The reference year is 2015, a year before the bankruptcy bill becomes an act of the Indian Parliament. The coefficients are all relative to the reference year. High judge to population ratio districts are those with the ratio above the sample average. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. Error bars present 95% confidence interval. Standard errors are clustered by district. The DDD estimates are reported in Table 4.

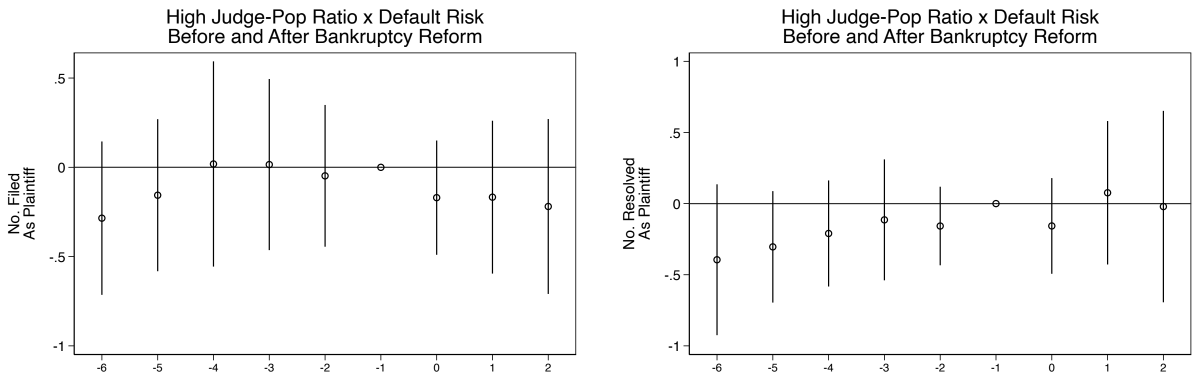
Figure 5: Economic Outcomes: By Baseline MRPK



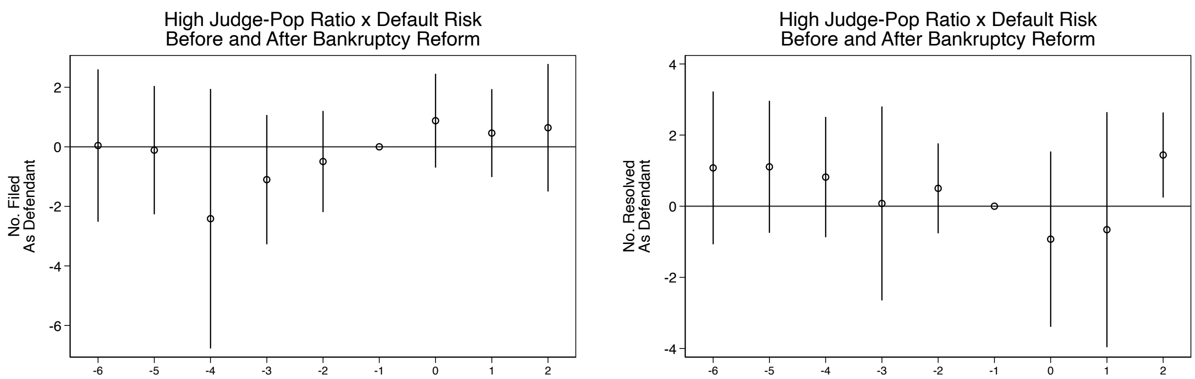
Notes: The figures above present the triple interaction estimates of event study implementation of Equation 1 using financial and economic outcomes as dependent variables for firms classified as high-MRPK in high judge-population ratio districts. The reference year is 2015, a year before the bankruptcy bill becomes an act of the Indian Parliament. The coefficients are all relative to the reference year. High judge to population ratio districts are those with the ratio above the sample average. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Error bars present 95% confidence interval. Standard errors are clustered by district. The DDD estimates are reported in Table 5.

Figure 6: Litigation in Courts by Firms: By Baseline Default-Risk

Panel A: As Plaintiff



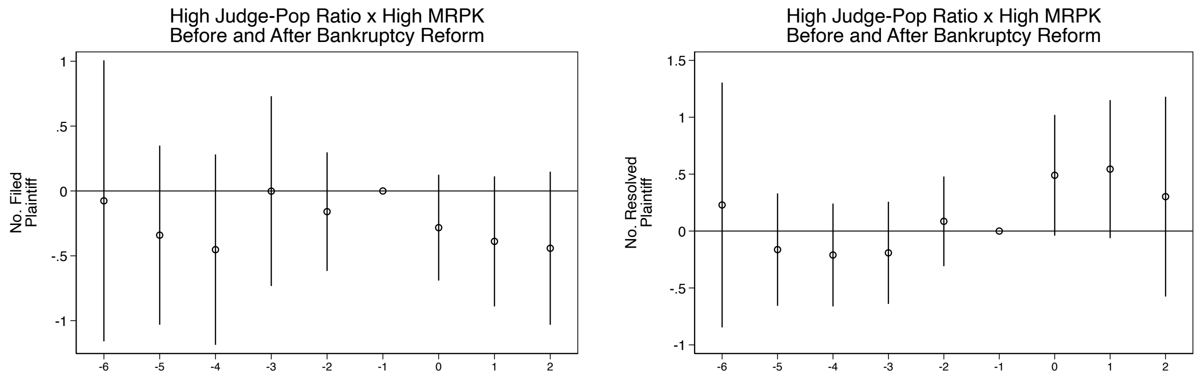
Panel B: As Defendant



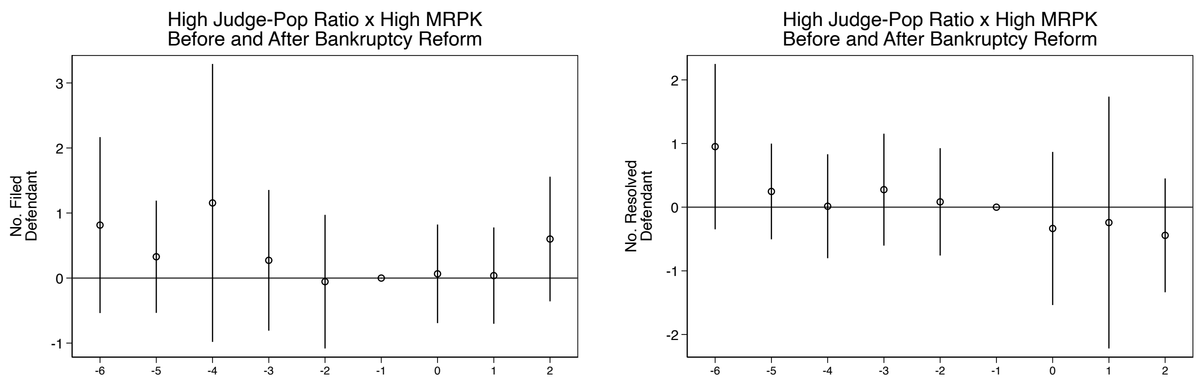
Notes: The figures above present the triple interaction estimates of event study implementation of Equation 2 using legal case-level outcomes in the corresponding district court as dependent variables for firms classified as high default risk in high judge-population ratio districts. The reference year is 2015, a year before the bankruptcy bill becomes an act of the Indian Parliament. The coefficients are all relative to the reference year. Note that the judicial case-level data is only available until 2018, so there are fewer post reform time periods compared to the analysis using firm-level outcomes. High judge to population ratio districts are those with the ratio above the sample average. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. Panel A presents the estimates on case-level outcomes when high-risk firms appear as plaintiff in a case. That is, when such firms initiate the suit in courts. Panel B presents the estimates when such firms appear as defendants in a case, i.e., when someone else files a suit against them. Error bars present 95% confidence interval. Standard errors are clustered by district. The DDD estimates are reported in Table 6.

Figure 7: Litigation in Courts by Firms: By Baseline MRPK

Panel A: As Plaintiff



Panel B: As Defendant



Notes: The figures above present the triple interaction estimates of event study implementation of Equation 2 using legal case-level outcomes in the corresponding district court as dependent variables for firms classified as high-MRPK in high judge-population ratio districts. The reference year is 2015, a year before the bankruptcy bill becomes an act of the Indian Parliament. The coefficients are all relative to the reference year. Note that the judicial case-level data is only available until 2018, so there are fewer post reform time periods compared to the analysis using firm-level outcomes. High judge to population ratio districts are those with the ratio above the sample average. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Panel A presents the estimates on case-level outcomes when high-MRPK firms appear as plaintiff in a case. That is, when such firms initiate the suit in courts. Panel B presents the estimates when such firms appear as defendants in a case, i.e., when someone else files a suit against them. Error bars present 95% confidence interval. Standard errors are clustered by district. The DDD estimates are reported in Table 7.

9 Tables

Table 1: Summary Statistics

	(1) No. Firms	(2) Mean	(3) SD
Judge to Population Ratio (per million)	3582	51.74	49.60
Estimated MRPK	3381	9.09	41.76
Credit Rating (1 lowest-8 highest)	3582	5.78	1.78
Public Ltd.	3582	0.80	0.40
Age (years)	3580	40.82	19.36
Share Manufacturing	3582	0.59	0.49
Share Construction	3582	0.11	0.31
Share Trade/Retail	3582	0.19	0.39
Share Services	3582	0.02	0.15
Sales Rev (Million INR)	3411	4605.24	25855.26
Total Assets (Million INR)	3582	5961.70	31772.94

Notes: The main sample includes over 3000 formal, non-financial sector firms registered in districts with courts classified as high or low judicial capacities (judge to population ratio) that form the main population of interest for this study. Note that the judge to population ratio in this sample is different from the national average of 18.6, which includes districts with no overlap with Prowess firms. Age is calculated as the difference between current year and the year of firm's incorporation. The remaining 8% of sample firms belong to other non-financial sectors represented by industrial classification (NIC) codes that could not be neatly binned into the sector categories above. The average sales revenue and asset value are computed for period prior to the reform.

Table 2: Firm Default Risk and Marginal Factor Productivity

	(1) High MRPK	(2) High MRPK	(3) High MRPK
High Default Risk	-0.0918***	-0.0404	-0.0460
	(0.0266)	(0.0265)	(0.0281)
Constant	0.482***	0.474***	0.478***
	(0.00883)	(0.00772)	(0.00788)
Observations	3582	3431	3347
Fixed Effect	None	Industry	Industry, District
Adj R-Squared	0.00291	0.257	0.259

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table reports firm-level correlations between default risk and their high-MRPK classification using data from pre-reform period. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Col 1 presents simple, bi-variate correlation. Cols 2-3 include location and industry fixed effects to account for risk or productivity factors driven either by location of registration or industry. Heteroskedasticity robust standard errors reported in parentheses.

Table 3: Bankruptcy Reform and District Judicial Capacity: Firms' Borrowing and Liquidity

	(1) Arc Sine Borrowing	(2) Arc Sine Net Liquidity	(3) Arc Sine Borrowing	(4) Arc Sine Net Liquidity
High Jdg Pop Ratio x High Default Risk x Post	-0.114	0.773***		
	(0.0868)	(0.262)		
High Default Risk x Post	0.0300	-0.404*		
	(0.0721)	(0.207)		
High Jdg Pop Ratio x High MRPK x Post			-0.0333	0.452*
			(0.0623)	(0.271)
High MRPK x Post			0.0180	-0.442*
			(0.0545)	(0.251)
Observations	46272	46308	38376	38400
No. Districts	164	164	150	150
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	7.390	2.310	7.480	2.030
SD Dep Var	2.210	6.520	2.290	6.710
Adj R-Squared	0.829	0.632	0.825	0.623

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: Col 1-2 above present the estimates from Equation 1 using borrowing and short-term liquidity outcomes as dependent variables for high-default-risk firm interactions. Col 3-4 present the estimates for high-MRPK firm interactions. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. High-judge-to-population ratio districts are those with the ratio above the sample average. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Standard errors are clustered by district. The event study figures are in Figure 3.

Table 4: Bankruptcy Reform and District Judicial Capacity: Firms' Production Outcomes by Default Risk

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
High Jdg Pop Ratio x High Default Risk x Post	-0.133***	-0.248***	-0.323	-0.121*
	(0.0383)	(0.0653)	(0.214)	(0.0685)
High Default Risk x Post	-0.0105	-0.00236	-0.0282	-0.00736
	(0.0401)	(0.0500)	(0.0950)	(0.0586)
Observations	39468	45732	34896	45876
No. Districts	147	163	145	163
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.830	5.050	5.220	8.650
SD Dep Var	1.720	1.840	2.950	1.860
Adj R-Squared	0.911	0.820	0.895	0.878

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using legal and interest expenditures, long-run investment (maturity > 1 year), and sales revenue as dependent variables for high-default-risk firm interactions. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. High-judge-to-population ratio districts are those with the ratio above the sample average. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. Standard errors are clustered by district. The event study figures are in Figure 4.

Table 5: Bankruptcy Reform and District Judicial Capacity: Firms' Production Outcomes by MRPK

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
High Jdg Pop Ratio x High MRPK x Post	0.0284	0.0270	0.296***	-0.0204
	(0.0514)	(0.0580)	(0.0720)	(0.0461)
High MRPK x Post	-0.0348	-0.0488	-0.0191	-0.132***
	(0.0252)	(0.0467)	(0.0744)	(0.0485)
Observations	32376	37908	28740	38004
No. Districts	133	150	128	149
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.890	5.140	5.440	8.690
SD Dep Var	1.760	1.900	2.980	1.940
Adj R-Squared	0.910	0.816	0.894	0.881

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using legal and interest expenditures, long-run investment (maturity > 1 year), and sales revenue as dependent variables for high-MRPK firm interactions. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. High-judge-to-population ratio districts are those with the ratio above the sample average. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Standard errors are clustered by district. The event study figures are in Figure 5.

Table 6: Firm Default Risk and Court Trials

	(1) No. Filed Defendant	(2) No. Resolved Defendant	(3) No. Pending Defendant	(4) No. Filed Plaintiff	(5) No. Resolved Plaintiff	(6) No. Pending Plaintiff
High Jdg Pop Ratio x High Default Risk x Post	1.008	0.0107	2.855*	-0.104	0.219	-0.285
	(0.614)	(1.143)	(1.566)	(0.174)	(0.238)	(0.294)
High Jdg Pop Ratio x Post	-0.846	0.456	-2.551*	-0.202	0.0467	-0.587
	(0.551)	(0.816)	(1.514)	(0.350)	(0.529)	(0.622)
High Default Risk x Post	-0.334	-0.238	-0.356	0.0828	-0.237	0.248
	(0.250)	(0.351)	(0.401)	(0.137)	(0.226)	(0.227)
Observations	17037	17037	17037	47340	47340	47340
No. Districts	146	146	146	234	234	234
Firm Fixed Effect	X	X	X	X	X	X
District-Year FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Mean Dep Var	0.530	0.140	0.390	0.170	0.0200	0.160
SD Dep Var	3.560	1.860	2.540	3.760	0.340	3.540
Adj R-Squared	0.0560	0.0000128	0.120	0.0847	0.0786	0.131

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 2 using legal case-level outcomes in the corresponding district court as dependent variables for firms classified as high default risk in high-judge-population-ratio districts. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. Note that the judicial case-level data is only available until 2018, so there are fewer post reform time periods compared to the analysis using firm-level outcomes. High-judge-to-population ratio districts are those with the ratio above the sample average. High-default-risk firms are those receiving low credit rating (under 4 on a scale 1-8, which map to standard ratings by international rating agencies like S&P or Moody's) in the period prior to the bankruptcy reform. Col 1-3 present the estimates when such firms appear as defendants in a case, i.e., when someone else files a suit against them. Col 4-6 presents the estimates on case-level outcomes when these firms appear as plaintiff in a case, i.e, when such firms initiate lawsuits in courts. Error bars present 95% confidence interval. Standard errors are clustered by district. The event study estimates are reported in Figure 6.

Table 7: Firm MRPK and Court Trials

	(1) No. Filed Defendant	(2) No. Resolved Defendant	(3) No. Pending Defendant	(4) No. Filed Plaintiff	(5) No. Resolved Plaintiff	(6) No. Pending Plaintiff
High Jdg Pop Ratio x High MRPK x Post	-0.0496	-0.519	0.0687	-0.228	0.389	-0.506
	(0.279)	(0.545)	(0.764)	(0.188)	(0.303)	(0.315)
High Jdg Pop Ratio x Post	-1.051**	0.666	-2.851**	-0.282	-0.322	-0.642
	(0.519)	(0.885)	(1.425)	(0.367)	(0.537)	(0.600)
High MRPK x Post	-0.875	0.662	-2.518*	0.341	-0.214	0.625
	(0.575)	(0.744)	(1.280)	(0.302)	(0.273)	(0.558)
Observations	15291	15291	15291	31761	31761	31761
No. Districts	144	144	144	213	213	213
Firm Fixed Effect	X	X	X	X	X	X
District-Year FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Mean Dep Var	0.440	0.0900	0.350	0.230	0.0200	0.210
SD Dep Var	3.100	0.890	2.530	4.520	0.390	4.260
Adj R-Squared	0.0692	-0.00140	0.129	0.0688	0.0630	0.110

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 2 using legal case-level outcomes in the corresponding district court as dependent variables for firms classified as high-MRPK in high judge-population ratio districts. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. Note that the judicial case-level data is only available until 2018, so there are fewer post reform time periods compared to the analysis using firm-level outcomes. High-judge-to-population ratio districts are those with the ratio above the sample average. High-MRPK firms are those with estimated pre-reform MRPK above median of the firm-level sample. Col 1-3 present the estimates when such firms appear as defendants in a case, i.e., when someone else files a suit against them. Col 4-6 presents the estimates on case-level outcomes when high-MRPK firms appear as plaintiff in a case. That is, when such firms initiate the suit in courts. Error bars present 95% confidence interval. Standard errors are clustered by district. The event study estimates are reported in Figure 7.

Table 8: Banks and Court Trials

	(1) No. Filed Bank Defendant	(2) No. Resolved Bank Defendant	(3) No. Pending Bank Defendant	(4) No. Filed Bank Plaintiff	(5) No. Resolved Bank Plaintiff	(6) No. Pending Bank Plaintiff
High Jdg Pop Ratio x Post	-0.0382	-0.124***	0.0281	0.0907	0.135	-0.125
	(0.0253)	(0.0369)	(0.0447)	(0.102)	(0.222)	(0.0821)
Observations	26073	26073	26073	28008	28008	28008
No. Districts	104	104	104	104	104	104
Bank Fixed Effect	X	X	X	X	X	X
District Fixed Effect	X	X	X	X	X	X
Mean Dep Var	1.560	0.250	1.310	1.930	0.290	1.640
SD Dep Var	9.240	2.860	7.380	17.27	5.910	13.52
Adj R-Squared	0.264	0.248	0.256	0.0529	0.0749	0.109

Standard errors in parentheses

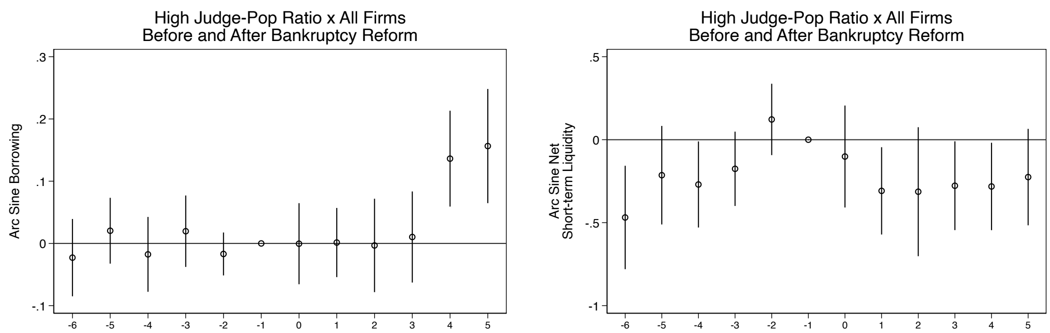
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 3 using legal case-level outcomes in the corresponding district court as dependent variables for cases involving banks. "Post" is defined as years after 2016, year after the bankruptcy bill becomes an act of the Indian Parliament. Note that the judicial case-level data is only available until 2018, so there are fewer post reform time periods compared to the analysis using firm-level outcomes. High-judge-to-population ratio districts are those with the ratio above the sample average. Col 1-3 present the estimates when banks appear as defendants in a case, i.e., when someone else files a suit against them, such as to prevent liquidation. Col 4-6 presents the estimates on case-level outcomes when banks appear as plaintiff in a case, for example, when they need to enforce a bankruptcy order. Error bars present 95% confidence interval. Standard errors are clustered by district.

Online Appendix

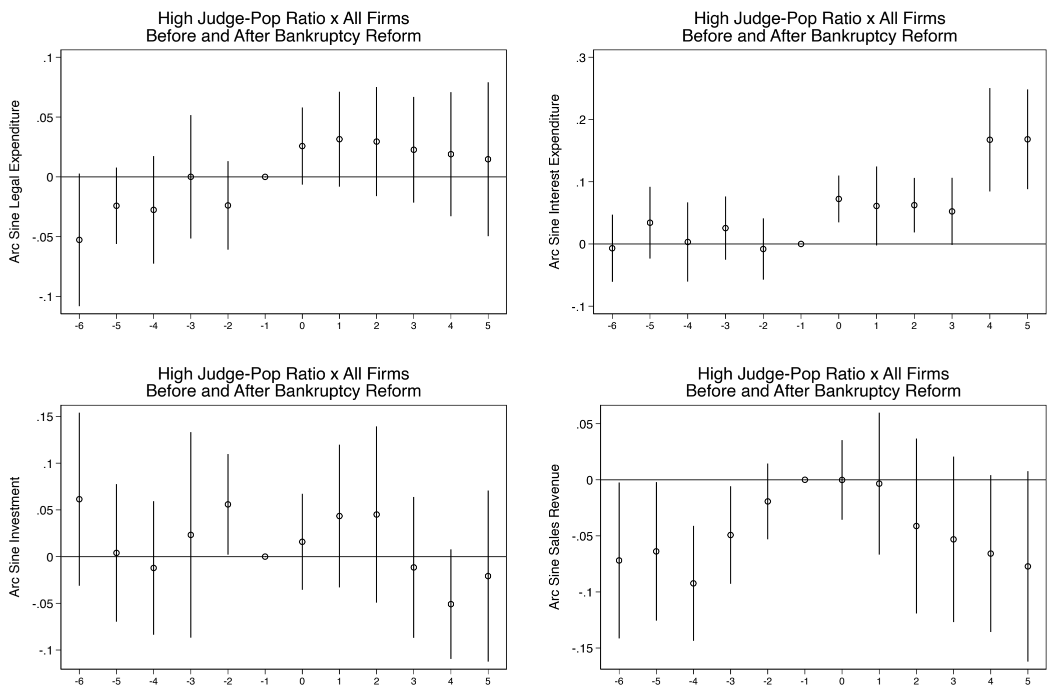
A.0.A. Additional figures and tables

Figure A.1: Borrowing/Liquidity effects of bankruptcy reform on all firms by district judicial capacity



Notes: The figures report the event study estimates of bankruptcy reform on all firms by comparing those registered in high-judicial-capacity districts, measured using baseline judge-to-population ratio, with those registered in low capacity districts using borrowing and short-run liquidity as outcome variables. The error bars denote 95% confidence intervals and standard errors are clustered by district. These specifications are used to test the trends in borrowing and liquidity outcomes of firms in the period before the reforms.

Figure A.2: Balance sheet effects of bankruptcy reform on all firms by district judicial capacity



Notes: The figures report the event study estimates of bankruptcy reform on all firms by comparing those registered in high-judicial-capacity districts, measured using baseline judge-to-population ratio, with those registered in low capacity districts using balance sheet outcome variables including legal and interest expenditures, long run investments and sales revenue. The error bars denote 95% confidence intervals and standard errors are clustered by district. These specifications are used to test the trends in outcomes of firms in the period before the reforms.

Table A.1: Bankruptcy Reform and District Judicial Capacity: All Firms

	(1) Arc Sine Borrowing	(2) Arc Sine Net Liquidity	(3) Arc Sine Legal Expenditure	(4) Arc Sine Interest Expenditure	(5) Arc Sine Investment	(6) Arc Sine Sales Revenue
High Jdg Pop Ratio x Post	0.0628*	-0.123	0.0381*	0.0851***	-0.0201	-0.00576
	(0.0330)	(0.106)	(0.0199)	(0.0228)	(0.0277)	(0.0215)
Observations	47220	47256	40488	46692	35784	46824
No. Districts	240	240	227	239	214	238
Firm FE	X	X	X	X	X	X
Industry-Year FE	X	X	X	X	X	X
Mean Dep Var	7.390	2.310	2.830	5.050	5.220	8.650
SD Dep Var	2.210	6.520	1.720	1.840	2.950	1.860
Adj R-Squared	0.832	0.635	0.911	0.820	0.896	0.879

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from DiD specification using time periods before and after the 2016 reform across high and low-judicial-capacity districts on borrowing and production outcomes of all firms in the sample districts. High-judge-to-population ratio districts are those with the ratio above the sample average. Standard errors are clustered by district.

Table A.2: Using Alternate Cut-off For High Judicial Capacity: Firm Borrowing and Liquidity

	(1) Arc Sine Borrowing	(2) Arc Sine Net Liquidity	(3) Arc Sine Borrowing	(4) Arc Sine Net Liquidity
Above Median Jdg-Pop x High Default Risk x Post	-0.190*	0.547		
	(0.108)	(0.387)		
High Default Risk x Post	0.0820	-0.413*		
	(0.0767)	(0.240)		
Above Median Jdg-Pop x High MRPK X Post			0.00872	0.549*
			(0.0630)	(0.321)
High MRPK x Post			0.00198	-0.555*
			(0.0620)	(0.313)
Observations	46272	46308	38376	38400
No. Districts	164	164	150	150
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	7.390	2.310	7.480	2.030
SD Dep Var	2.210	6.520	2.290	6.710
Adj R-Squared	0.829	0.632	0.825	0.623

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use median as the cut-off instead of average. Standard errors are clustered by district.

Table A.3: Using Alternate Cut-off For High Judicial Capacity: Production Outcomes of High Risk Firms

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
Above Median Jdg-Pop x High Default Risk x Post	-0.0674	-0.170*	-0.276	-0.0367
	(0.0544)	(0.0880)	(0.175)	(0.0921)
High Default Risk x Post	-0.0245	-0.00138	-0.00229	-0.0286
	(0.0485)	(0.0606)	(0.117)	(0.0589)
Observations	39468	45732	34896	45876
No. Districts	147	163	145	163
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.830	5.050	5.220	8.650
SD Dep Var	1.720	1.840	2.950	1.860
Adj R-Squared	0.911	0.820	0.895	0.878

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use median as the cut-off instead of average. Standard errors are clustered by district.

Table A.4: Using Alternate Cut-off For High Judicial Capacity: Production Outcomes of High MRPK Firms

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
Above Median Jdg-Pop x High MRPK X Post	-0.0166	0.0384	0.244**	0.0616
	(0.0489)	(0.0616)	(0.123)	(0.0559)
High MRPK x Post	-0.0158	-0.0584	-0.0392	-0.170***
	(0.0274)	(0.0546)	(0.102)	(0.0503)
Observations	32376	37908	28740	38004
No. Districts	133	150	128	149
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.890	5.140	5.440	8.690
SD Dep Var	1.760	1.900	2.980	1.940
Adj R-Squared	0.910	0.816	0.894	0.881

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use median as the cut-off instead of average. Standard errors are clustered by district.

Table A.5: Using Pre-Reform Judge Vacancy: Firm Borrowing and Liquidity

	(1) Arc Sine Borrowing	(2) Arc Sine Net Liquidity	(3) Arc Sine Borrowing	(4) Arc Sine Net Liquidity
Below Median Vacancy x High Default Risk x Post	-0.139	0.462		
	(0.119)	(0.319)		
High Default Risk x Post	0.0703	-0.411*		
	(0.0763)	(0.234)		
Below Median Vacancy x High MRPK X Post			-0.0136	0.159
			(0.0599)	(0.315)
High MRPK x Post			0.0141	-0.357
			(0.0568)	(0.232)
Observations	46080	46116	38184	38208
No. Districts	162	162	148	148
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	7.390	2.310	7.480	2.030
SD Dep Var	2.210	6.520	2.290	6.710
Adj R-Squared	0.829	0.632	0.825	0.623

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use below median pre-reform judge vacancy rate as the cut-off instead of judge-to-population ratio. Standard errors are clustered by district.

Table A.6: Using Pre-Reform Judge Vacancy: Production Outcomes of High Risk Firms

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
Below Median Vacancy x High Default Risk x Post	-0.0313	-0.0392	-0.132	0.0466
	(0.0609)	(0.106)	(0.165)	(0.0921)
High Default Risk x Post	-0.0413	-0.0594	-0.0590	-0.0706
	(0.0492)	(0.0656)	(0.169)	(0.0597)
Observations	39312	45540	34740	45684
No. Districts	145	161	143	161
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.830	5.050	5.220	8.650
SD Dep Var	1.720	1.840	2.950	1.860
Adj R-Squared	0.911	0.820	0.895	0.878

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use below median pre-reform judge vacancy rate as the cut-off instead of judge-to-population ratio. Standard errors are clustered by district.

Table A.7: Using Pre-Reform Judge Vacancy: Production Outcomes of High MRPK Firms

	(1) Arc Sine Legal Exp	(2) Arc Sine Interest Exp	(3) Arc Sine Investment	(4) Arc Sine Sales Revenue
Below Median Vacancy x High MRPK X Post	-0.0187	0.0650	-0.0449	0.0967*
	(0.0549)	(0.0609)	(0.148)	(0.0534)
High MRPK x Post	-0.0140	-0.0695	0.108	-0.189***
	(0.0384)	(0.0500)	(0.0968)	(0.0472)
Observations	32220	37716	28584	37812
No. Districts	131	148	126	147
Firm FE	X	X	X	X
District-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Mean Dep Var	2.890	5.140	5.440	8.690
SD Dep Var	1.760	1.900	2.980	1.940
Adj R-Squared	0.910	0.816	0.894	0.881

Standard errors in parentheses

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Notes: The table above present the estimates from Equation 1 using a different definition of high judicial capacity. Specifically, I use below median pre-reform judge vacancy rate as the cut-off instead of judge-to-population ratio. Standard errors are clustered by district.