

COURTS REDUX: MICRO-EVIDENCE FROM INDIA

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How does the ability of trial courts in resolving disputes on time affect local credit market and firm behavior? I provide an answer to this question using data generated from 6 million trial records across 195 district courts in India, merged with local-level bank lending and firms' balance sheets. I exploit quasi-random variation in within-court judge vacancies to causally examine how courts' rate of trial resolution influences market and firm behavior. I find that reducing judge vacancy improves the rate of trial resolution, credit circulation, and increases local firms' wage bill and value of production. Reducing vacancy by hiring more judges would generate orders of magnitude larger benefit relative to its cost. (*JEL* O16, O43, K41, G21)

I. INTRODUCTION

Courts play a central role in enforcing contracts and property rights, which supports the development of the formal financial sector, investment, and economic growth (La Porta et al. 1998; Djankov et al. 2003). Long lags in trial resolution can increase uncertainty and transaction costs that prevent effective contracting and weaken *de facto* rights (Johnson et al. 2002). While this is well supported in theory (North 1986; Glaeser et al. 2001), there is little micro-empirical evidence on the day-to-day functioning of courts anywhere, let alone in the context of a developing economy.

District courts in India had over 11 million cases pending for more than 3 years as of 2019, implying a 10 times more backlog per capita relative to similar courts in the United

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States. In addition to the effect of such delays on the overall trust in market transactions (Nunn 2007), this also constrains factors of production stuck under litigation from being put to productive use. This situation is not only exclusive to India and other similar developing economies but also common among the judiciary in many OECD countries (Dimitrova-Grajzl et al. 2012; Coviello et al. 2014). Given the paucity of well identified causal evidence on the functioning of ordinary trial courts and its consequences on market and economic outcomes, there is a need for empirical research using economic microfoundations and disaggregated data.

In this paper, I seek to estimate the benefits from improving local judicial capacity on market and economic outcomes in the context of district courts in India. I measure judicial capacity as the annual rate of trial resolution or disposal rate, defined as the percentage of total court-level caseload that is resolved in a given year. However, judicial capacity could be endogenous to the outcomes of interest both due to unobserved factors as well as potential reverse causality. To address causal identification, I exploit quasi-random variation in district judge vacancy to examine two sets of real economic outcomes. First, I estimate the effect on the local credit market including district-level loan repayment and bank lending. Second, I examine the consequences on formal sector firms, incorporated within the court’s jurisdiction, including their long term borrowing, wage bill, and value of production.¹

Quasi-random variation in district judge vacancy arises due to two key institutional features of the Indian judiciary. First, there is an existing undersupply of judges or structural vacancies. Second, judges have short tenure and are frequently rotated to a different district court within the state, avoiding the judge’s home district as well as their past court assignments.² This shocks the number of judges available for adjudication or judge occupancy rate ($100 - \%vacancy$) within a court over time. To illustrate, consider a court with 10 total judge positions, of which 2 are vacant in year 1. The rotations occur every year in a specific month, typically the start of the financial year. Suppose in year 2, two judges completing their tenure are transferred out and one judge is transferred in from another district. This changes judge occupancy from 80% in year 1 to 70% in year 2. This process continues year on year, such that the level of judge occupancy within the court in any given year is as good as random.

Such a variation in these vacancies enable me to exploit two different empirical strategies

¹Ordinary trial courts are also known as district courts in India with jurisdiction over the corresponding administrative district. These are similar to the county seats of state and federal trial courts in the United States. They are the first interface of the judicial system to resolve disputes through civil and criminal litigation. Therefore, these courts have the highest level of trial workload, many of which are resolved without going through appeals at higher courts. Districts in India also correspond to local economies and is the smallest geographic aggregation for studying policy implications.

²Each state high court is responsible for judge assignments, and administer the rotations every year.

including an instrumental variables (IV) strategy - using judge occupancy as an instrument for disposal rate, as well as an event-study design to demonstrate causality. I implement this by generating a novel dataset on court, credit market, and firm level variables for a sample of 195 industrial districts by assembling the universe of six million trial-level microdata from the corresponding courts between 2010 and 2018. The event study shows no evidence of pre-trends or strategic manipulation of judge vacancies in relation to the rate of trial resolution, bank lending and repayment, and firm-level outcomes. Further, the IV strategy generates similar estimates as the event study where both first and second stage results are economically meaningful and have relevant policy implications.

There are four key results. First, I find a significant first stage that shows that a 1 percentage point decrease in judge vacancy (conversely 1 percentage point increase in occupancy) increases overall disposal rate as well as the disposal rate of debt related trials between 0.98 and 0.8 percent, respectively. In other words, adding one more judge - which translates to 7.2 percentage points reduction in vacancy on average - generates about 200 more resolved trials per court per year. This is a large effect given the baseline annual disposal rate is only 14 percent of an average trial load of 20000 new and pending cases per court per year.³

Second, the results imply 0.24 and 0.35 disposal rate elasticities of district-level loan repayment from the manufacturing sector and total repayment to public sector banks, respectively. In terms of vacancy, an additional judge increases repayment by 1.4 and 2 percent, respectively. Lending to the manufacturing sector initially decreases but quickly recovers and expands in subsequent periods. Given the magnitude of average district-level outstanding loans at USD 9 billion, these repayment rates imply millions of dollars for recirculation as fresh credit. Focusing on local credit market seems concordant with the fact that banks are heavy users of district courts relative to any other type of firms as seen in the microdata. Specifically, close to 50 percent of all banks in the sample are present as litigants in the sample courts, with 80 percent of trials initiated by them relating to debt-recovery. In contrast, only 13 percent of non-financial firms are found as litigants. Further, the number of trials per firm is twice as large among the financial sector relative to other sectors.

Third, given the overall credit market effect, I find a corresponding increase in local firms' repayment of outstanding loans, measured as change in year-on-year amount borrowed from banks. Since these are large firms that borrow heavily from banks, an increase in repayment

³Resolved trials also include trials that are dismissed without a final judgement order. Disposal rate is a relevant metric of judicial capacity, especially from the point of view of tied-up capital in pending debt recovery trials, where the volume of repayment reflects the fraction of trials that are resolved in a given year. I also show that judge vacancy increases the median duration of debt related trial. Further, I show that disposal rate is highly correlated with different measures of court output including trial duration, and therefore can be considered as a sufficient statistic for judicial capacity.

from such firms brings back more credit into subsequent circulation. Isolating the channel of credit access from other potential channels, I find suggestive evidence supporting the idea that firms use long term borrowing from banks to finance their investment in plants and machinery. So, the observed drop in total borrowing from banks likely reflects liquidation of unproductive capital seen in the form of declining value of plants and machinery. However, at the same time, I observe an increase in unsecured borrowing (without any collateral) by these firms on average, typically used to finance operational expenditure.

Fourth, I find a positive effect of improved disposal rate on wage bill, sales revenue, and profit on average. The disposal rate elasticities are 0.265, 0.18, and 0.655, respectively. Putting it differently, an additional judge increases wage bill, sales, and profit by 2.66, 1.85, and 6.9 percent respectively. Given the effects on access and cost of credit, I further explore whether this reflects an efficiency gain by examining heterogeneous effects based on firms' ex-ante asset size as well as their ex-ante credit rating. The drop in the value of plants and machinery are mainly driven by larger firms and firms with worse credit rating. These findings are consistent with a simple lending and litigation model where the lender takes into account enforcement quality and borrower characteristics in their lending decisions. The credit response both at the market and firm-level suggests that courts also alter the incentives for subsequent lending, where banks circulate freed up capital towards more productive uses.⁴

Finally, a back-of-the-envelope calculation of the benefit-cost ratio of reducing judge vacancy shows that the benefits are orders of magnitude larger than the cost. Using the inter-quartile range of profit and wage bill, and assuming constant elasticity, an additional judge increases a firm's profit between USD 0.68 and 3.56 million and wage bill between USD 0.17 and 4.22 million. Given the average income tax incidence on salaried individual at 7.3 percent and corporate tax rate of 15 percent, the state can earn between 3 and 20 times more revenue than the expenditure incurred from hiring a judge.⁵

This paper contributes to three strands of the academic literature. First, this presents a well-identified causal evidence of the effect of judicial capacity improvements on local formal sector production. These estimates are likely a lower bound since I examine ordinary trial courts that are just one, albeit an important component of the formal judicial institu-

⁴Over 80 percent of all commercial banks are public sector banks, particularly in non-metropolitan India, which have also been facing mounting bad loans (NPA) since 2011. These banks are under pressure from political leadership for waiving agricultural loans coinciding with electoral cycles, leaving them with fewer levers for efficient credit allocation policy. The loan officers have greater discretion on any additional capital that they are able to recover, which is typically outside the credit limits set top-down by higher-level administrative committees of these banks.

⁵The calculation presented is an approximation to illustrate the magnitude of effects. The true benefit-cost ratio would take into account the distribution of firms and the heterogeneity of elasticities across this distribution.

tions. Complementary investments in fast-track and specialized courts for debt recovery and bankruptcy resolution will likely have a compounded effect by enabling firm creation and exit, and by increasing access to formal contract enforcement institutions to the informal sector. In this regard, this paper builds on the works by [Djankov et al. 2003](#); [Chemin 2009a,b](#); [Visaria 2009](#); [Chemin 2012](#); [Ponticelli and Alencar 2016](#); [Amirapu 2017](#); [Kondylis and Stein 2018](#); [Boehm and Oberfield 2018](#). The literature hitherto has taken an aggregate view of this relationship using one-time cross-sectional differences in judicial capacity, challenged by a lack of microdata. Further, to my knowledge, these do not shed light on factors affecting judicial capacity other than the role of legal origins and procedural laws. The richness of my dataset and the plausibly exogenous variation in annual judge vacancies enable me to overcome these limitations to credibly show that the daily functioning of trial courts matter for the economy.

Second, this paper emphasizes that judge vacancy is an important state capacity constraint that exacerbates the rates of trial resolution in district courts. This is consistent with the discussion in [Kapur \(2020\)](#) that India has low levels of investment in local state personnel. This builds on a growing literature on state capacity ([Muralidharan et al. 2016](#); [Dhaliwal and Hanna 2017](#); [Finan et al. 2017](#)) by examining the much under-studied sub-national judiciary among state institutions ([Dal Bo and Finan 2016](#)). I show that reducing vacancies generates a large benefit-cost ratio.⁶ This complements [Yang 2016](#), who shows that judge vacancy increases trial dismissals by prosecutors in the US criminal justice system, reducing the extent of incarceration with mixed social welfare implications ([Dobbie et al. 2018](#); [Bhuller et al. 2019](#); [Norris et al. 2020](#)).

Finally, this paper contributes to understanding the role of courts in facilitating credit markets, given a large literature documenting the importance of external, institutional finance for economic growth ([La Porta et al. 1998](#); [Acemoglu and Johnson 2005](#); [von Liliensfeld-Toal et al. 2012](#); [Vig 2013](#); [Ponticelli and Alencar 2016](#)). This is particularly salient in the context of developing economies where firms and individuals are typically credit constrained ([Rajan and Zingales 1998](#); [Burgess and Pande 2005](#); [Banerjee and Duflo 2014](#)). This paper also highlights the role of tied-up capital in a context where credit supply is limited relative to its demand. Capital released from litigations potentially enables local bank branches to reallocate credit better.

The rest of the paper is organized as follows. In section I, I provide the context and describe the data. Section II lays out a theoretical framework linking judicial capacity with

⁶The number of sanctioned judgeships in India, which already has approval for incurring the associated public expenditure, is 19 judges per million in contrast to over 100 judges per million in advanced economies. The vacancies I study suggest that the trial courts don't even meet approved judge strength.

firm outcomes through the credit market channel. In section III, I detail the identification strategy and discuss the assumptions to establish causal inference. Section IV discusses the results, concluding in Section V.

II. CONTEXT, MEASUREMENT, AND MATCHING OUTCOMES

India has consistently ranked low in the World Bank’s Doing Business ranking on contract enforcement (ranked 163 in 2018). [Figure A.1](#) compares India with the rest of the world with respect to reported trial duration, and depicts a negative association between log GDP per capita and log trial duration in a simple cross-country regression. In this paper, I use microdata on trials from district courts in India to illuminate how day-to-day functioning of trial courts affect key aspects of local economic development.

The judiciary in India is a three tier unitary system, with one Supreme Court for the country followed by High Courts at the state level, and finally the district or trial courts at the level of an administrative district that are the first interface of the judicial system. In this paper, I examine the functioning of the District and Sessions Court (hereinafter called district court), which is typically the court of first instance for disputes involving firms. There is one district court per district, which is also the court of appeal over other minor courts, including magistrate’s courts, small cause courts, etc., within its jurisdiction.⁷

II.A. Court variables

I web scraped the universe of 6 million publicly available trial records active between 2010 and 2018 from a sample of 195 district courts from the judiciary’s E-Courts website. These districts were selected to ensure an overlap with registered formal sector firms in predominantly non-metropolitan industrial districts and is representative of other similar districts in India. Each record details the trial meta data as well as lists hearing dates with the corresponding trial stage.⁸

Constructing annual court variables: From individual trial records, I construct court-level annual workflow panel data. I define the key explanatory variable, the rate of

⁷The High Courts and the Supreme Court of India serve mostly appellate functions whereas their original jurisdiction pertains to constitutional matters or conflicts involving the organs of state. The district courts system is the main institution responsible for administering justice and enforcing rule of law for day-to-day economic and social matters and therefore, forms the population of interest for this paper.

⁸E-courts is a public facing e-governance program covering the Indian judiciary. While the setting up of infrastructure for the computerization of case records started in 2007, the public-facing website - www.ecourts.gov.in and <https://njdg.ecourts.gov.in> - went live in late 2014. The fields include date of filing, registration, first hearing, decision date if disposed, nature of disposal, time between hearings, time taken for transition between case stages, litigant characteristics, case issue, among other details.

trial resolution or the disposal rate, as the ratio between trials resolved and total workload in a given year calculated as a percentage. The denominator is the sum of cases that are newly filed and those that are pending for decision as of a given calendar year. This measure is highly correlated with the ratio of resolved trials to newly filed trials (coefficient of 0.92), and therefore, also accommodates demand for litigation. The data also enables me to calculate the percentage of cases that are appeals from junior courts as well as the rate of dismissal of trials. These are also significantly correlated with disposal rate but have an ambiguous interpretation as a measure of court performance.⁹ For robustness, I construct an index as the first principal component across all these measures using Principal Component Analysis.

Constructing judge occupancy: The trial data also records the courtroom number and the judge post to whom the case has been assigned to. Since the data represents the universe of trials between 2010 and 2018, I am able to identify whether a specific judge post is vacant depending upon the annual workflow observed for that post. To illustrate, the courtrooms in a district court are numbered 1, 2, 3,... and the judge posts are labeled Principal District Judge (PDJ), Additional District Judge (ADJ) 1, ADJ 2, etc. Any workflow in a given calendar year corresponding to a specific courtroom and judge post is recorded as a trial resolution, outcome of a hearing, interim orders, or filing of a new trial. Therefore, I encode the specific judge post as present if I observe non-zero workflow in a given year and as vacant, otherwise. Aggregating this at the level of the court relative to maximum number of judges observed over the study period presents the rate of occupancy measured in percentage terms. The calculated vacancies compare with the numbers mentioned in the Law Commission reports as well as media reports, and therefore provide a source of measuring annual judge vacancy in the absence of a centralized source of judicial personnel records.¹⁰

⁹For example, these may indicate quality or “fairness” of the district courts but it is hard to be certain. For example, appeals are not only made if the objective quality of a judgements in district courts were higher but could also be made for strategic reasons such as not having to pay damages. Therefore, I use disposal rate as my preferred measure of court performance in all the specifications. Correlations between these measures are presented in [Table A.1](#).

¹⁰The district judges are assigned to a specific district court where they serve a tenure of 1-2 years. Once a judge is assigned to a court, she is assigned a courtroom and given a docket of cases for hearing by the administrative judge of the court. An ideal measurement of vacancy would be constructed through judge attendance rosters from the courts. Unfortunately, such a database does not exist centrally and it wasn’t possible for me to contact each of the 195 courts to obtain their attendance rosters. My approach of constructing vacancy is a good approximate of the actual vacancy as verified through media reported aggregate numbers. Moreover, even if some judges sit on dockets with more slow-moving cases relative to others in the same court, they need to show non-zero workflow for their annual performance appraisal. Since I construct annual judge occupancy as the percentage of all judge posts that are not vacant each year aggregated across the entire district court rather than measuring each judge’s actual workflow, this is likely a reliable measure.

II.B. Outcome variables

Credit market outcomes: I measure local credit market outcomes using annual district-level summary of banking statistics provided by the Reserve Bank of India (RBI) that includes total number of loans, and total outstanding loan amount, disaggregated by sector.

Firm-level outcomes: I use CMIE-Prowess dataset covering 49202 firms to measure annual firm-level outcomes. The data are collated from annual reports, stock exchange reports, and regulator reports covering the universe of all listed companies (≈ 5000 listed on Bombay and National Stock Exchanges) as well as through sample-surveys of unlisted public and private companies representing formal, registered firms. The data represents “over 60 percent of the economic activity in the organized sector in India, which although a small subset of all industrial activity, accounts for about 75 percent of corporate taxes and 95 percent of excise duty collected by the Government of India” (Goldberg et al. 2010). Since the organized sector accounts for $\approx 40\%$ of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), this dataset captures a large share of value addition in the economy. Firm specific outcomes include annual financials and borrowing variables. Additionally, detailed identifying information including firm name and registered office location enables me to match them with court-level and trial datasets, respectively.

Sample construction: Of the 49202 firms, 13298 firms are registered within the jurisdiction of 161 of the 195 sample district courts.¹¹ Remaining 34 district courts result in no match. Finally, 4739 firms were incorporated before 2010 - the start of the study period, and have at least 2 years of annual financial reporting between 2010 and 2018, that form the sample for my analysis. Additionally, I classify these firms as small or large firms based on their average asset size in the period prior to 2010. Specifically, I classify those below the median value of pre-2010 assets as small firms and those above median as large firms. Further, I also examine the credit history of these firms to classify them as those with high credit rating (therefore considered as safe firms for lending) and those with low credit rating based on their average ratings prior to 2010.

Next, I fuzzy-merge the sample of firms in Prowess with the trial dataset using firm names and manually verify the resulting matches. Overall, 6417 of 49202 firms (13 percent) have ongoing litigation in the sample courts, of which 4047 firms have litigation that were filed within the study period (i.e. 2010-2018). Appendix Figure A.2 describes the firm sample

¹¹Matching firms by their registered office location presents the relevant legal jurisdiction for the firm, as also followed in von Lilienfeld-Toal et al. (2012). Registered office location is also the corporate headquarters in many instances, and is the relevant jurisdiction where potential litigations, when the firm is on the offense, are filed. The relevant court for a given dispute type is determined by the Code of Civil Procedure, 1908.

construction process in detail.¹²

II.C. Summary statistics

Panel A of [Table I](#) presents summary statistics for the court variables. On average, there are 18 judge posts per district court, with an occupancy of 77 percent over the sample period. Average disposal rate is 14 percent with a standard deviation of 12, meaning that it would take nearly seven years to clear all backlog if there were no new litigation. Using the timestamps on individual trials that were resolved within the study period, resolution takes 420 days on average, with a standard deviation of 570 days. The key difference between the disposal rate measure and the average duration of trial is that the former includes the universe of all trials within the study period whereas the latter only includes duration for trials that were resolved within this period. Therefore, disposal rate measure avoids concerns pertaining to the selection of trials in its construction process.

Panels B and C describe credit market and local firm-level outcomes. Banks make about 300,000 loans every year and have about USD 9.4 billion worth outstanding loans per district. The summary on annual firm-level financials indicate that these are large firms, with USD 4.7 billion in sales revenue, 0.1 billion in accounting profits, with about 2000 employees on average on their rolls. They also routinely borrow from banks with average loan size of USD 1.5 billion across all banks. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

II.D. A descriptive analysis of litigation behavior

While the sample constructed with firms matched by their registered office location to the corresponding court provides the main sample to analyze local firm behavior, the sample constructed by matching firms to the trial records provides the set of litigating firms irrespective of their location of registered office. Litigating firms are older relative to other firms, more likely to be a public limited company, more likely to be government owned (stated owned enterprise), business group owned, or foreign owned. Among financial institutions, banks are litigation intensive. Note that the court where a firm can litigate depends on the nature of the trial as detailed in the Code of Civil/Criminal Procedure. For example, in the context of debt-recovery, banks have to file their litigation as a plaintiff in the court corresponding

¹²Note that the firms can be engaged in litigation in any district other than their registered office location. Specifically, banking firms have ongoing trials in the court corresponding to the jurisdiction of the borrower. For matching, therefore, I employ a nested approach following heuristics as listed in the appendix. I only retain one-to-one match between a firm and a trial.

to the borrower’s location. Therefore, this sample provides information on the litigation intensity of specific sectors per district.

Panels in [Figure I](#) show that banks litigate intensively with close to 50 percent of all banks in the firm sample matched with the trial microdata. They mainly engage as plaintiffs, i.e. initiator of the litigation, as observed in over 80 percent of the litigation. Further, the average number of litigation per firm among financial sector firms including banks is more than twice the average number of litigation per non-financial sector firm. Litigation involving banks pertain to debt recovery, violation of monetary instrument contract (e.g. bounced checks), and importantly execution petitions that bring into effect past verdicts. Parsing judgements from a random subsample of litigations involving banks indicates that about two-thirds pertain to credit default and about a fifth pertain to inheritance/property related disputes. Over 83% of the credit related disputes have outcomes in favor of the bank. This occurs either by undergoing full trial and obtaining a judgement in their favor or by reaching a settlement with the defaulting borrower, leading to its dismissal. Moreover, the industry structure of banks is based on credit contracts, which automatically make them contract intensive compared to non-financial firms. Given these, examining the effects of improved judicial capacity on local credit markets and subsequently, how this translates into local firms’ production decisions forms the main idea of this paper.

III. CONCEPTUAL FRAMEWORK

Credit behavior: The summary of litigation behavior by banks helps motivate a simple model of their lending decisions where repayment can be enforced through the possibility of litigation. Borrowers need external credit to finance investment in new and existing projects, that have some stochastic probability of success. The bank considers borrower wealth, that follows a given ex-ante distribution, to decide whether to lend or not. Further, bank will lend only if their expected return from lending is greater than the market return. Upon completion of the contract period, the borrower either repays or evades, which is costly. Evasion leads to default, which initiates debt recovery process and subsequently, litigation. This recovery process incurs a cost to both lender and borrower, as a decreasing function of court’s trial resolution rate. That is, better disposal rate implies lower litigation related costs, ceteris paribus. Some borrowers may choose to litigate if their payoff is higher under litigation. Other borrowers may choose to settle with the lender and avoid continuing the litigation process. A sub-game perfect Nash equilibrium (SPNE) through backward induction provides a minimum borrower wealth threshold below which the lender does not lend. Since the ensuing equilibrium is determined by stochastic shocks faced by the borrower in their

production process as well as the extent of debt contract enforcement by the district courts, this wealth threshold is a decreasing functioning of the court’s disposal rate. Further, the interest charged by lenders also decreases for every level of borrowing with an increase in disposal rate. The framework is discussed in detail in Appendix Section A2.

Production behavior: As banks begin to lend to newer firms and lower overall interest rates, firms re-optimize their production decisions. In addition to better access to credit, improved courts could also directly benefit their production processes through lower transaction costs, for example, with input vendors or through lower hold-up in labor disputes. I assume these transaction costs to also vary by the firm’s ex-ante asset size, where larger firms might incur additional monitoring and enforcement costs on their own. While the effect on borrowing is hypothesized to vary by firm size, the average effect on input use, production and profit is expected to increase.

Empirical tests Specifically, following the framework, I test for the following hypotheses in relation to an improvement in judicial capacity:

- H1: Wealthier borrowers (firms) are more likely to accept litigation as respondents.
- H2: Due to increased repayment from better debt contract enforcement, wealth threshold for lending decreases and interest rates weakly decrease for all levels of borrowing.
- H3: Firm sales and input use increase with judicial capacity through their ability to borrow. Conversely, a reduction in available borrowing would lower input use.
- H4: Firm profits increase with judicial capacity, particularly for larger firms. The effect is heterogenous based on the trade-off between increased input costs and benefits from reduction in other transaction and monitoring costs.

IV. ESTIMATION AND IDENTIFICATION STRATEGY

The main relationship of interest to examine is between court-level disposal rate and real economic outcomes, including credit market and firm behavior, given in equation (1) below.

$$(1) \quad Y_{f dt+k} = \phi_d + \phi_{st} + \theta D_{dt} + \mathbf{X}_f' \Delta + \epsilon_{f dt+k} ; k \geq 0$$

$Y_{f dt+k}$ is the firm f ’s outcome of interest in years $t + k$, accounting for current and lagged effects. D_{dt} is disposal rate of the corresponding court d in year t . \mathbf{X}_f is a vector of firm specific controls including firm age, age-squared, and sectoral dummies. ϕ_{st} , ϕ_d correspond to state-year and district fixed effects, and $\epsilon_{f dt+k}$ is the idiosyncratic error term.

For district-level analyses of credit markets, I estimate a similar specification using whether a court in a given year had bank specific litigation in its workload as weights. The dependent variables are district-level total number of loans and total outstanding loan aggregated across all banks:

$$Y_{dt+k}^m = \phi_d^m + \phi_{st}^m + \theta^m D_{dt} + \epsilon_{dt+k}^m ; k \geq 0$$

However, D_{dt} is likely endogenous if courts process litigation faster in better districts or could be slower if fast-growing districts increase litigation workload. That is, there are likely omitted variable bias (for example, court-specific unobserved technology or litigation management skills) as well as potential reverse causality. Therefore, I instrument D_{dt} with judge occupancy rate, $Occup_{dt}$, which is the percentage of judge positions that are occupied (and correspondingly, not vacant) using 2SLS estimation strategy. The first stage estimating equation is given in (2). I cluster standard errors by district-year, which is the level of treatment variation (Bertrand et al. 2004; Cameron and Miller 2015). As a robustness check, I also cluster by state-year and district to check for any spatial correlation across districts resulting from judge rotation and serial correlation within a district, respectively.

$$(2) \quad D_{dt} = \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X}'_f \Pi + \nu_{f dt+k} ; k \geq 0$$

$$(3) \quad Y_{f dt+k} = \phi_d + \phi_{st} + \theta \hat{D}_{dt} + \mathbf{X}'_f \Delta + \epsilon_{f dt+k} ; k \geq 0$$

Judge occupancy varies quasi-randomly within a district court over time. This mainly arises from a policy of judge assignment and existing structural vacancy within the judiciary. District judges are recruited by the respective state high courts and only serve within the state. They serve a short tenure between 1-2 years in each seat and are subsequently transferred to a different district with no prior association (“non-repeat” constraint). Given the problem of structural vacancy of judges in district courts across India, which is nearly 25 percent of all current positions as frequently reported in the [media](#), this system of frequent rotation shifts the vacancies exogenously within a given court. The independence of the judiciary in addressing vacancy is further curtailed by their lack of fiduciary power. Funding allocation for the running of all courts within the state, including judge salaries, is determined by the executive branch. This relative separation of powers further limits potential strategic manipulation of vacancy rates by either arms of the state. The assignment process is detailed in [Section A.II](#).

This feature serves two purposes: First, the reduced form effects of a reduction in judge vacancy is itself important for policy. Second, the exogenous variation observed in judge occupancy conditional on district and state-year fixed effects makes the variable a good

instrument for court-level disposal rate.

IV assumptions: To express the causal effects in potential outcomes framework, let $Y_i(D, Z)$ be the potential outcome for unit i , given continuous valued endogenous explanatory variable - disposal rate - D_i and Z_i , continuous valued judge occupancy rate instrument. For this approach to yield a causal estimate, the following assumptions need to be satisfied:

First stage and monotonicity: Panels A and B [Figure II](#) and [Table II](#) show that the relationship between judge occupancy and disposal rate is strong and log-linear. A one percentage point increase in judge occupancy increases disposal rate by 1 percent. In other words, one additional judge increases disposal rate by 1 percentage point or resolves 200 more trials given a baseline disposal rate of 14 percentage points and an average trial load of 20000 trials per court.

To enable interpretation of the IV estimate as some form of weighted local average treatment effect (LATE) ([Angrist and Imbens 1995](#)), the instrument needs to satisfy an additional assumption of monotonicity. Monotonicity assumption requires that the first stage potential outcomes $D_i(Z_i)$ are always increasing or decreasing in Z_i . The estimate is positive and of similar order of magnitude in different sub-samples of district courts by their size and underlying district population terciles ([Table III](#)). Binned regression by deciles of judge occupancy as well as by different case-types further support this assumption ([Figure A.4](#)).

Independence/Event-Study: I argue that the variation induced in the occupancy rate within a district due to a combination of the judge rotation system and existing vacancies is likely orthogonal to court workflow, credit, and local firms' potential outcomes. I provide empirical evidence on pre-trends using an Event-Study approach (implemented as a distributed lag model), which also presents important reduced form effects of judge vacancy not only on local judicial capacity but also on key local economic outcomes.

$$(4) \quad D_{dt} = \gamma_d + \gamma_{st} + \sum_{s=-3}^{s=3} \psi_s \text{Occup}_{dt+s} + \nu_{dt}$$

$$(5) \quad \Delta \text{Pop}_d = \nu_s + \rho \Delta \text{Occup}_d + \eta_d$$

$$(6) \quad \Delta D_{dt} = \gamma'_d + \gamma'_{st} + \sum_{s=-3}^{s=3} \psi'_s \Delta \text{Occup}_{dt+s} + \nu'_{dt}$$

$$(7) \quad Y_{f dt} = \kappa_d + \kappa_{st} + \sum_{s=-3}^{s=3} \Omega_s \text{Occup}_{dt+s} + \mathbf{X}'_f \Gamma + \epsilon_{f dt}$$

[Equation 4](#) presents the event-study specification with court-level disposal rate as the dependent variable and variation in judge occupancy in year t as the event. [Equation 5](#) tests for correlation between judge occupancy and change in population between preceding two

census rounds before the study period for a given district. If population changes were to affect judge occupancy rates - for example, if occupancy rates were higher in faster growing districts - then the coefficient on judge occupancy, ρ , would be non-zero. Equation 6 presents the event-study specification with changes in court-level disposal rate as the dependent variable to examine whether dynamic concerns about court performance affects judge occupancy. Equation 7 presents the event-study specification with firm-level outcomes as the dependent variable. The “event” in these specifications is a continuous valued variable and therefore includes a distributed lag model in-lieu of event-time dummies as in a standard event-study model (Schmidheiny and Siegloch 2020). The test for independence would look for absence of any significant pre-period correlations between the dependent variable and judge occupancy (examining “pre-trends”), i.e. testing whether $\psi_s = 0$, $\psi'_s = 0$, and $\Omega_s = 0$ for $s < 0$ in the specifications above.

“Balance” tests: Patterns in data reveal that each year, judge occupancy increases for a fraction of the districts, stays the same for some, and declines for the remaining relative to the preceding year. So, the “control” group is districts with no change in the occupancy rate in a given year. Panel B of Figure II, estimates (4), revealing that there is no correlation between past disposal rate and current period judge occupancy whereas a reduction in vacancies in the current period has a persistent effect on the disposal rates in the subsequent 2-3 years, coinciding with the typical judge tenure. Panel C of Figure II, estimating (5), shows that there is no correlation between population growth rate and judge occupancy rate.¹³ Panel D of Figure II plots the event coefficients from specification in (6) to examine whether any dynamic concerns about court performance affects judge vacancies. Figure III and Figure IV present the correlations between judge occupancy and credit-market, firm-level outcomes estimating (7), showing no significant pre-trends.

Exclusion restriction: This requires that judge occupancy affects outcomes of interest only through court’s trial resolution rate. Exclusion restriction may be violated, for example, if judge occupancy directly affected firm and credit-related outcomes, say, through effects on crime. I find no significant effect of judge occupancy on overall crime within a given district. However, a certain type of criminal offense typically lower on the scale of severity, known as bailable offence, increases subsequent to an increase in judge occupancy as a downstream effect, i.e. via disposal rate. Bailable crime includes those relating to breaking trust of legal instruments and disrespect towards rule of law, including those concerning “bounced check” (dishonored bank checks) under Negotiable Instruments Act. Banks are known to use

¹³Further, judge occupancy exhibits no correlation with the underlying district population in any year in the study period as seen in Figure A.3. The structural problem of vacancy increases over time across all courts.

this as a strategy to incentivize debt repayment by encouraging submission of post-dated checks towards loan installments (Daksh 2017). This also corresponds to the fact that bail petitions form a significant workload of judges and have a higher disposal rate than other case-types. An increase in judge occupancy corresponds to a substantially higher increase in the disposal rate of bail petitions, suggesting that judge occupancy has an effect on outcomes only through trial resolution.¹⁴

Heterogeneous effects: Based on the conceptual framework, I examine heterogeneous reduced form effects of judge vacancy on firm-level outcomes. The key heterogeneity is by firms' ex-ante asset size that classify whether a firm is small or large. A second heterogeneity I study is by firms' ex-ante credit rating, indicating whether a firm is safe or risky borrower.

$$(8) \ Y_{fdt+k} = \alpha_d^s + \alpha_{st}^s + \delta_1^s(Small_f \times Occp_{dt}) + \delta_2^s Occp_{dt} + \delta_3^s Small_f + \mathbf{X}'_f \Gamma^s + \epsilon_{fdt}^s$$

$$(9) \ Y_{fdt+k} = \alpha_d^{cr} + \alpha_{st}^{cr} + \delta_1^{cr}(Safe_f \times Occp_{dt}) + \delta_2^{cr} Occp_{dt} + \delta_3^{cr} Safe_f + \mathbf{X}'_f \Gamma^{cr} + \epsilon_{fdt}^{cr}$$

V. RESULTS

In this section, I discuss empirical evidence supporting the role of improved trial resolution in district courts, through a reduction in judge vacancy, in affecting credit markets and production decisions of local firms. Central to this relationship is the importance of courts in helping banks recoup tied-up capital in debt recovery litigations, which in-turn could influence how banks reallocate credit across borrowers.

The IV design helps estimate the elasticity of the economic outcomes with respect to courts' rate of trial resolution whereas the event study strategy presents reduced form effects of judge vacancy on these outcomes. In addition, the event study also helps address potential endogeneity concerns related to variation in judge vacancy. Although the point estimates from the two specifications are not directly comparable as they present different weighted averages of treatment effects, they confirm that the effects are in the same direction.

V.A. Litigation resolution, debt recovery, and credit allocation

The first result of this paper is that a reduction in judge vacancy increases the fraction of resolved cases relative to existing workload within a court. Resolution indicates either a settlement between the litigating parties with interim orders or completion of a full trial with judgement orders. As shown in Table II, reducing judge vacancy by one percentage point (conversely, increasing judge occupancy rate by same amount) increases the disposal rate

¹⁴These are seen in Figure A.4 Panel B and Figure A.6 depicting the role of judges in resolving bail petitions and effects on crime.

by one percent, which is similar across different subsample of courts (Table III).¹⁵ In other words, adding one more judge to reduce vacancy results in approximately 200 additional resolved trials within a court-year. Further, the event-study graphs in Figure II show an absence of pre-trends in judge vacancies, suggesting this relationship to be causal.

The capacity of these courts to reduce pending litigations matter particularly for the financial sector including banks, that have many pending and new litigations awaiting resolution. A majority of litigation involving banks are money suits, including debt recovery trials. Additionally, they are also engaged in specific types of trials such as execution petitions that require the court’s directions to implement past judgement orders. For example, in the case of debt recovery litigation, a litigating bank may require enforcement of a past judgement in their favor directing the delinquent borrower to pay back an agreed amount. An execution order allows the bank to use law enforcement officials to take possession of property or assets owned by the debtor.

The relationship between judge vacancy and disposal rate remains similar after accounting for the number of bank-related litigation as weights in district-level regressions (see Column 4 Table IV). Further, encountering judge vacancy during a trial’s life cycle also increases the median duration of such trials. So addressing vacancy not only increases the fraction of trials that are resolved but also reduces the trial duration of ongoing trials. With every marginal case resolved, the banks are able to recover unproductive capital given the large loan sizes of secured business loans and retail/personal loans such as vehicle, education, or home loans.¹⁶

Loan recovery and overall lending: Table IV presents the OLS, IV, reduced form, and the first stage estimates using district-level specifications with total outstanding loan amount as the dependent variable. The panels report the results by specific sub-sample, including total pending loans across all banks, among public sector banks, and by the sector of loan allocation. The results, particularly for public sector banks and manufacturing loans, indicate that an improvement in court disposal rate reduces total outstanding loan amount, that include increases in repayment. For these loan-types, an increase in disposal rate by one percent decreases total outstanding loan by 0.35 percent and 0.24 percent respectively. In terms of judges, reducing vacancy by one judge decreases total outstanding by 2 percent and 1.4 percent respectively. Given the average district-level outstanding loan at USD 9.4

¹⁵The coefficients need to be multiplied by 100 to get elasticities in percentage terms in the log-linear specification.

¹⁶The cost of an Indian-made entry-level car - Maruti Alto 800 - is about USD 4000. Tertiary and professional education within India costs between USD 1000 - 10000, depending on the university. Many also take education loan for foreign education that is more expensive. Average housing loans in tier 2 and 3 cities in India is about USD 35000.

billion, this implies that reducing judge vacancy by one judge brings back about USD 188 million for recirculation.¹⁷

Correspondingly, I note that the total number of loans at the district-level increases with an increase in disposal rate and with a reduction in judge vacancy. The increase is prominent particularly for retail or personal loans (see [Table A.2](#)). The event-study results depicted in Panels A and B, [Figure III](#), shows that while the number of loans - particularly for manufacturing - initially decline, they increase after a lag.

Local firms' credit access: [Table V](#) shows that smaller delinquent borrowers among firms are more likely to settle instead of pursuing litigation, supporting the proposition that initial wealth endowment matters whether or not a delinquent borrower engages in litigation. Further, the overall rate of litigation involving delinquent borrowers reduces as judicial capacity improves. This is plausible because the judgement is typically in favor of the lender and improved capacity may imply faster settlement even outside of courts.

Commensurate with the findings at the overall credit market level, total borrowing among local formal sector firms - who are among the largest borrowers from banks - declines initially whereas unsecured borrowing (i.e. without any collateral) increases, as seen in the event study results in Panels C and D, [Figure III](#).

Total borrowing declines by approximately 1 percent per one percent improvement in disposal rate or by 12 percent per judge (Column 1 [Table VI](#)). A caveat is that these results are applicable among firms reporting bank borrowing. As seen in the number of observations in [Table VI](#), not all firms either borrow or report borrowing in their annual balance sheet. However, this "attrition" or selection of firms in the data does not systematically vary with judge vacancy. Moreover, the credit market level results indicate an overall expansion in lending and in particular to the manufacturing sector that includes many more firms than those in this sample.

On interest incidence, calculated as the ratio between total interest expenditure and total borrowing, I find a suggestive negative relationship across all firms as suggested in the conceptual framework (Column 2 [Table VI](#)). This indicates that the banks respond to better judicial capacity by not just recirculating stuck capital but also reduce the price on loans.

Further, examining the change in borrowing and interest rates by firms' ex-ante asset size distribution suggests that changes in smaller firms' borrowing are no different from larger firms whereas the interest rate is about 1.5 times lower, although these estimates are imprecise and noisy (Panel A, Columns 1 and 2, [Table VII](#)). A key point to note is that

¹⁷Since judge occupancy is reported in percentage terms, I arrive at these numbers by multiplying the reduced form coefficients by 7.2 - which is the percentage increase in occupancy by adding one judge - and further scaling by 100, given the log-linear specification.

all the firms in the sample are registered, formal sector firms. So even smaller firms among these are large. To understand the effects across the distribution of firm size including micro, small and medium enterprises (MSME), and informal sector firms requires annual balance sheet information for these firms as well, which, to my knowledge, is not available in the form of secondary/administrative dataset yet.

Another dimension of heterogeneity that I examine is by firms' ex-ante credit rating. While borrowing substantially declines for firms with low ex-ante credit rating, the decline is suggestively smaller for higher rated firms (Panel B, Columns 1 and 2, [Table VII](#)).

These credit market and borrowing effects following temporal variation in judge vacancy within a district is also consistent with the fact that the bank loan officers themselves are frequently rotated and therefore, are not forward looking as per models based on rational expectations. Rather, credit allocation is likely based on current capital availability and officer specific incentives.¹⁸

V.B. Firms' production outcomes

Credit market effects are likely to influence local firms' production decisions in addition to general improvement in the overall contract enforcement environment, including better enforcement of labor and supply-chain trade contracts. The event study results show absence of any pre-trends and lagged effects of judge vacancy on firms' inputs and production outcomes ([Figure IV](#)).

Columns 3-6 of [Table VI](#) reports the effects of judicial capacity improvement on firms' sales, profit, wage bill, and value of plants and machinery following the specification in [Equation 3](#). The results imply that while wage bill and profit increase significantly following an improvement in judicial capacity - 0.265 and 0.655 percent increase for every one percent increase in court disposal rate or 1.9 and 6.9 percent increase for every additional judge - the value of plants and machinery declines by 0.224 percent for every one percent increase in disposal rate or by 1.6 percent for every additional judge.

The observed opposing effects on labor and capital can be partly explained by the effects of local credit market, which experiences an increased repayment. Firms use long term secured bank credit to finance investment in capital goods whereas use unsecured borrowing for financing worker salaries and other operational expenses. That is, the types of credit are different for investment in long-term capital and for running day to day operations. Any changes in requirement to repay secured bank loans could result in liquidation of capital if their turn-over isn't sufficient to finance repayment. This could also partly explain why we

¹⁸[Banerjee and Duflo \(2014\)](#) discuss the incentives faced by loan officers who are actually backward looking rather than forward looking, allocating credit to prevent defaults, a phenomena called "ever-greening".

see an increase in firm profits as liquidation net of repayment would enter the balance sheet as income.

However, despite a reduction in the value of capital goods, the increase in wage bill could partly reflect an improvement in labor productivity, especially if capital goods were functioning at slack capacity.¹⁹ An improvement in labor productivity could drive an increase in sales (although not statistically significant but the magnitude of the estimates is large at 1.85 percent increase per judge) and profit.

Examining the heterogeneity in firms' response to reduction in judge vacancy by their ex-ante asset size, I observe improvement in wage bill and profits across both large and small firms whereas the decline in the value of plants and machinery is somewhat off-set in small firms (Columns 3-6, Panel A, [Table VII](#)). Heterogeneity by firms' ex-ante credit rating suggests that firms with higher rating experience an increase in wage bill with a reduction in judge vacancy in contrast to lower rated firms. The point estimates on the value of plant and machinery also suggest an offsetting effect on higher rated firms. This suggests that there are substantial heterogeneity in how judicial capacity affects outcomes across the distribution of local firms.

V.C. Firm fixed effects and balanced panel of firms

Given that not all firms report information on all variables nor do they participate in the survey exercise led by CMIE every year to generate the Prowess dataset,²⁰ I also focus on a subset of firms reporting information every year between 2010 and 2018. This results in a balanced panel of 1278 firms, most of which are large, older firms, including many publicly listed companies. The balanced panel helps account for firm-level time invariant unobservables in the form of firm fixed effect, and helps address concerns about firms' selection into the sample.

Examining the reduced form effects of judge vacancy on this group of firms (Panel A [Table VIII](#)) confirms a reduction in borrowing indicating increased repayment and a reduction in the value of plants and machinery. On the other hand, these firms also witness a reduction in wage bill whereas the effect on profits is small and statistically insignificant.

Heterogeneity by ex-ante firm size (Panel B [Table VIII](#)) and credit rating (Panel C [Table VIII](#)) indicate that both smaller and larger firms within this sample increase repayment as seen as lower outstanding bank borrowing as do firms with worse credit rating. The effect on repayment is smaller and statistically indistinguishable from zero among higher rated

¹⁹For example, it is a [well known problem](#) that Indian manufacturing operates 30-40 percent below their capacity.

²⁰I document that the "attrition" of firms in the data is not correlated with judge vacancy.

firms. The negative effects from a reduction in judge vacancy on firms’ production outcomes are entirely driven by the smaller firms within this subsample. On the other hand, I find a positive effect on the production outcomes of large firms (very large among all firm size distribution) as well as firms with better credit rating.

V.D. Credit access as a causal channel

The results on the overall credit market and firm-level borrowing indicates that the credit market channel plays an important role. While the firm-level results indicate a plausible increase in repayment through decreasing outstanding bank borrowing, the credit market-level results indicate an increase in total lending over time, both to the manufacturing sector as a whole as well as towards personal loans. Some of the micro and small enterprises rely on personal loans for business expansions in addition to the use of such loans for consumption of durables (Banerjee et al. 2015; Surendra 2020). Connecting this with the conceptual framework above, the decline in borrowing corresponds to lower value of capital assets, indicating plausible liquidation of slack capital. Further, there is an increase in unsecured loans, personal loans, as well as lending to more “reliable” borrowers such as those with high credit rating or very large firms. Improvement in the production outcomes among such firms helps explain the observed positive effect on wage bill and profit on average.

In order to show that firms’ long term borrowing from banks is an important mechanism, I include borrowing, B_{fdt+k} , as an explanatory variable on the RHS of the main reduced form specification as shown in Equation 11. Since judicial capacity also affects borrowing, including it on the RHS creates the problem of “bad-control”. Therefore, I exploit a shock to the banking system by using temporal spurts in rural bank branch expansion within a district to instrument for firm’s borrowing. This first stage is presented in Equation 10. This approach is similar to one proposed by Imai et al. (2011) to enable correct estimation of mediation effects.

$$(10) \quad B_{fdt+k} = \alpha_d + \alpha_{st} + \beta_1 Bank\ Shock_{dt} + \beta_2 Occup_{dt} + \mathbf{X}'_f \Gamma_2 + \mu_{fdt+k} ; k \geq 0$$

$$(11) \quad Y_{fdt+k} = \psi_d + \psi_{st} + \omega_1 \hat{B}_{fdt+k} + \omega_2 Occup_{dt} + \mathbf{X}'_f \Gamma_1 + \epsilon_{fdt+k}$$

$Bank\ Shock_{dt}$ is determined by a national level committee on banking and central bank (RBI) policies (Burgess and Pande 2005), and is plausibly independent of the capacities of district judiciary. I construct the shock as a dummy variable that takes the value of 1 (but 0 otherwise) when the share of total new rural bank branches opened in a given year is above 75th percentile of all rural branch openings within the district. To serve as a valid instrument, the bank shock should be conditionally independent of the potential outcomes

of not only firm production outcomes and firm borrowing (mediator) but also independent of judge vacancy (Figure A.8).

Table IX presents the first stage and 2SLS estimates, respectively. The first stage implies that bank shock increases firm borrowing by 10 percent. While the estimation with firm-level production outcomes as dependent variables is noisy, the point estimates suggest substantial elasticities of these outcomes with respect to borrowing. In particular, the elasticity of plant value is close to 1 and significant at 10 percent. This suggests that an increase in bank borrowing is plausibly used to finance capital expansion. Therefore, repayment is linked to the ability of the invested capital to generate substantial positive turnover. Any default is tied to banks' claim on the piece of capital financed by the loan and results in its liquidation/sale.

V.E. Robustness Checks

I conduct a series of statistical tests to examine the robustness of construction of various indicators used in the empirical analysis as well as that of the estimation strategies including the plausible endogeneity of judge vacancy.

Alternate construction of court measures: Since I construct judge occupancy from the trial-level meta data as the ratio between observed number of judges in a given calendar year and maximum number of judges observed across the study period, I verify whether it is robust to variations in its construction. Row 2 in Table II presents the first stage estimates when the total number of judge positions in a given court - denominator in the judge occupancy rate - is fixed as of the first year in the study period. The point estimate is positive and of similar magnitude as the main estimate.

Since I observe maximum number of judges within a given court in the trial meta data that I use as the denominator to calculate judge occupancy, I examine whether this construction could potentially violate the exogeneity of judge vacancy. Therefore, I employ an event-study approach using the year of full occupancy as the event of interest (Panel A Figure A.9). I find no significant pre-trends and the post-period effect is qualitatively similar to the main reduced form estimate on court disposal rate.

On measuring judicial capacity, I use an index constructed as the first principal component using Principal Component Analysis instead of the rate of trial resolution/disposal rate (Column 2 Table II). The point estimate is of similar magnitude as the main first stage estimate.

Verification using judge tenure data: I verify whether judge tenure is correlated with past measures of court performance as well as judge occupancy. Any strategic manipulation of tenure could affect the exogeneity of judge occupancy. In order to do this, I web scrape

tenure information on the head judge (Principal District Judge or PDJ) from each of the district court websites using their joining and leaving dates. The average tenure is about 1.5 years, in line with the general guideline on district judge tenure, and that the system of rotation leads to “gap days” before their successor takes charge. This effect of rotation on PDJ vacancy is likely an underestimate as PDJ positions do not remain vacant for long. Importantly, I find that their tenure or “seniority” is uncorrelated with past occupancy rates and post period disposal rate, suggesting a lack of strategic manipulation of tenure to affect vacancy rates.²¹

Alternate identification using standard event study: The main specification uses a combination of event-study-distributed-lags model with continuous explanatory variable - judge vacancy - along with an IV strategy. The IV helped show that the quasi-random variation in judge vacancy affects outcomes of interest through the ability of the district court to resolve cases in a timely manner. In this section, I employ a more standard event-study approach using dummy variables for event-time instead of the continuous variables approach to examine whether the results are qualitatively similar.

$$(12) \quad Y_{f dt} = \rho_d + \rho_{st} + \sum_{k=-7}^{k=7} \gamma_k \mathbb{1}\{|t - E_d| = k\} + \zeta_{f dt}$$

Event E_d is defined as the first year of positive shock to judge occupancy, defined as at least 10 percent increase in judge occupancy over the preceding year’s value. While this is not the same definition of “treatment” as defined in the main analysis, the results should be qualitatively similar if the hypotheses are true. Further, because these “events” stagger across district courts in different years, I transform the data stacked-by-event as in [Cengiz et al. \(2019\)](#) to address potential bias in the point estimate due to incorrect weighting of “treatment” and “control” groups.

[Figure A.12](#) shows the event study graphs using the above specification. The results are qualitatively similar to the main reduced form estimation using continuous judge occupancy measure.

Two-way fixed effects correction: Since all the specifications account for two-way fixed effects (district fixed effects along with state-year fixed effects), I verify whether the point estimates are robust to heterogeneity in treatment effects following the procedure (`did_multiplot`) laid out by [de Chaisemartin and D’Haultfœuille \(2020\)](#).

Panel B [Figure A.9](#) presents the adjusted estimates for the first stage. The adjustment

²¹Currently, there is no centralized repository of judge personnel data across all district courts in India and is not part of the E-courts system. [Figure A.10](#) presents the distribution of PDJ tenure, associated vacancy from rotations, and event study graphs of other court performance measures.

procedure returns the first stage coefficient similar in magnitude and sign as the main estimate. [Table A.3](#) compares the adjusted estimates with the main reduced form estimates for firm-level outcomes. While the procedure attenuates the point estimate for many variables, it retains the same sign except for profit and value of plant and machinery. A key take-away from this exercise is that the average treatment effect of reduction in judge vacancy on borrowing, interest rate, sales, and wage bill is relatively robust to firm-level heterogeneity. On the other hand, effects on profit and capital likely depend on the firm type, for example, whether the firm is delinquent with respect to outstanding loans.

Clustering standard errors: In all specifications, I cluster standard errors at the level of “treatment” variation, i.e. by district-year. However, the system of judge rotation could introduce correlation in judge occupancy between districts within a state. To address this “spatial” correlation, I also cluster by state-year (Panel A [Table A.4](#)). Further, judge occupancy within a district court could be serially correlated if they follow an $AR(n)$ process if addition or removal of judges from a court occurs every n years.²² Therefore, I also estimate the specifications by clustering at district-level instead of district-year (Panel B [Table A.4](#)). The coefficients continue to remain statistically significant even after clustering at these different levels.

V.F. Benefit-cost analysis

The analysis suggests that reducing judge vacancy in district courts translates into significant improvements in local credit markets and firms’ production outcomes. Expansion in wage expenditure suggests that either formal sector employment increases or that the labor employed by these firms experience a gain in their compensation (with higher wages potentially reflecting an improvement in labor productivity). Evidence also supports an increase in sales revenue and profit. Given judge salaries are a part of public expenditure, what are the likely returns from adding one more judge to a court with vacancies? In [Table X](#), I calculate the benefit-cost ratio using the estimates from above analysis and a few assumptions. I use the inter-quartile range of values of profit and wage bill to compute the increase in firm-level surplus and salaried income across this range, assuming constant treatment effects. Since both enterprise and salaried individual pay corporate and income tax on their net income, the effect translates into significant revenue for the state. I assume 15 percent corporate tax, which is the lowest rate for newly established manufacturing units, and 7.3 percent as the

²²Judge occupancy is positively correlated with its one-period lagged value, weakly correlated with two-period lagged value, negatively correlated with lags 3 and 4, and uncorrelated with further lags.

average individual income tax.²³ I discount the stream of benefits using 10 percent discount rate over a period of 2 years since the benefits lag an increase in judge occupancy.

Adding one more judge to a district court costs USD 35,000 to the state that includes salary as well as other benefits. This suggests that the benefit-cost ratio is at least 2.7:1 considering only an increase in tax revenue from income and corporate tax by at least one firm in a district even if that firm is at the 25th percentile of the overall distribution in firm profits and wage bill. Considering overall value addition in the local economy suggests a much larger benefit-cost ratio. Since state (provincial) governments are responsible for district judge salaries, the increase in local economic output should provide sufficient incentives to reduce judge vacancies.

V.G. Discussion

The results indicate that the shocks to trial court capacity result in credit market adjustments and an increase in local firm production with a lag of 1-2 years. This is mainly through the role played by courts in facilitating recovery of tied-up capital and subsequent credit reallocation by banks among borrowers in the district. This leads to an expansion in production through higher wage bill, and increases firm profits on average. While there could be many channels through which courts can influence firms such as reducing hold up problems in labor disputes, the context and the data shows the importance of credit markets under improved contract enforcement environment. Further, the stability in the first stage estimates by underlying district population implies that addressing judge occupancy will likely have a strong effect for the large majority of non-metropolitan districts in India.

The sample districts in this study cover most industrial districts in India with the exception of Delhi NCR and Mumbai areas. Since the fraction of manufacturing firms and banking firms in these districts are similar to the fraction of such firms in other districts not included in the study (Table A.5), the results are likely to be externally valid.

Finally, this paper presents a different aspect of the relationship between trial courts and local firms in relation to the key results presented in Ponticelli and Alencar (2016) in the context of Brazilian trial court capacity and changes in bankruptcy laws. First, I study the relationship in the absence of any changes in national or state laws, which are netted out as state-year fixed effects. Second, I exploit quasi-random temporal variation in judge vacancy within a district court in contrast to the cross-sectional variation in trial court

²³These assumptions are motivated by articles in the news media, with sources mentioned in Table X. I calculate the average individual income tax using media reports on average filed annual income of a salaried tax-payer in India for the year 2018-19, which is INR 690,000 or roughly USD 10,000. Applying exemptions, an individual with this income pays an effective tax of 7.3 percent.

jurisdiction examined in the Brazilian context. Third, this paper emphasizes the role played by trial courts in recovering tied-up capital in ordinary debt recovery litigation that does not necessarily evoke bankruptcy proceedings. Bankruptcy itself is a costly procedure and is typically the measure of last resort after trying other methods of recovering defaults. Easy and relatively fast debt recovery facilitates credit circulation within an economy.

VI. CONCLUSION

To conclude, I present well-identified causal estimates of ordinary trial court capacity on formal sector firm growth using trial level microdata from 195 district courts and quasi-random variation in judge vacancy. I show that the current state of trial resolution is abysmally low and around 23 percent of judge posts are vacant on average. Therefore, reducing vacancy substantially increases the rate of trial resolution. This is an important factor determining courts' capacity in enforcing credit contracts, freeing tied-up capital, and enabling credit circulation that has significant ramifications for local firms' production.

This role of courts is concordant with the observation that banks form the largest litigant group relative to any other type of firm. Initiating litigation against defaulting borrowers is a necessary first step before taking collateral into possession or initiating bankruptcy proceedings. Consequently, firms that borrow substantially from banks experience the need to repay in a timely fashion, as seen in the data. However, other firms benefit from an increase in credit access, expanding production. I show that access to finance is important for capital expansion.

This paper highlights judge vacancy as an important state capacity constraint, consistent with the current demand by legal and policy experts to strengthen the district judiciary in India. Given the benefits in the form of an expansion of industrial production, the state will be able to more than recover the costs of hiring additional judges from increased tax revenue and an expansion in employment.

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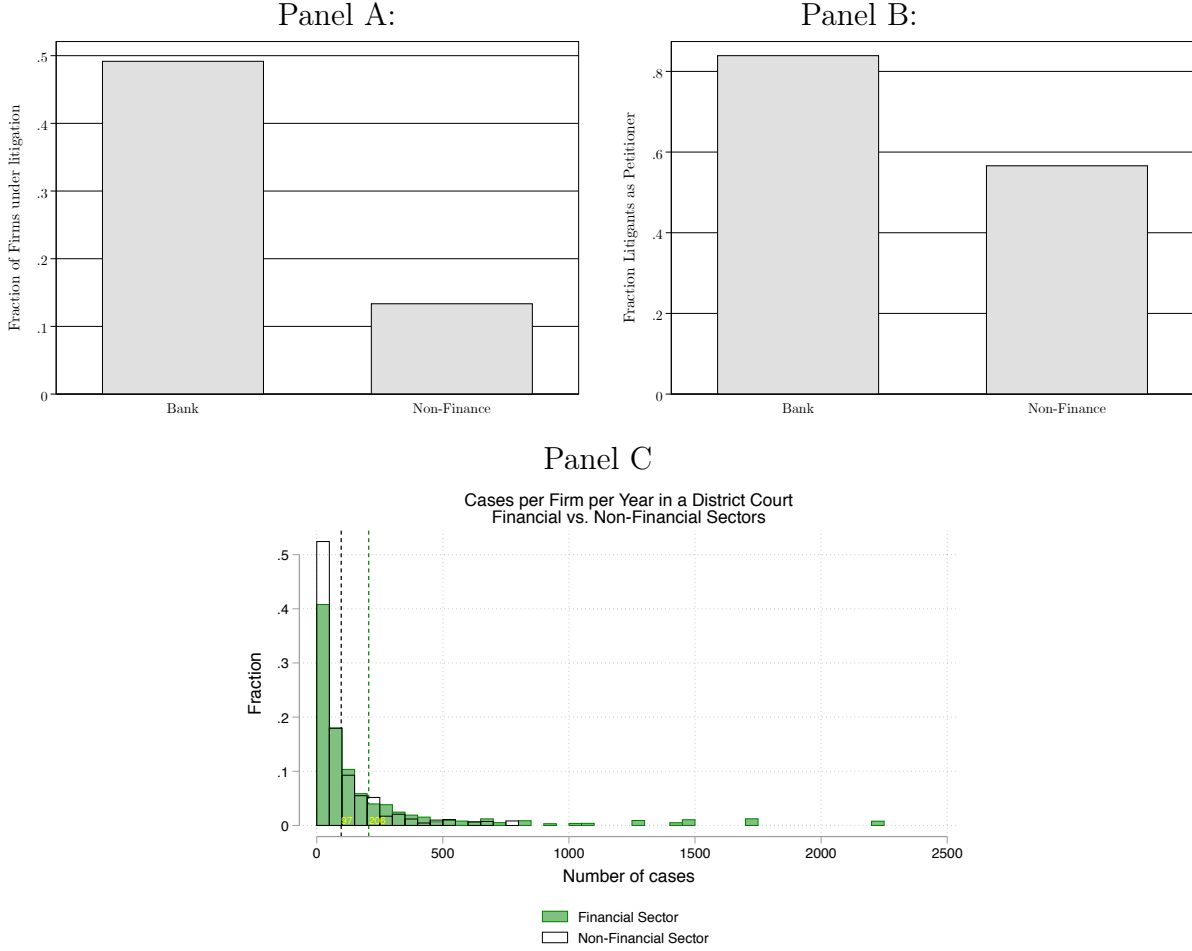
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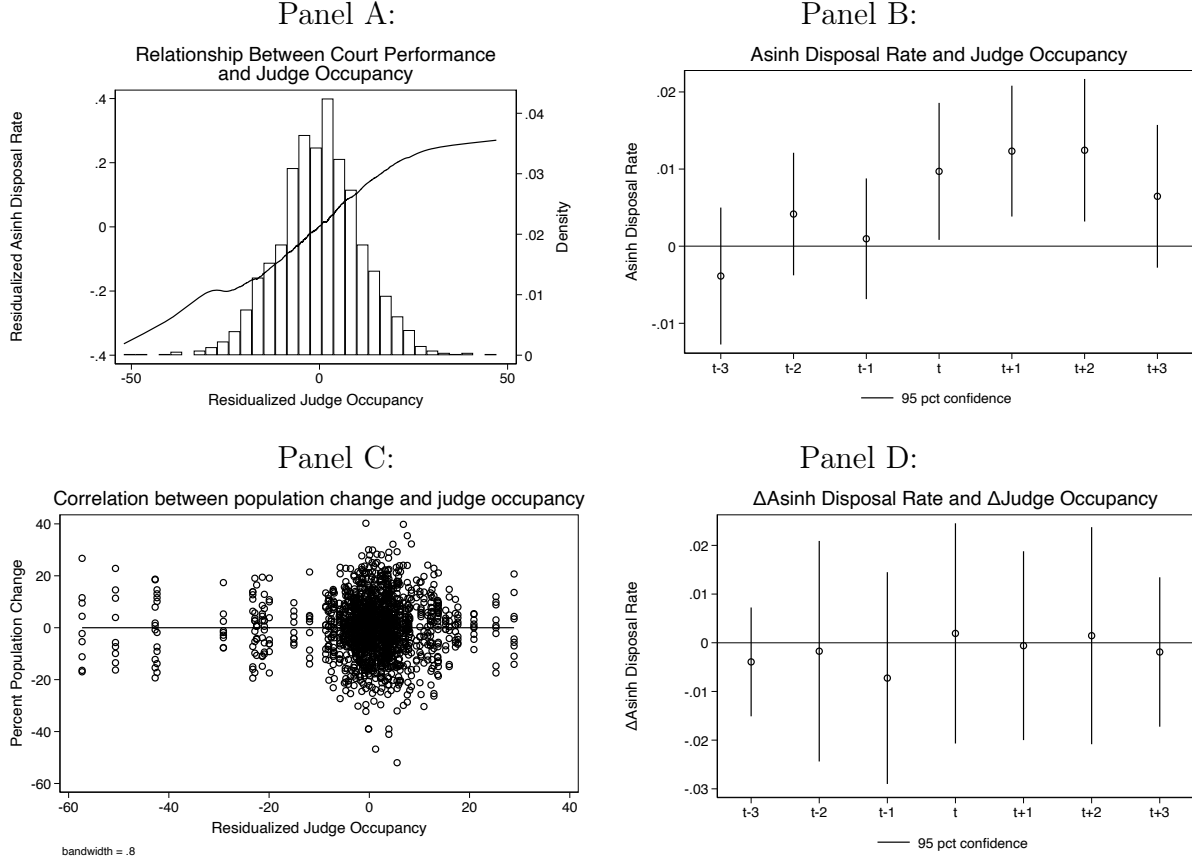
VII. Figures

Figure I: Litigation by firm type



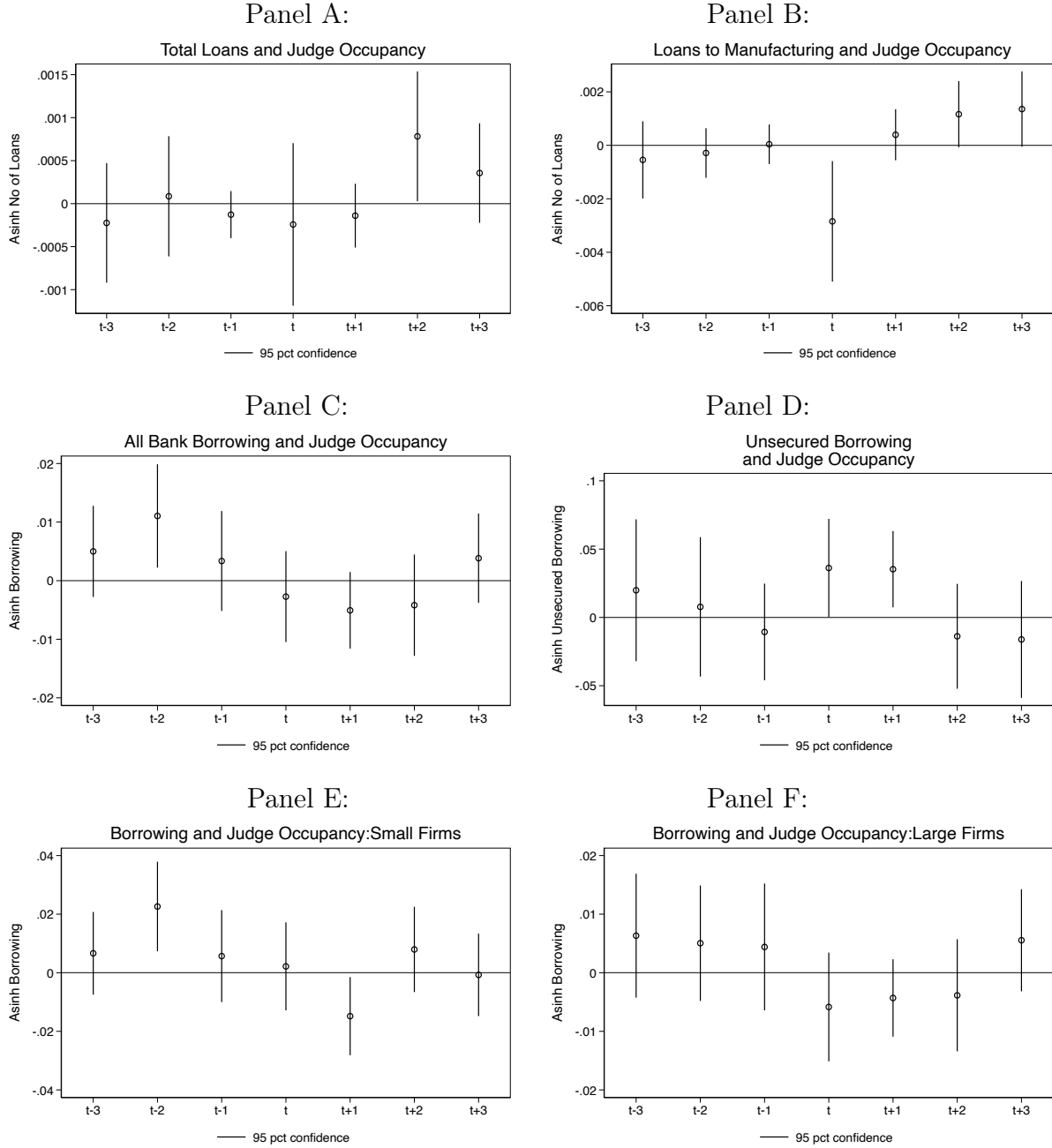
Notes: Panel A shows what fraction of firms in the study sample are also found as a litigant in the trial microdata, grouped by whether they are banking sector firm or belong to non-financial sector. Panel B shows what fraction of the cases that the litigant firm appears as a petitioner (plaintiff), grouped by whether the firm belongs to banking sector or non-financial sector. Panel C shows the distribution of number of cases per firm by financial and non-financial sector, showing that the average number of cases per firm in the financial sector (206 cases/firm) is more than twice as many as the average number of cases per firm in the non-financial sector (97 cases/firm).

Figure II: Disposal rate and judge occupancy: First stage and exogeneity



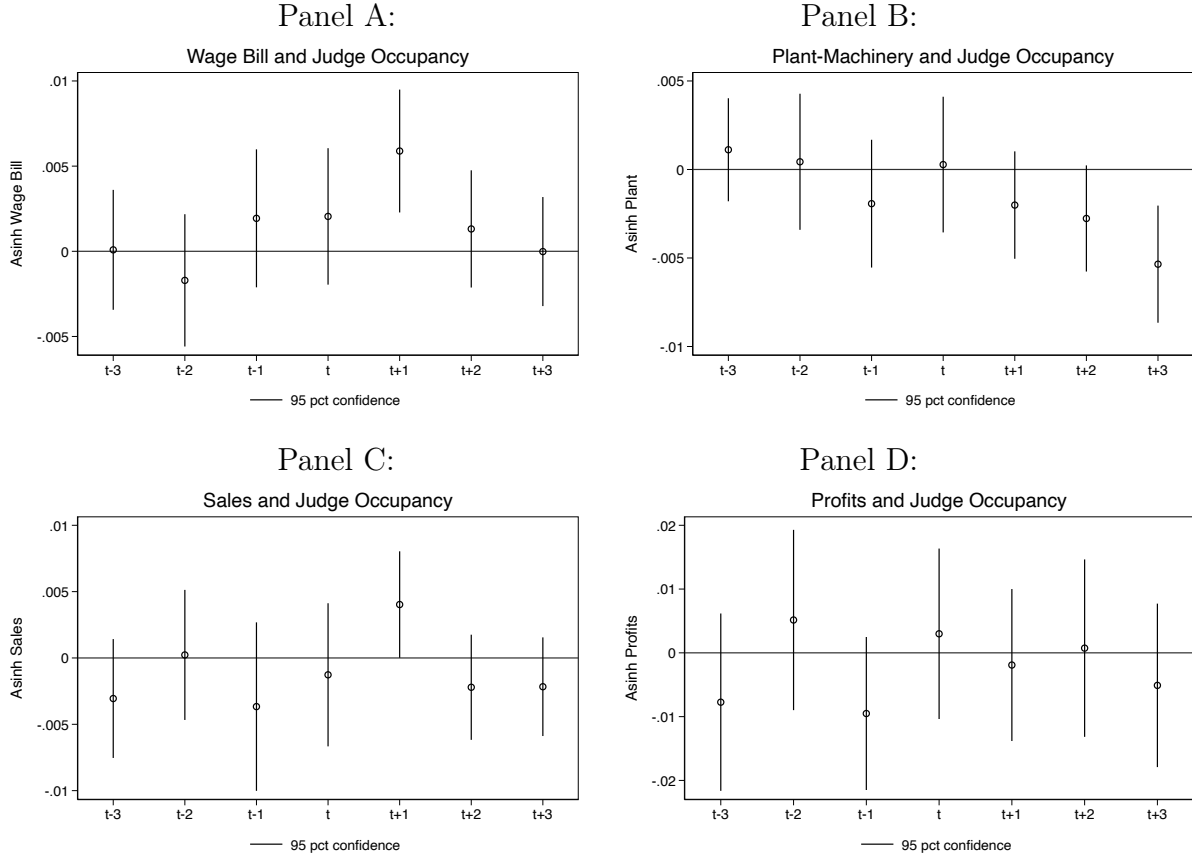
Notes: Panel A above shows the relationship between disposal rate and judge occupancy, after controlling for district, year, and state-year fixed effects, using flexible lowess specification between asinh (inverse hyperbolic sine transformation) disposal rate and judge occupancy. Panel B plots the relationship between judge occupancy at time t with respect to asinh disposal rate using a distributed lags event-study framework, after accounting for district, year, and state-year fixed effects (estimating Equation 4). Panel C is a scatter-plot regressing percent change in district population between 2001 and 2011 census enumeration on judge occupancy, after residualizing district, year, and state-year fixed effects (estimating Equation 5). Panel D plots the relationship between changes in judge occupancy at time t with respect to changes in asinh disposal rate using a distributed lags event-study framework, after accounting for district, year, and state-year fixed effects (estimating Equation 6). The x-axis presents the time difference between the year the dependent variable is measured and the year judge vacancy is measured. For example, the value at $t - 3$ presents the regression coefficient on judge occupancy measured at $t + 3$ when the dependent variable - asinh disposal rate - is measured at t . Similarly, value at $t + 3$ presents the regression coefficient on judge occupancy measured at $t - 3$ when asinh disposal rate is measured at t . Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure III: Credit Market-level and firm-level outcomes



Notes: Panels A and B present the reduced form effect on all banks' total lending and lending towards manufacturing in a given district (local credit market), respectively, using a distributed lags event-study framework (Equation 7). Panels C and D present the reduced form effect on all firm-level long term borrowing and unsecured borrowing (without requiring collateral) across the sample firms, also using a distributed lags event-study framework (Equation 7). Finally, Panels E and F present the same specifications on the subsample of ex-ante small and large asset size firms, respectively. The x-axis presents the time difference between the year the dependent variable is measured and the year judge occupancy is measured. For example, the value at $t - 3$ presents the regression coefficient on judge occupancy measured at $t + 3$ when the dependent variable - for e.g., district level lending - is measured at t . Similarly, value at $t + 3$ presents the regression coefficient on judge occupancy measured at $t - 3$ when lending is measured at t . The firm sample includes all firms whose registered offices are co-located in the same district as the corresponding court. All standard errors are clustered by district-year.

Figure IV: Firm production - Factor-use, sales, and profit



Notes: The graphs above plot the reduced form coefficients on judge occupancy with firm production variables as the dependent variable, using a distributed lags event-study framework ([Equation 7](#)). The x-axis presents the time difference between the year the dependent variable is measured and the year judge vacancy is measured. For example, the value at $t - 3$ presents the regression coefficient on judge occupancy measured at $t + 3$ when the dependent variable - for e.g., wage bill - is measured at t . Similarly, value at $t + 3$ presents the regression coefficient on judge occupancy measured at $t - 3$ when factor use is measured at t . The sample includes all firms whose registered offices are co-located in the same district as the corresponding court. All standard errors are clustered by district-year.

VIII. Tables

Table I: Summary statistics

(1)						
	No. of Units	Observations	Mean	Std Dev	Min	Max
Panel A: Court Variables						
Total Judge Posts	195	1755	18	19	1	108
Percent Judge Occupancy	195	1723	77	21	10	100
Disposal Rate (%)	195	1755	14	12	0	86
Case Duration (days)	195	5706852	420	570	0	4022
Panel B: Bank Variables						
No. Loans	195	1746	301939	288696	4057	3049797
Outstanding Amount (real terms, billion USD)	195	1746	9.39	21.27	0.049	255.1
Panel C: Firm Variables						
Long Term Borrowing (real terms, billion USD)	3281	11111	1.47	7.6	0	251.2
Revenue from Sales (real terms, billion USD)	6139	30162	4.74	21.38	0.09	796.7
Accounting Profits (in real terms, billion USD)	6374	32837	0.11	2.77	-144.35	130.68
Wage Bill (in real terms, billion USD)	6104	30261	0.316	1.64	-0.012	70.35
No. of Workers ('000)	985	4216	2.28	7	0.001	154
Plant value (real terms, billion USD)	5295	27473	2.45	14	-0.13	449.57

Notes: Panel A summarizes the court level variables computed from trial-level disaggregated data. Panel B summarizes district-level bank lending variables. Panel C summarizes firm-level variables of all incumbent firms. All monetary variables are measured in USD million in real terms, using 2015 as the base year.

Table II: First stage - Judge occupancy and the rate of trial resolution

	Asinh Disposal Rate	Index	Asinh Disposal Rate	Asinh Disposal Rate	Asinh Disposal Rate
Judge Occupancy	0.00978*** (0.00182)	0.00745*** (0.00231)		0.00978*** (0.00216)	0.00978*** (0.00214)
Judge Occupancy Alt			0.00624*** (0.00139)		
Observations	1714	1478	1701	1714	1714
Wald F-Stat	28.81	10.43	20.06	20.48	20.93
Adj R-Squared	0.697	0.743	0.696	0.69	0.69
SE Cluster	district-year	district-year	district-year	state-year	district

Standard errors in parentheses

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

Notes: This table presents the first stage estimates on judge vacancy in a log-linear specification with disposal rate as the court-level outcome. Column 2 presents the coefficient on judge occupancy in a regression where the dependent variable is an index generated as the first principal component from principal component analysis using disposal rate, case duration, rate of appeal, rate of dismissal, incoming cases, resolved cases, and the ratio of resolved to incoming cases as a combined measure of court-level performance. Row 2 presents an alternate method of constructing judge occupancy, where I fix the denominator as the total number of judges as the first year in the study period. All specifications include district and state-year fixed effects. Standard errors are clustered as indicated in the table.

Table III: First stage - By sub-groups of district courts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	Court Size tercile 1	Court Size tercile 2	Court Size tercile 3	Pop. Density tercile 1	Pop. Density tercile 2	Pop. Density tercile 3
Judge Occupancy	0.00978*** (0.00182)	0.0118*** (0.00324)	0.0112*** (0.00272)	0.00701** (0.00351)	0.00895*** (0.00239)	0.0151*** (0.00389)	0.00607* (0.00331)
Observations	1714	544	619	539	539	542	549
Wald F-Stat	28.81	13.25	16.88	3.990	14.0	15.13	3.370
Adj R-Squared	0.697	0.740	0.676	0.711	0.712	0.605	0.778
Complier Ratio	1	1.210	1.140	0.720	0.920	1.550	0.620

Standard errors in parentheses

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

Notes: In this table, I compare the overall first stage estimates on judge occupancy with those estimated using different sub-samples of the district courts. Columns 2-4 present the first stage by terciles of court size and Columns 5-7 by terciles of district population density. Complier ratio, denoted in the last row, is the ratio of the first stage estimates as reported for the subsample and the estimate of the overall sample. All specifications include district and state-year fixed effects. Standard errors are clustered at the district-year level.

Table IV: District-level total outstanding bank loans

	(1) OLS	(2) IV	(3) Reduced Form	(4) First Stage
Panel A: All Banks				
Log Disposal Rate	0.0042 (0.0149)	-0.03 (0.048)		
Judge Occupancy			-0.000237 (0.000374)	0.00791*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.98	-0.082	0.98	0.59
Wald F-Stat				21.65
Panel B: Public Sector Banks				
Log Disposal	-0.0145 (0.031)	-0.352** (0.139)		
Judge Occupancy			-0.00278** (0.000945)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.96	-0.374	0.96	
Wald F-Stat (First Stage)				21.62
Panel C: Manufacturing Loans				
Log Disposal	-0.009 (0.0275)	-0.243** (0.111)		
Judge Occupancy			-0.00192** (0.0008)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.97	-0.27	0.97	
Wald F-Stat				21.62
Panel D: Personal Loans				
Log Disposal	0.0288*** (0.009)	0.0365 (0.038)		
Judge Occupancy			0.00029 (0.0003)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.987	-0.052	0.987	
Wald F-Stat				21.65
Panel E: Agriculture Loans				
Log Disposal	0.00036 (0.0086)	0.057 (0.048)		
Judge Occupancy			0.00045 (0.00037)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.98	-0.105	0.97	
Wald F-Stat				21.65

Standard errors in parentheses

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

Notes: Results presented in this table report on total outstanding loan amount aggregated at the district-level at time $t + 1$. The panels report by specific sub-sample of analysis, with Panel A reporting all outstanding loans across all banks within a district. Panel B examines outstanding loans for public sector banks, which form a large share of the banking system. Panels C-E report by sector of loan allocation. All specifications include district and state-year fixed effects. Standard errors are clustered at the district-year level.

Table V: Potential defaulters' litigation behavior

	Ever Litigate (Among Defaulters)	Litigate this year (Among Defaulters)
Small Firms x Judge Occupancy		0.0000625 (0.000385)
Judge Occupancy		-0.000788** (0.000349)
Small Firms	-0.120*** (0.0156)	-0.0415 (0.0346)
Observations	18536	5992
Adj R-Squared	0.293	0.093

Standard errors in parentheses

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

Notes: Dependent variable in Column 1 is a binary variable, coded as 1 if a firm has ever appeared as a respondent/defendant in the trial microdata. Dependent variable in Column 2 is a binary variable coded as 1 for each year in the sample dataset if a litigating firm appeared as a respondent in a case registered that year. Small firm is coded as 1 if the firm is below median in the distribution of asset sizes of all firms before 2010. The sample is restricted to the set of "potential" defaulters among firms, determined using their history of credit rating. All specifications include district and state-year fixed effects. Standard errors are clustered by district-year.

Table VI: Firms' production outcomes

	Asinh Δ Borrowing	Asinh Δ Interest	Asinh Sales	Asinh Profit	Asinh Wage Bill	Asinh Plants-Machinery
OLS	0.173 (0.113)	0.0484 (0.039)	0.0457* (0.0241)	0.0827 (0.0589)	0.0386** (0.0177)	-0.0156 (0.019)
IV	-0.92** (0.44)	-0.217 (0.15)	0.181 (0.113)	0.655** (0.318)	0.265** (0.111)	-0.224** (0.112)
RF	-0.0163** (0.0071)	-0.0041 (0.0027)	0.00257 (0.00158)	0.0096** (0.00388)	0.0037** (0.00133)	-0.0032** (0.00132)
FS	0.0178*** (0.0033)	0.0187*** (0.0034)	0.0142*** (0.004)	0.0146*** (0.004)	0.014*** (0.004)	0.0144*** (0.004)
Observations	7907	7696	20133	21055	20139	17845
Adj R-Squared	0.019	0.036	0.137	0.046	0.19	0.19
K-P Wald F-Stat	29.35	29.84	12.64	13.38	12.26	12.77

Standard errors in parentheses

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

Notes: This table reports results from specification in [Equation 3](#). Credit and production variables lead the explanatory variable by 1 and 2 years, respectively. The regressions include district and state year fixed effects. Additional controls include firm age, age-squared, and sectoral dummies. The sample of firms include all those that were incorporated before 2010, excluding the financial sector firms. All standard errors are clustered at the district-year level.

Table VII: Firms' production outcomes - Heterogenous effects

Panel A: By Asset Size		Asinh Δ Borrowing	Asinh Δ Interest	Asinh Sales	Asinh Profit	Asinh Wage Bill	Asinh Plants-Machinery
Small Firm x Judge Vacancy		-0.00282 (0.00726)	-0.00459 (0.00363)	-0.00414 (0.00375)	0.00081 (0.00494)	0.000911 (0.00285)	0.0031 (0.00331)
Percent Judge Occupancy		-0.0154** (0.0076)	-0.00307 (0.00283)	0.00374** (0.00168)	0.0093** (0.00432)	0.0034** (0.00141)	-0.00386** (0.00160)
Small Firm		0.4 (0.637)	0.29 (0.323)	-2.17*** (0.338)	-0.801* (0.445)	-2.228*** (0.262)	-2.755*** (0.304)
Observations		7907	7696	20133	21055	20139	17845
Adj R-Squared		0.019	0.037	0.31	0.05	0.34	0.34
Panel B: By Credit Rating		Asinh Δ Borrowing	Asinh Δ Interest	Asinh Sales	Asinh Profit	Asinh Wage Bill	Asinh Plants-Machinery
High Credit Rating x Judge Vacancy		0.0285 (0.0182)	0.00766 (0.00484)	-0.00355 (0.00421)	-0.00734 (0.0164)	0.00718* (0.00368)	0.00317 (0.00428)
Percent Judge Occupancy		-0.0709*** (0.0188)	-0.0105* (0.00541)	0.0031 (0.00349)	0.0212 (0.0153)	-0.00486 (0.00297)	-0.00466 (0.00368)
High Credit Rating		-2.208 (1.563)	-0.437 (0.424)	1.459*** (0.368)	2.24 (1.439)	0.672** (0.338)	0.874** (0.380)
Observations		2468	2522	5343	5392	5326	5188
Adj R-Squared		0.025	0.061	0.15	0.09	0.26	0.20
Standard errors in parentheses							
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$							

Notes: Credit and production variables lead the explanatory variable by 1 and 2 years, respectively. The regressions include district and state year fixed effects. Additional controls include firm age, age-squared, and sectoral dummies. The sample of firms include all those that were incorporated before 2010, excluding the financial sector firms. All standard errors are clustered at the district-year level.

Table VIII: Balanced panel of firms

	Asinh Δ Borrowing	Asinh Δ Interest	Asinh Sales	Asinh Profit	Asinh Wage Bill	Asinh Plants-Machinery
Panel A: Balanced Panel						
Percent Judge Occupancy	-0.00842** (0.00342)	0.00091 (0.0017)	-0.004 (0.003)	-0.00041 (0.0048)	-0.0047** (0.0023)	-0.00774** (0.0029)
Panel B: By Asset Size						
Small Firm x Judge Vacancy	-0.0033 (0.0021)	-0.00123 (0.00133)	-0.0686*** (0.0048)	-0.0201*** (0.00386)	-0.0552*** (0.0038)	-0.071*** (0.0044)
Percent Judge Occupancy	-0.0073** (0.0036)	0.00133 (0.00178)	0.0192*** (0.00346)	0.0064 (0.0051)	0.014*** (0.0026)	0.0164*** (0.0033)
P-val $\delta_1^s + \delta_2^s = 0$	0.002	0.96	0.00	0.007	0.00	0.00
Panel C: By Credit Rating						
High Credit Rating x Judge Vacancy	0.00485 (0.003)	0.00154 (0.00154)	0.0569*** (0.0057)	0.0297*** (0.0055)	0.047*** (0.0046)	0.064*** (0.0056)
Percent Judge Occupancy	-0.01** (0.0034)	0.00041 (0.0017)	-0.0226*** (0.00346)	-0.01** (0.005)	-0.02*** (0.0027)	-0.0286*** (0.0033)
P-val $\delta_1^{cr} + \delta_2^{cr} = 0$	0.24	0.33	0.00	0.002	0.00	0.00
Firm Fixed Effect	X	X	X	X	X	X
Observations	11424	11424	11424	11424	11424	11424
No. Firms	1278	1278	1278	1278	1278	1278
Adj R-Squared	0.018	-0.03	0.77	0.34	0.77	0.77

Standard errors in parentheses

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

Notes: Credit and production variables lead the explanatory variable by 1 and 2 years, respectively. The regressions include firm, district and state year fixed effects. The sample of firms include all those reporting every year across 2010-2018 period. Missing values imputed as 0s only for this table. All standard errors are clustered at the district-year level.

Table IX: Effect of exogenous increase in borrowing on firms' production

	Asinh Borrowing	Asinh Sales	Asinh Profit	Asinh Wage Bill	Asinh Plant Value
Bank Shock (t)	0.102* (0.054)				
Judge Occupancy (t)	-0.0016 (0.0025)	0.004 (0.003)	0.00898 (0.0112)	0.00423 (0.0026)	-0.000343 (0.0043)
Asinh Borrowing (t+1)		0.83 (0.54)	-0.075 (2.38)	0.555 (0.396)	0.997* (0.598)
Observations	10605	7792	7992	7775	7439
Adj R-Squared	0.13	0.0064	- 0.11	0.24	0.26
F-Stat	69.76				
Standard errors in parentheses					
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$					

Notes: The table report estimates from 2SLS estimation on the set of firms with reported borrowing data, instrumenting endogenous borrowing with bank shock. Credit and production variables lead the explanatory variable by 1 and 2 years, respectively. The regressions include district and state year fixed effects. Additional controls include firm age, age-squared, and sectoral dummies. The sample of firms include all those that were incorporated before 2010. All standard errors are clustered at the district-year level.

Table X: Cost-benefit calculation

Parameter	Value	Units	Source
IQR Profit	(-9.9, 51.5)	Million USD	Prowess
IQR Wage bill	(6.4,158.5)	Million USD	Prowess
Profit ϵ	$0.96 \times 7.2 = 6.9$	% change per judge	Estimation
Wage Bill ϵ	$0.37 \times 7.2 = 2.66$	% change per judge	Estimation
25 th pctile Firm Δ Profit	$\frac{6.9}{100} \times 9.9 = 0.68$	Million USD	Calculation
75 th pctile Firm Δ Profit	$\frac{6.9}{100} \times 51.5 = 3.56$	Million USD	Calculation
25 th pctile Firm Δ Wage Bill	$\frac{2.66}{100} \times 6.4 = 0.17$	Million USD	Calculation
75 th pctile Firm Δ Wage Bill	$\frac{2.66}{100} \times 158.5 = 4.22$	Million USD	Calculation
Corporate Tax Rate	15	Percent	Govt. of India
Income Tax Rate	7.3	Percent	LiveMint
Discount Rate	10	Percent	Assumption
Annual Judge Salary + Other costs	0.035	Million USD	Personal Interviews
Range of benefit-cost	$\frac{\frac{0.17+0.68}{1.1^2}}{0.035} \approx 20$	Ratio	Calculation
(Social)	$\frac{\frac{3.56+4.22}{1.1^2}}{0.035} \approx 184$		
Range of benefit-cost	$\frac{(0.073 \times 0.17) + (0.15 \times 0.68)}{0.035} \approx 2.7$	Ratio	Calculation
(Tax Revenue)	$\frac{(0.073 \times 4.22) + (0.15 \times 3.56)}{0.035} \approx 20$		

Notes: Adding one judge in a court with average judge strength of 18 positions (average court size in the sample) with 23% vacancy translates to a 7.2 percentage point increase in judge occupancy. I multiply the reduced form estimates with 7.2 to obtain the corresponding elasticities with respect to adding one more judge, assuming constant elasticity. I calculate average income tax incidence on salaried individual tax payer using average reported annual income of INR 690,000 and the applicable progressive tax slab on this reported income: income upto INR 500,000 is exempt and the remaining INR 190,000 is taxed at 20%. This gives an average tax incidence of 7.3%. Corporate tax rate of 15% is the lowest rate applicable on reported corporate income for new manufacturing units. I discount the benefits that occur with a lag of 2 years to present value to enable comparability of benefits with costs that would be incurred in the present.

Supplementary Appendix for “COURTS REDUX: MICRO-EVIDENCE FROM INDIA” For Online Publication Only

A.I Data Appendix

A.I.A. Representativeness of district courts sample

[Figure A.13](#) illustrates the sample districts covered in the dataset. While firms in the sample districts are three years older than the average firm in the excluded districts, publicly listed as well as privately held limited liability firms are similarly represented in the sample districts. Additionally, firms in banking and manufacturing sector are also similarly represented. Since the focus is non-metropolitan districts, firms common in metro areas such as those owned by government and business groups are less represented. [Table A.5](#) in the appendix provides the details on the distribution of firm types across sample and excluded districts.

Since the e-courts system came into full operation from 2010, I consider 2010-2018 - which is the entire period over which the trial data is available - as the period of study. This gives me the population (universe) of all trials that were active anytime between these years - either pending from before 2010, or filed between 2010 and 2018.¹

A.I.B. Other complementary datasets

I use population census data, district-wise annual crime data for balance checks, and consumer price indices to convert the financial variables in real terms.²

A.I.C. Outcome variables

Intermediate outcomes: Borrowing/Lending These variables depict the intermediate steps linking court capacity to credit markets.

¹Scraping resources and funding constraints limited assembling the dataset for the entire country. Even though some districts had started digitization of court records from before 2010, almost all districts with functioning District and Session Courts were incorporated into the e-courts program by 2010. Therefore, the sample for this study was selected from the set of districts that were already digitized, which covered most of the country with possible exceptions of few, very remote districts.

²All data used here, with the exception of Prowess, are publicly available. District wise credit data are available through the Reserve Bank of India [data warehouse](#). National Crime Records Bureau annual crime statistics available on their [website](#).

1. Bank Lending: Bank lending variables are obtained from RBI data on district wise number of loan accounts and total outstanding loan amount (in INR Crore) annually aggregated across 27 scheduled commercial banks (national level banks).
2. Total Bank Borrowings: Long term (over 12 months) borrowings (in INR million) from banks by non-financial firms reported in Prowess data.

Impact variables: Following variables represent inputs, production, and value addition mapping onto firm’s production decisions.

1. Annual revenue from sales: This variable captures income earned from the sales of goods and non-financial services, inclusive of taxes, but does not include income from financial instruments/services rendered. This reflects the main income for non-financial companies.
2. Accounting profits (income net of expenditure): I generate this variable by subtracting total expenditure reported by the firm from total reported income.
3. Wage bill: This captures total payments made by the firm to all its employees, either in cash or kind. This includes salaries/wages, social security contributions, bonuses, pension, etc.
4. Net value of plants and machinery: This incorporates reported value of plants and machinery used in production net of depreciation/wear and tear.

A.I.D. Matching firms with trial data

I follow the steps below to match firms with registered cases in the e-courts database:

1. Identify the set of cases involving firms on either sides of the litigation (i.e. either as a plaintiff/petitioner, or as a defendant/respondent, or as both) using specific naming conventions followed by firms. Common patterns include firm names starting with variants of “M/S”, ending with variants if “Ltd”, and so on. This produces about 1.2 million cases, or 20% of the universe of cases.
2. Create a set of unique firms appearing in above subset of case data. I note that same firm appears as a litigant in more than one district. This is because the procedural laws pertaining to civil and criminal procedures determine where a specific litigation can be filed based on the issue under litigation.

3. Map firm names as they appear in the case data in step 2 with firm names as they appear in Prowess dataset using common patterns with the aid of regular expressions. This takes care of extra spaces, punctuation marks, as well as common spelling errors such as interchanging of vowels. Further, I also account for abbreviations. For example, "State Bank of India" appears in the case dataset as "State Bank of India", "SBI", "S.B.I", and similar variants. I map all these different spellings to the same entity "State Bank of India".
4. Remove matches where firm names are used as landmark in the addresses of litigants. To do this, I detect prefix words such as "opposite to", "above", "below", "near", and "behind" followed by a firm name.
5. Create primary key as the standardized name, from step 3 to match with both case as well as firm datasets.
6. When more than one firm match with a case, that is when there are multiple entities involved as either petitioners or respondents, I select one matched firm at random. These many-to-one matches are about 5% of the matches.

A.II District judge assignment policy

The procedure for judge rotation is decided and implemented by the corresponding state High Court administrative committee. Specifically, the assignment process is based on serial dictatorship mechanism by seniority that is uniform across the country, detailed as follows:

1. District court judges are senior law professionals. Judges are either directly recruited from the bar council or through a competitive exam subject to a minimum number of years of legal experience.
2. At the beginning of each year, the High Court committee creates a list of all judges completing their tenures (i.e. 1 - 2 years) in their current seat.
3. Each district judge is asked to list 3-4 rank-ordered locations for their next posting.
4. This should exclude their home and past served districts (in any capacity as a legal professional).
5. The judges are then matched to a district court based on this ranking, taking into consideration others' preferences, vacancies, and seniority.

A.III A model of credit market with enforcement costs

A.III.A. Credit Market

I follow and extend the credit contract model in [Banerjee and Duflo \(2010\)](#) to include the possibility of litigation given the rate of trial resolution in the corresponding local court. Specifically, I consider a lender-borrower sequential game with lender's choice to enforce debt contract through litigation. This is similar to the role of social sanctions in the group liability model discussed in [Besley and Coate \(1995\)](#). The solution to the game provides an optimal contract that details the interest rate schedule and a wealth threshold for borrowing.

At the start, borrower needs to invest, K , in a project which returns $f(K)$. Her exogenous wealth endowment is W . She needs an additional $K_B = K - K_M$ from the lender to start the project, where K_M is the amount she raises from the market. The lender earns a return $R > 1$ if the borrower repays on time. The project succeeds with probability s , upon which the borrower decides to repay or evade. Evasion is costly as the borrower incurs an evasion cost ηK_B leading to a payoff $f(K) - \eta K_B$. The lender loses the entire principal, $-K_B$. Repayment results in $f(K) - RK_B$ as payoff to the borrower and the lender earns RK_B . On the other hand, the borrower automatically defaults if her project fails, in which case the lender can choose to litigate to monetize borrower's assets to recover their loan. The game is depicted in [Figure A.14](#). Litigation is costly and lender incurs a cost, $C_L(\gamma) > 0$, $\frac{\partial C_L}{\partial \gamma} < 0$, as a function of judicial capacity, γ . The borrower can also choose to litigate with costs, $C_B(\gamma) > 0$, $\frac{\partial C_B}{\partial \gamma} < 0$, or settle out of court. Once the lender chooses to litigate and borrower accepts, lender mostly win as seen in the data. The intuition behind this relationship behind litigation costs and judicial capacity can be explained by the fact that the litigants need to spend more on travel, logistics, and lawyer fees if the trial takes a long time to be resolved.³

When her project fails, the borrower litigates only if the value of her assets net litigation costs is positive. At the same time, the lender seeks to liquidate part of borrower's assets, δW , to recover the loan, where δ is the depreciation rate. Lender earns a payoff of $\Gamma \delta W - C_L(\gamma)$ under litigation, where $\Gamma < 1$ is the fraction of the disputed amount that the court is able to help recover. The borrower earns a payoff $\Gamma \delta W - E[C_B(\gamma)]$, where her litigation costs $C_B(\gamma)$ is unknown ex-ante. Therefore, the condition for the borrower to accept litigation instead of opting to settle, given project failure, is

$$(1) \quad \Gamma \delta W - E[C_B(\gamma)] > -\delta W \implies W > \frac{E[C_B(\gamma)]}{(1 - \Gamma)\delta} = \tilde{W}$$

³Introducing a probability of winning, $p \gg 1-p$ does not add much to the exposition and for tractability, I skip this stochastic component. [Sadka et al. \(2018\)](#) notes overconfidence among individual litigants that supports the idea why borrowers continue to litigate when decisions typically favor the lender.

This gives a distribution of borrowers, $1 - F(\tilde{W})$, likely to litigate, where $F(\cdot)$ is the distribution of firms by their ex-ante wealth endowment. Using backward induction, litigation under project failure would be the lender's dominant strategy if

$$(2) \quad \begin{aligned} & (1 - F(\tilde{W}))(\Gamma\delta W - C_L(\gamma)) + F(\tilde{W})\delta W > -K_B \\ \implies & W > \frac{(1 - F(\tilde{W}))C_L(\gamma) - K_B}{((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta} = W^* \end{aligned}$$

This gives a minimum wealth threshold, W^* , for lending. Under project success, the borrower can choose to default if she can successfully evade. However, default gives rise to the possibility of litigation. In this situation, borrower will litigate if

$$(3) \quad \begin{aligned} & f(K) - \Gamma RK_B - E[C_B(\gamma)] > f(K) - RK_B \\ \implies & RK_B > \frac{E[C_B(\gamma)]}{(1 - \Gamma)} = \delta\tilde{W} \end{aligned}$$

This gives a distribution of firms willing to litigate under default. Since K_B only depends on the project, with an ex-ante distribution given by CDF, $G(\cdot)$, and R is fixed by the lender, a fraction $1 - G(\tilde{W})$ of borrowers will litigate. Therefore, by backward induction, litigation will be lender's weakly dominant strategy if

$$(4) \quad \begin{aligned} & (1 - G(\tilde{W}))(\Gamma RK_B - C_L(\gamma)) + G(\tilde{W})RK_B \geq -K_B \\ \implies & R \geq \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} \end{aligned}$$

The possibility of default and costly litigation makes the lender account for these costs in the credit contract, by including a wealth threshold for borrowing, W^* and setting the interest rate schedule. The returns from lending to ensure adequate recovery of loan under default gives the following schedule:

$$(5) \quad R = \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B}$$

The contract design thus generates a set of borrowers that will $\{default, litigate\}$ and another set that will either $\{default, settle\}$ or $\{repay\}$ based on their ex-ante wealth and project size. Finally, lender's participation constraint is given by

$$(6) \quad \begin{aligned} & s \left(G(\tilde{W})RK_B + (1 - G(\tilde{W}))(\Gamma RK_B - C_L(\gamma)) \right) + \\ & (1 - s) \left((1 - F(\tilde{W}))(\Gamma\delta W - C_L(\gamma)) + F(\tilde{W})\delta W \right) \geq \phi K_B \end{aligned}$$

The timing of the game where the lender and borrower decide on their strategies are depicted as an extensive form game in [Figure A.14](#).

Proposition 1: Litigation response from borrower As judicial capacity, γ , increases, the wealth threshold for litigation decreases. That is, $\frac{\partial \tilde{W}}{\partial \gamma} < 0$.

Proof for Proposition 1: Differentiating (1) with respect to γ gives $\frac{\partial \tilde{W}}{\partial \gamma} \propto \frac{\partial C_B(\gamma)}{\partial \gamma} < 0$.

Constraints (2) and (5) define the credit contract. Additionally $R \geq \phi$ else the lender would rather invest in external markets than engaging in lending. This gives the relationship between returns, R , borrowing, K_B , and the threshold wealth, W^* required to borrow, as depicted in [Figure A.15](#).

Proposition 2: Credit market response to judicial capacity As judicial capacity, γ , increases, the credit market response varies as follows:

1. Effect on W^* is negative. That is, an increase in judicial capacity lowers the threshold of wealth required for lending.
2. Effect on R is negative for each level of borrowing. That is, the interest curve shifts inward.
3. Borrowing becomes cheaper, which expands total borrowing, particularly at lower levels of wealth W .

Proof for Proposition 2: Differentiating (2) and (5) with respect to γ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as below. For the distribution functions, I assume $g(\tilde{W}), f(\tilde{W}) \rightarrow 0$ since only large firms engage in litigation.

$$\begin{aligned}
\frac{\partial R}{\partial \gamma} &= \frac{\overbrace{\frac{\partial C_L(\gamma)}{\partial \gamma}}^{-ve} \overbrace{(1 - G(\tilde{W}) - C_B g(\tilde{W}))}^{+ve}}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} - \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{(((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B)^2} \left(\overbrace{g(\tilde{W}) \frac{\partial C_B}{\partial \gamma} (K_B - \Gamma)}^{\approx 0} \right) \\
\Rightarrow \frac{\partial R}{\partial \gamma} &< 0 \\
\frac{\partial W^*}{\partial \gamma} &= \frac{\overbrace{(1 - F(\tilde{W})) \frac{\partial C_L}{\partial \gamma} - C_L f(\tilde{W}) \frac{\partial C_B}{\partial \gamma}}^{-ve}}{((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta} - \frac{(1 - F(\tilde{W}))C_L(\gamma) - K_B}{(((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta)^2} \underbrace{f(\tilde{W}) \frac{\partial C_B}{\partial \gamma} (\delta - \Gamma)}_{\approx 0} \\
\Rightarrow \frac{\partial W^*}{\partial \gamma} &< 0
\end{aligned}$$

A.III.B. Firm Production

Consider a representative firm with production function $Q = Q(X_1, X_2)$ where $Q(\cdot)$ is twice differentiable, quasi-concave, and cross partials $Q_{X_1 X_2} = Q_{X_2 X_1} \geq 0$. Further assume that the firm is a price taker. The firm's problem is to maximize their profits as follows:

$$(7) \quad \text{Max}_{X_1, X_2} (\Pi = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - \phi m_i(\gamma))$$

$$s.t \ w_1X_1 + w_2X_2 + \phi m(\gamma) \leq K_i(\gamma) \ i \in \{S, L\}$$

where w_1 and w_2 are the unit costs of inputs X_1 and X_2 , $m_i(\gamma)$ is the monitoring costs arising in the production process, which weakly decreases with improvements in judicial capacity, i.e. $\frac{\partial m_i}{\partial \gamma} \leq 0$. i represents firm size based on their initial wealth endowment, denoted by S for small firms and by L for large ones. Further, I assume that fixed costs form a large share of monitoring costs for small firms such that $\frac{\partial m_S}{\partial \gamma} \approx 0$ whereas for large firms, $\frac{\partial m_L}{\partial \gamma} < 0$ reflecting a lowering of the variable cost. $K_i = K_M + K_B$, is the total capital available to finance production, including borrowing from bank K_B as in [Banerjee and Duflo \(2014\)](#). From the credit market model below, we know that as judicial capacity, γ , improves, banks begin to lend to smaller firms and the overall interest rate on bank lending, $R(\gamma, \cdot)$ drops.

Proposition 3: Effects of judicial capacity on firm production As judicial capacity, γ , increases, the firm responds as follows:

1. Optimal input use X_1, X_2 increases on an average.
2. Output and profits increase on an average.
3. Heterogeneity in effects are as follows:
 - (a) For large firms, L , optimal inputs and profits increase if decrease in monitoring costs and cheaper credit more than offsets the increase in input expenditure.
 - (b) For marginal small firms, S , optimal inputs and profits increase if increase in borrowing is sufficiently large to offset the increase in input expenditure.
 - (c) For inframarginal small firms, S , optimal inputs and profits remain unchanged because borrowing and monitoring costs for these firms remain unchanged.

Proof for Proposition 3: From the credit model, borrowing increases with an increase in judicial capacity i.e. $\frac{\partial K_i}{\partial \gamma} > 0$ for the marginal borrowers, i.e. those with $W \approx W^* - \epsilon$, with $\epsilon > 0$, a small positive real number.

Constrained Optimization:

$$\mathcal{L} = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - m_i(\gamma) + \lambda(K_i - w_1X_1 - w_2X_2 - m_i(\gamma))$$

FOC:

$$\frac{\partial \mathcal{L}}{\partial X_1} = pQ_{x_1} - w_1 - w_1\lambda = 0$$

$$\frac{\partial \mathcal{L}}{\partial X_2} = pQ_{x_2} - w_2 - w_2\lambda = 0$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = K_i - w_1X_1 - w_2X_2 - m_i(\gamma) = 0$$

To examine how the optimal production choices vary with exogenous variation in the institutional quality parameter, γ , I use Implicit Function Theorem where X_1, X_2, λ are endogenous variables and γ as the exogenous variable to the firm's problem. A key distinction arises based on whether the firm belongs to the group of small or large firms. For $i = S$ and $W \approx W^* - \epsilon$, $K_i = K_M + K_B$ when γ increases. For $i = L$, $\frac{\partial K_i}{\partial \gamma} = 0$. Applying Cramer's Rule:

$$\begin{aligned} Det[J] &= 2pw_1w_2 \underbrace{Q_{x_1x_2}}_{+ve} - p(\underbrace{w_2^2 Q_{x_1x_1}}_{-ve} + \underbrace{w_1^2 Q_{x_2x_2}}_{-ve}) > 0 \\ \frac{\partial X_1}{\partial \gamma} &= -\frac{Det[J_{x_1}]}{Det[J]} = -\frac{p(\overbrace{\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma}}^{+ve})(w_1 \underbrace{Q_{x_2x_2}}_{-ve} - w_2 \underbrace{Q_{x_1x_2}}_{+ve})}{Det[J]} > 0 \\ \frac{\partial X_2}{\partial \gamma} &= -\frac{Det[J_{x_2}]}{Det[J]} = -\frac{p(\overbrace{\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma}}^{+ve})(w_2 \underbrace{Q_{x_1x_1}}_{-ve} - w_1 \underbrace{Q_{x_2x_1}}_{+ve})}{Det[J]} > 0 \\ \frac{\partial \lambda}{\partial \gamma} &= -\frac{Det[J_\lambda]}{Det[J]} = -\frac{p^2(\overbrace{\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma}}^{+ve})(\overbrace{Q_{x_1x_1}Q_{x_2x_2} - Q_{x_2x_1}Q_{x_1x_2}}^{\text{depends on functional form}})}{Det[J]} = ? \end{aligned}$$

This implies that the optimal input choices increase for all firms with an improvement in contract enforcement through local courts. On the other hand, how the shadow value responds depends on the functional form of the underlying production function. For example, if the production function is Cobb Douglas, then $\frac{\partial \lambda}{\partial \gamma} = 0$.

Finally, an application of the envelope theorem enables examining how the value function changes with the exogenous court performance, γ :

$$\frac{dV(\gamma)}{d\gamma} = \frac{\partial \Pi^*}{\partial \gamma} + \lambda \frac{\partial g^*(\gamma)}{\partial \gamma} \text{ where } g(.) \text{ is the constraint}$$

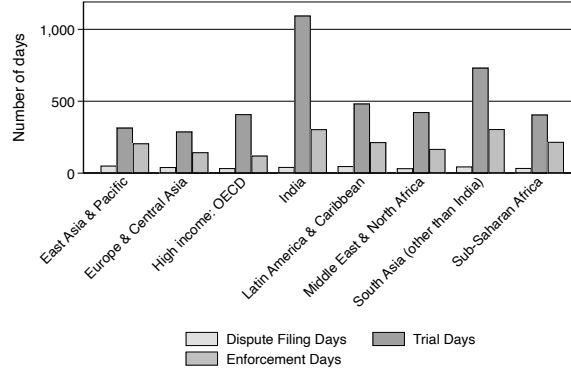
$$\begin{aligned}
\frac{\partial \Pi^*}{\partial \gamma} &= \underbrace{(pQ_{x_1} - w_1)}_{\text{This is } \lambda} \frac{\partial X_1^*}{\partial \gamma} + \underbrace{(pQ_{x_2} - w_2)}_{\text{This is } \lambda} \frac{\partial X_2^*}{\partial \gamma} - \underbrace{\frac{\partial m_i}{\partial \gamma}}_{\text{-ve}} > 0 \\
\frac{\partial g^*}{\partial \gamma} &= \underbrace{\left(\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma} \right)}_{\text{marginal benefit}} - \underbrace{\left(w_1 \frac{\partial X_1^*}{\partial \gamma} + w_2 \frac{\partial X_2^*}{\partial \gamma} \right)}_{\text{marginal cost}}
\end{aligned}$$

$\frac{\partial g^*}{\partial \gamma} > 0$ if marginal benefits from an improvement in judicial capacity exceeds marginal cost, in which case, welfare improves. If this is not true, then the welfare effect is potentially ambiguous. Heterogeneity based on firm size distribution imply:

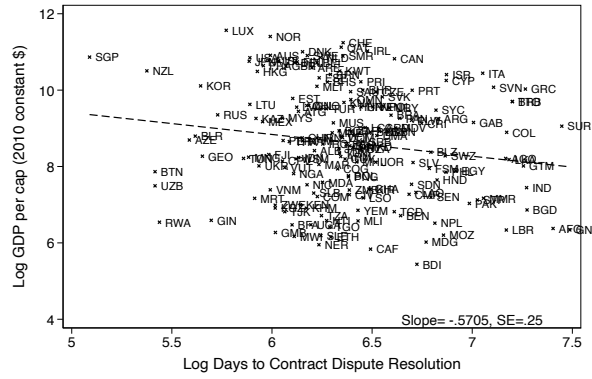
1. For large firms, $i = L$, the marginal benefit $0 - \frac{\partial m_L}{\partial \gamma}$ is mainly due to reduction in monitoring costs since there is no change in their borrowing from banks. If this reduction in monitoring costs is greater than the marginal increase in input costs, then profits for such firms will increase.
2. For marginal small firms, $i = S$ and $W \approx W^* - \epsilon$, the marginal benefit $K_B - \frac{\partial m_S}{\partial \gamma}$ is due to both availability of borrowing from banks K_B as well as a reduction in monitoring costs. I assume that the monitoring costs for small firms do not decrease substantially since a large share is fixed cost for these firms. If the increase in borrowing is large enough to offset the increase in input costs, then profits for such firms will increase.
3. For inframarginal small firms, $i = S$ and $W \ll W^*$, neither their optimal inputs nor their profits change since $\underbrace{\left(\frac{\partial K_S}{\partial \gamma} - \frac{\partial m_S}{\partial \gamma} \right)}_{\substack{=0 \\ \approx 0}} \approx 0$.

A.IV Appendix: Figures

Figure A.1: Cross-country comparison
Panel A



Panel B



Notes: Data source: Doing Business database, World Bank. The contract enforcement variable is calculated from the perspective of the court of first instance. In Panel A, the figure graphs time delays in filing, adjudication, and judgement enforcement concerning contractual disputes. In Panel B, variable on the x-axis measures the log transformation of trial duration and variable on the y-axis measures the log transformation of GDP per capita. Country codes are presented as value labels of the scatter plot.

Figure A.2: Construction of firm sample

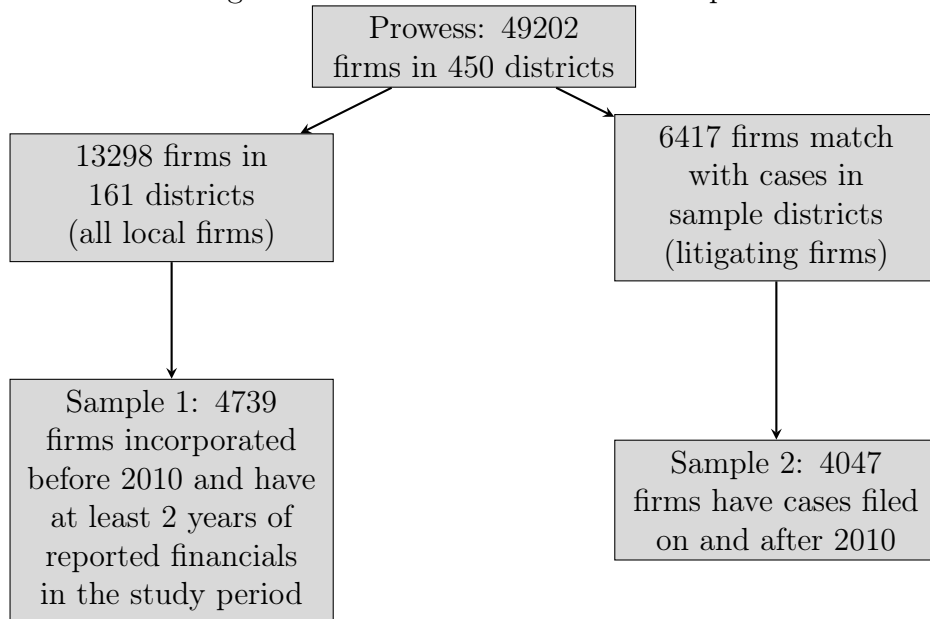
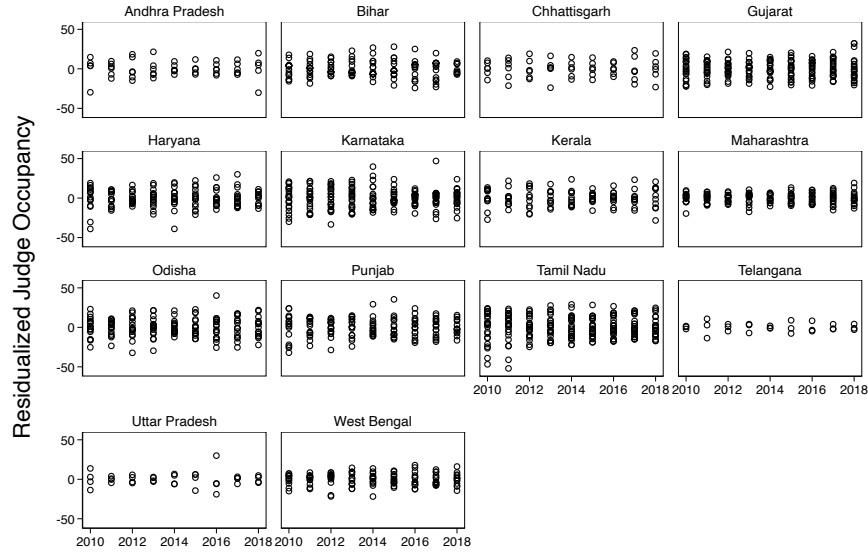
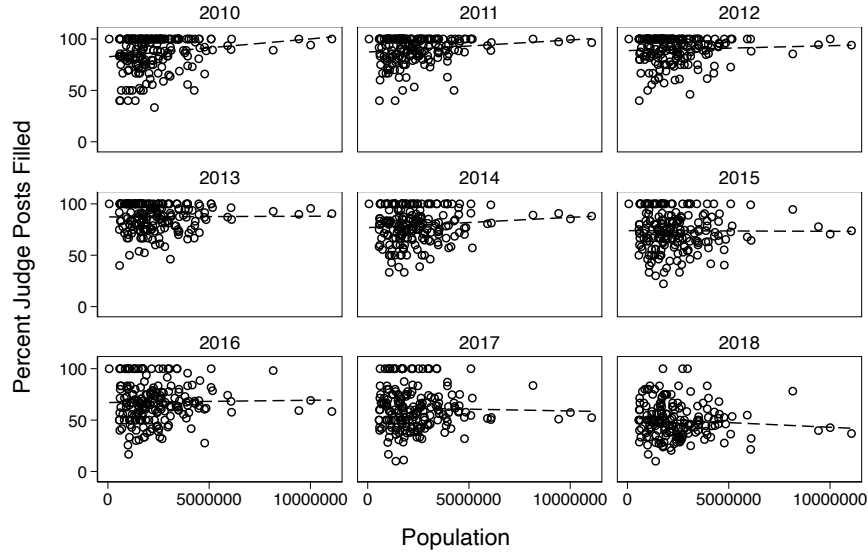


Figure A.3: Variation and exogeneity of judge occupancy
Panel A:



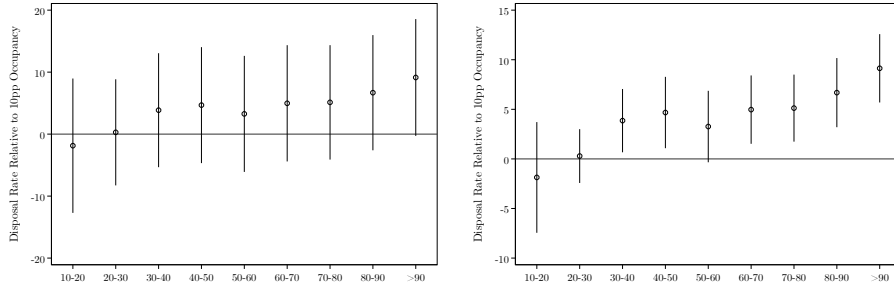
Panel B:



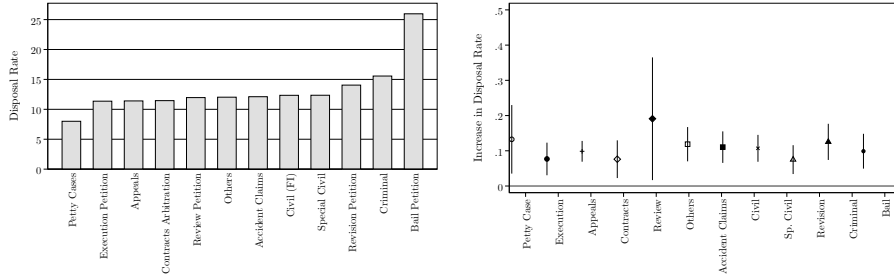
Notes: Panel A presents a scatter plot of the variation in judge occupancy, after netting out district and state-year fixed effects. Panel B plots raw judge occupancy against 2011 census population of the corresponding district over the entire study period.

Figure A.4: Heterogeneous effects of judge occupancy on disposal rate

Panel A: By Judge Occupancy Bins

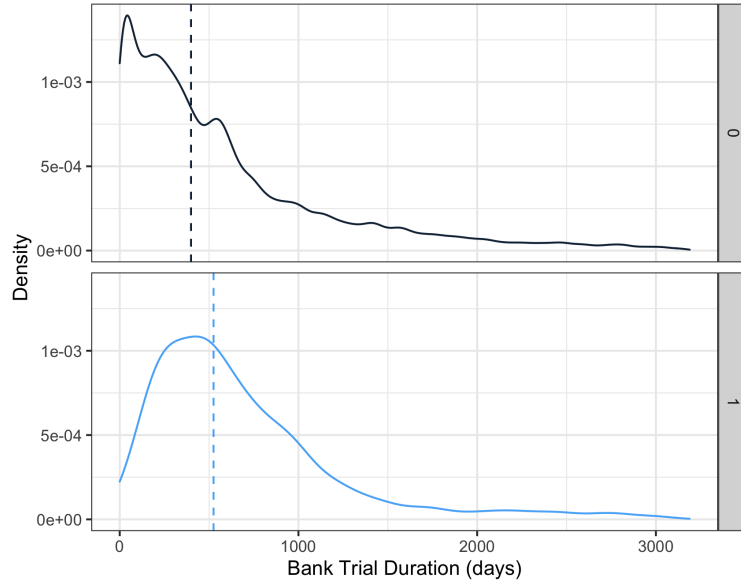


Panel B: By Case-Type



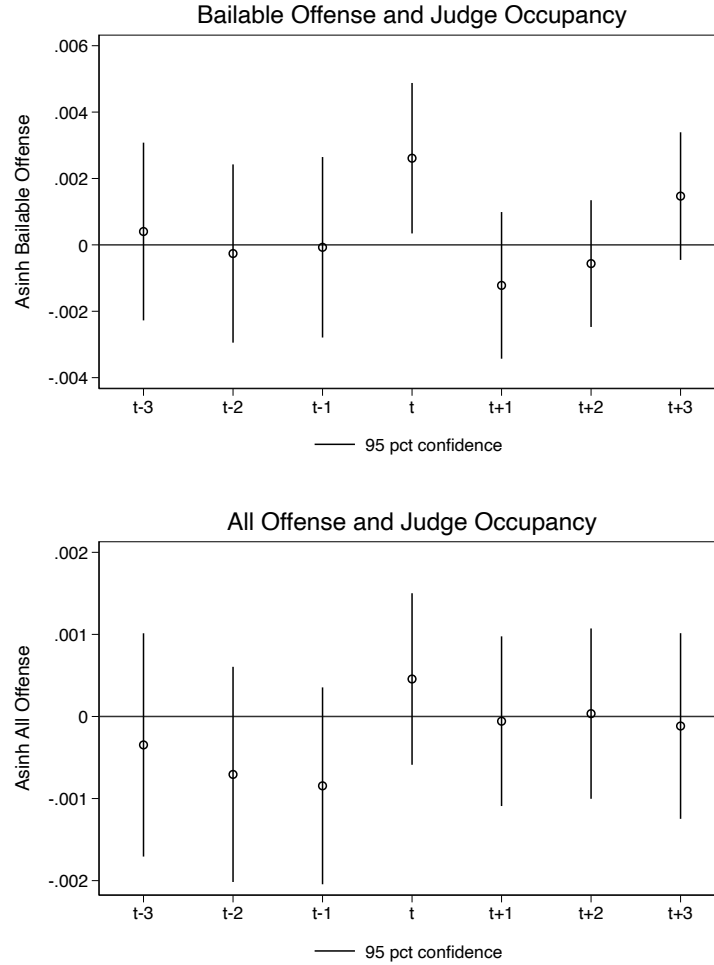
Notes: Panel A presents the regression coefficients on judge occupancy, binned by decile, with disposal rate as the dependent variable. The leave-out group is judge occupancy bin 0-10. Standard errors are clustered by district-year on the left and by district on the right. Panel B presents average disposal rate by case-type and the regression coefficient on judge occupancy by each of these case-types. Here, standard errors are clustered by district-year.

Figure A.5: Median trial duration involving banks increases with vacancy



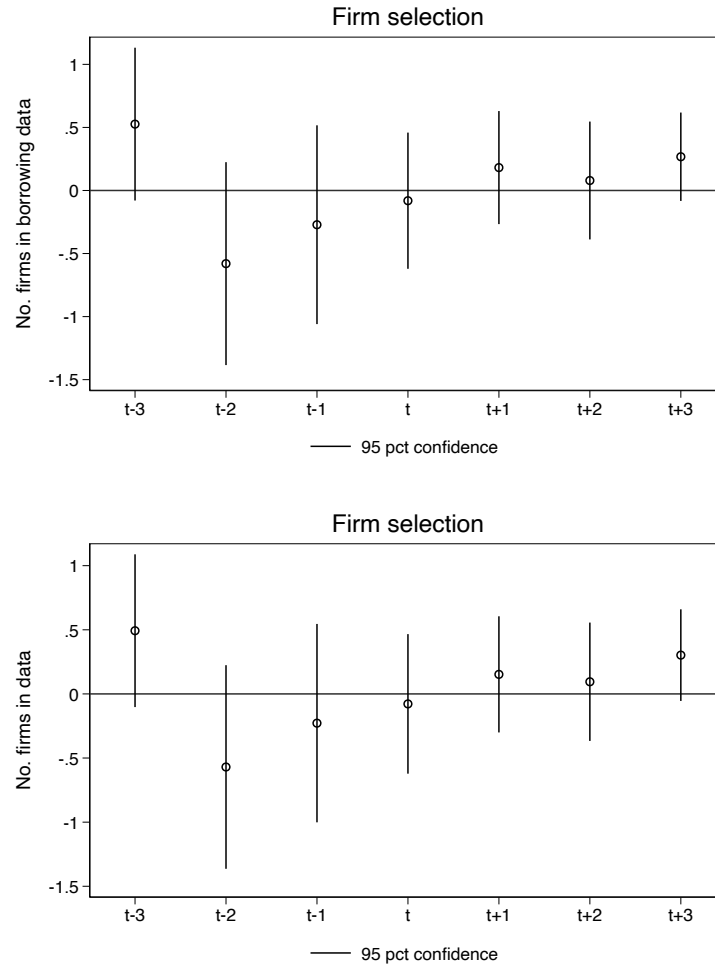
Notes: Above figure presents the density of trial duration for litigation involving banks by whether or not such a litigation experiences judge vacancy during its lifetime. The median duration of litigation encountering judge vacancy is 525 days compared to 399 days for those that do not, reflecting a 32% increase at the median. From the perspective of stuck capital, what fraction of trials are resolved in a year matters more for recovery.

Figure A.6: Banks also file criminal petition for debt recovery



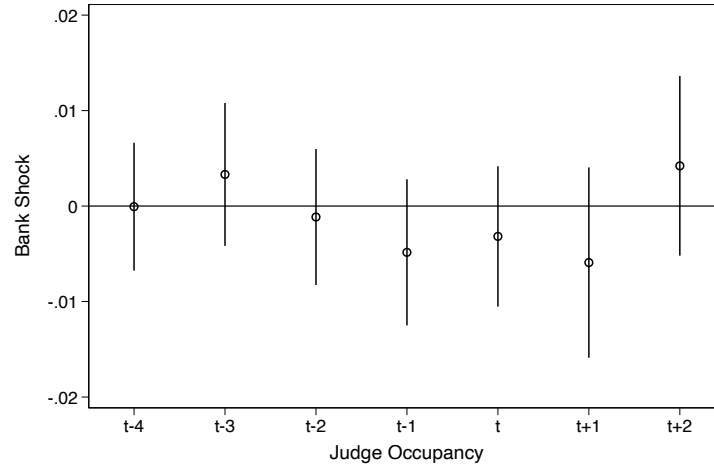
Notes: The graphs presents the effect of judge vacancy on bailable crime as well as all crime outcomes, respectively. Important bailable offenses include banks filing criminal petition when the debtor's check is dishonored citing insufficient balance in their checking account. This is a bailable criminal offense according to Sec 138 of the Negotiable Instruments Act. Anecdotal evidence from conversations with lawyers and bankers reveal that banks use the criminal provision under this specific law to incentivize timely debt repayment and/or expedite implementation of the execution order of previous judgement. The x-axis as before, represents the event-study time-line of the current period dependent variable relative to the leads and lags of judge occupancy. Standard errors are clustered at the district-year level.

Figure A.7: Firm attrition in Prowess data



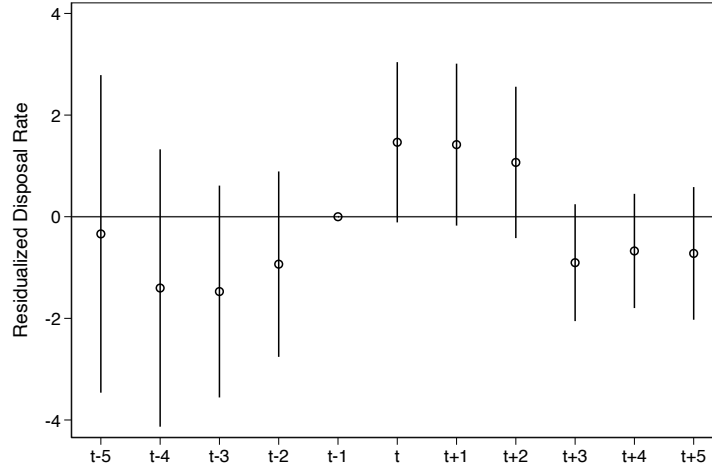
Notes: The graphs presents whether firms exhibit selective attrition based on judge vacancy. The x-axis as before, represents the event-study time-line of the current period dependent variable relative to the leads and lags of judge occupancy. Standard errors are clustered at the district-year level.

Figure A.8: Exogeneity of bank-shock instrument

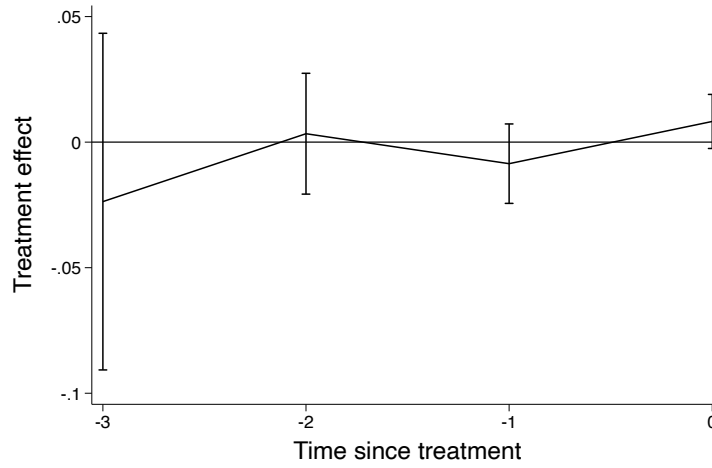


Notes: The graphs present the coefficients on leads and lags of judge occupancy variable with bank shock as the dependent variable. The x-axis presents the time difference between the year the dependent variable is measured and the year judge occupancy is measured. For example, the value at $t - 2$ presents the regression coefficient on judge occupancy two years prior to bank shock. Similarly, value at $t + 2$ presents the regression coefficient on judge occupancy two years post bank shock. All standard errors are clustered by district-year.

Figure A.9: First stage: Robustness
Panel A:

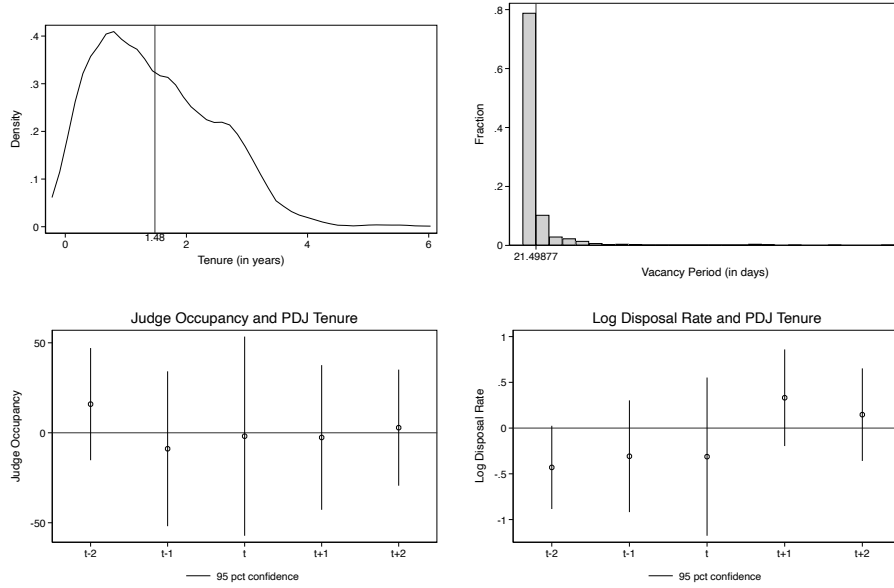


Panel B:



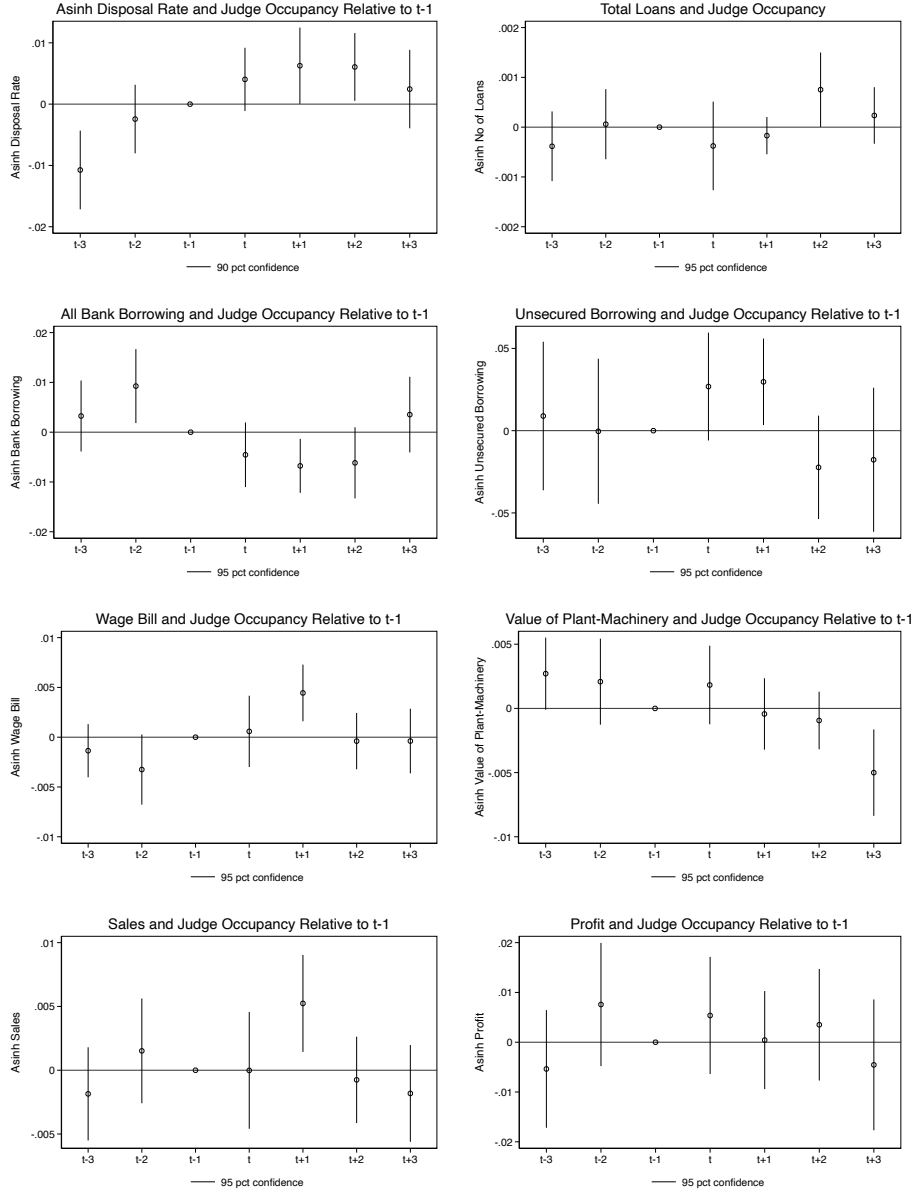
Notes: In Panel A, event year ($t = 0$) is defined as the calendar year where I observe 100 occupancy rate of district court judges. That is, the event year corresponds to the calendar year with maximum observed number of judges in a given court, that I use as the denominator in constructing judge occupancy. Panel B presents the estimation results from *DIDm* specification by [de Chaisemartin and D'Haultfœuille \(2020\)](#) that accounts for treatment effect heterogeneity. The procedure returns a coefficient 0.00823 on judge occupancy, which is statistical indistinguishable from the main estimate of 0.00978 in [Table II](#). Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure A.10: Judge tenure: An example of Principal District Judge



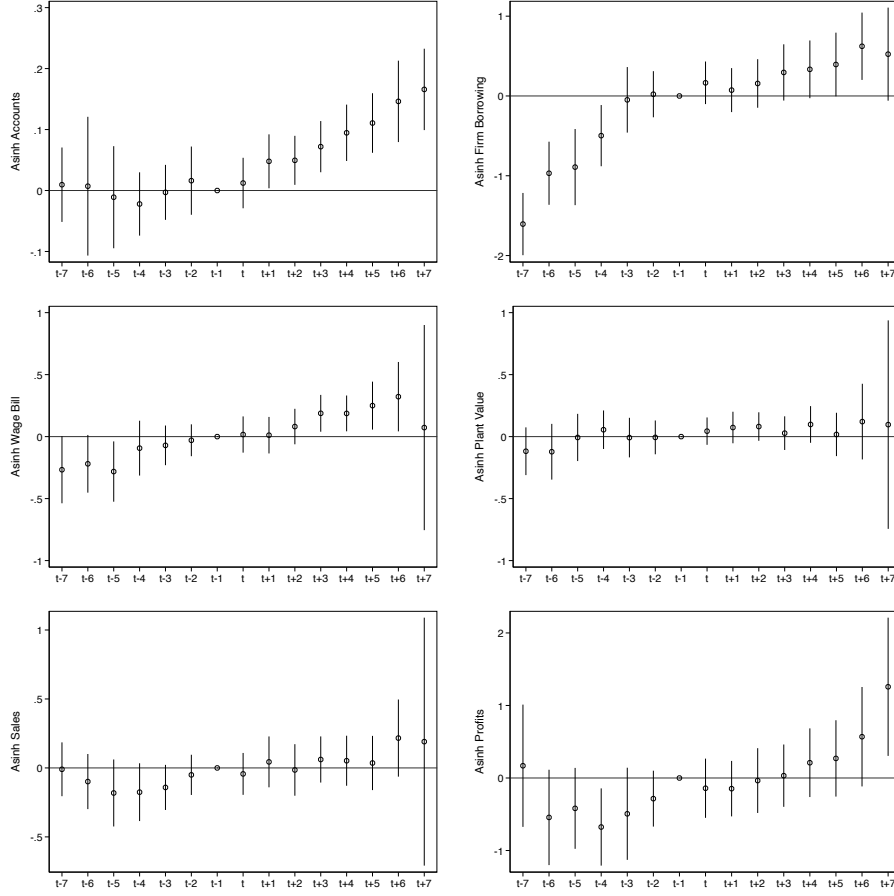
Notes: I use data on judge start date and end date in a given district court, available mainly for the Principal District Judge (PDJ) from a subset of the sample court websites displaying this information. Using this, I construct the tenure period, gap between the tenure of two consecutive judges for the same position, and measure correlations between tenure length and judge occupancy and log disposal rates, respectively. These graphs show that the average tenure of district court judges is short. Further, merging this with sample court data (resulting in 83 matched districts) shows that the tenure length is plausibly independent of court performance including overall judge occupancy and log disposal rate from the preceding periods. The x-axis of the event-study graphs using distributed lag model represents the time-line of the dependent variable relative to the leads and lags of the explanatory variables. Standard errors are clustered by district-year.

Figure A.11: Reduced form event study relative to $t - 1$



Notes: The figures present reduced form estimates relative to period $t - 1$ as in standard event study figures. Value of judge vacancy at period $t - 1$ is netted out of each period judge vacancy within the event window. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure A.12: Alternate identification: Event study estimates



Notes: The figures present event study estimates using the event of a positive judge shock, defined as the first occurrence of a 10% increase over previous year's judge occupancy, to identify the effects of judicial capacity on credit (no. bank loans in the district and amount borrowed by firms) and firm outcomes (value added, sales, wage bill, and value of plant, respectively). The event study specification is run on a dataset created by stacking datasets by each event date, such that only the treated group as per the given event and pure control (i.e. untreated as of that event data) are present in each of the event specific dataset. This follows methodology as in [Cengiz et al. \(2019\)](#). Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure A.13: Sample district courts

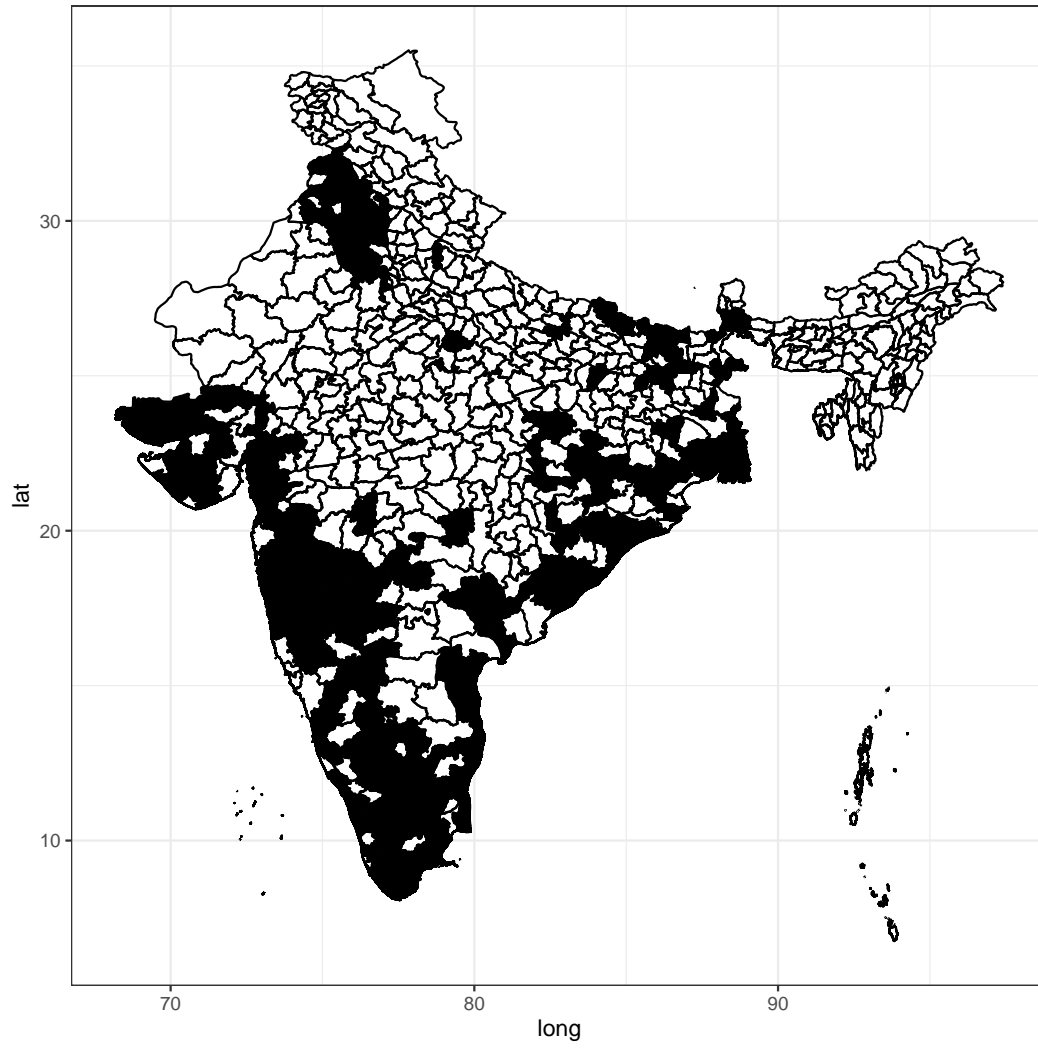


Figure A.14: Model: Lender-borrower game

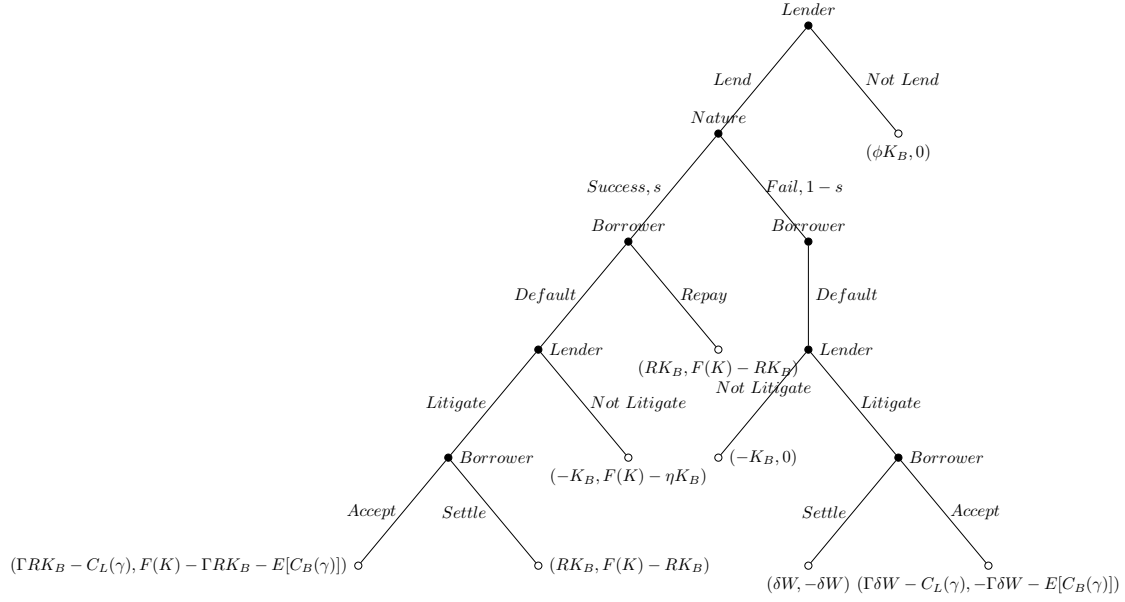
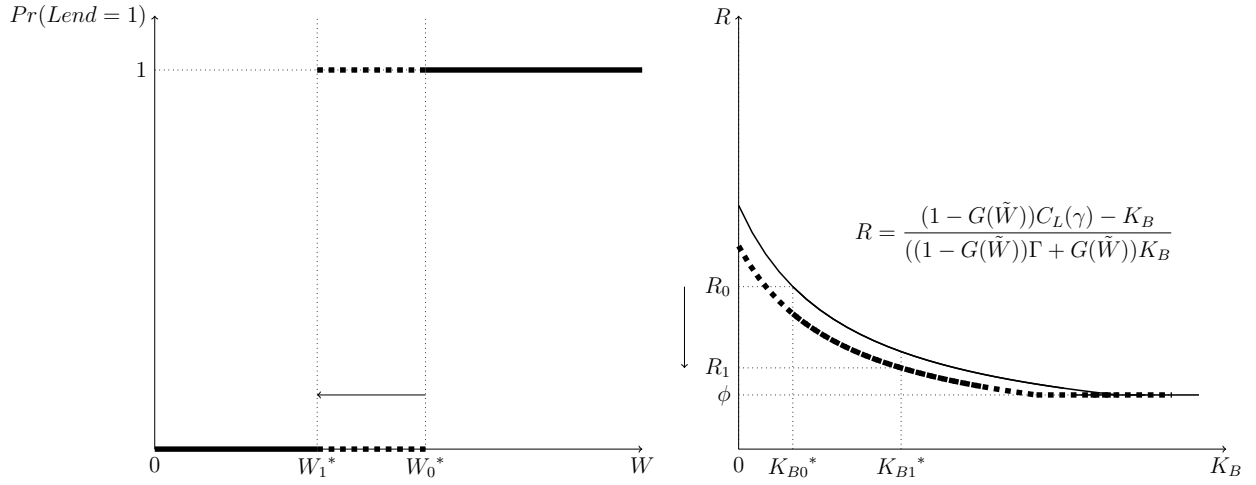


Figure A.15: Model: Credit contract



A.V Appendix: Tables

Table A.1: Correlations between the measures of overall court output

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Disposal Rate (1)	1.00						
Log Speed Firm (2)	0.92***	1.00					
Log Number Filed (3)	0.65***	0.67***	1.00				
Log Number Disposed (4)	0.69***	0.84***	0.75***	1.00			
Log Case Duration (5)	-0.07**	0.14***	-0.08**	0.03	1.00		
Log Share Dismissed (6)	0.25***	0.22***	0.11***	0.21***	-0.06*	1.00	
Log Appeal (7)	0.09***	0.10***	0.14***	-0.10***	0.10***	0.08**	1.00
Observations	1755						

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: All measures of course performance are constructed using the trial level data, aggregated at the level of court-year.

Table A.2: District-level total number of loans

	(1)	(2)	(3)	(4)
	OLS	2SLS	RF	FS
Panel A: All Banks				
Log Disposal Rate	0.00044 (0.00675)	0.067* (0.04)		
Judge Occupancy			0.000528* (0.000297)	0.00791*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.97	-0.129	0.974	0.59
Wald F-Stat				21.65
Panel B: Public Sector Banks				
Log Disposal	-0.024 (0.0163)	0.053 (0.086)		
Judge Occupancy			0.00042 (0.00067)	0.0078*** (0.002)
Observations	4620	4611	4611	4611
Adj R-Squared	0.93	-0.088	0.93	
Wald F-Stat				21.62
Panel C: Manufacturing Loans				
Log Disposal	-0.0369** (0.0163)	-0.051 (0.099)		
Judge Occupancy			-0.0004 (0.00078)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.92	-0.062	0.92	
Wald F-Stat				21.66
Panel D: Personal Loans				
Log Disposal	0.0262** (0.0106)	0.175** (0.062)		
Judge Occupancy			0.00139*** (0.00043)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.97	-0.228	0.97	
Wald F-Stat				21.66
Panel E: Agriculture Loans				
Log Disposal	-0.0057 (0.0079)	-0.0191 (0.0426)		
Judge Occupancy			-0.00015 (0.00033)	0.0079*** (0.0017)
Observations	4620	4611	4611	4611
Adj R-Squared	0.98	-0.067	0.98	
Wald F-Stat				21.66

Standard errors in parentheses

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

Notes: Results presented in this table examines district-level total number of loans by specific sub-samples at time $t + 1$. Panel A reports total number of loans across all banks, Panel B reports only for public sector banks, whereas Panels C-E report total loans by sector of lending. Regressions are weighted by number of litigations involving banks within a court-year. All standard errors are clustered at the district-year level.

Table A.3: Robustness check: Coefficients adjusted for TWFE heterogeneity

	(1)	(2)
	DID-M	Reduced Form
Asinh Δ Borrowing	-0.143	-0.0163
Asinh Δ Interest	-0.0089	-0.004
Asinh Sales	0.00144	0.00257
Asinh Profit	-0.0083	0.0096
Asinh Wage Bill	0.0028	0.0037
Asinh Plant Value	0.001	-0.0032

Standard errors in parentheses

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

Notes: Column 1 reports the coefficients from *DIDm* specification by [de Chaisemartin and D’Haultfoeuille \(2020\)](#) that accounts for treatment effect heterogeneity and Column 2 reports coefficients from the main reduced form two-way fixed effect specification.

Table A.4: Robustness check: By levels of clustering standard errors

	(1) OLS	(2) 2SLS	(3) Reduced Form
Panel A: Cluster by State-Year			
Asinh Δ Borrowing	0.173 (0.113)	-0.92** (0.43)	-0.0163** (0.00646)
Asinh Δ Interest	0.0484 (0.0412)	-0.217 (0.161)	-0.0041 (0.0028)
Asinh Sales	0.0457 (0.0323)	0.181 (0.144)	0.0026 (0.002)
Asinh Profit	0.083 (0.0636)	0.655** (0.224)	0.0096** (0.003)
Asinh Wage Bill	0.0386** (0.0183)	0.265** (0.115)	0.0037** (0.0014)
Asinh Plant Value	-0.0156 (0.0216)	-0.224* (0.119)	-0.0032** (0.0015)
Panel B: Cluster by District			
Asinh Δ Borrowing	0.173 (0.124)	-0.92* (0.528)	-0.0163** (0.0078)
Asinh Δ Interest	0.0484 (0.0436)	-0.217 (0.162)	-0.0041 (0.0027)
Asinh Sales	0.0457 (0.0337)	0.181 (0.152)	0.0026 (0.0021)
Asinh Profit	0.083 (0.0692)	0.655 (0.436)	0.0096* (0.0051)
Asinh Wage Bill	0.0386 (0.0261)	0.265* (0.147)	0.0037* (0.0019)
Asinh Plant Value	-0.0156 (0.027)	-0.224* (0.132)	-0.0032* (0.00163)

Standard errors in parentheses

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

Notes: The row headers indicate the dependent variable. Columns 1 and 2 present the coefficients on disposal rate from OLS and 2SLS estimations respectively, and column 3 presents the reduced form coefficients on judge occupancy. All standard errors are clustered as indicated by the panel header.

Table A.5: Description of firms registered in sample court districts

(1)					
	In Sample Mean	In Sample SD	Not in Sample Mean	Not in Sample SD	Difference p-val
Number of firms per district	1854.135	1946.777	1447.903	1121.478	0.000
Firm Age (yrs)	27.996	18.818	24.777	14.894	0.000
Entity Type:					
Private Ltd	0.353	0.478	0.352	0.478	0.893
Public Ltd	0.641	0.480	0.642	0.479	0.848
Govt Enterprise	0.000	0.017	0.001	0.033	0.016
Foreign Enterprise	0.000	0.012	0.000	0.008	0.493
Other Entity	0.006	0.076	0.005	0.069	0.243
Ownership Type:					
Privately Owned Indian Co	0.750	0.433	0.717	0.450	0.000
Privately Owned Foreign Co	0.025	0.157	0.026	0.160	0.623
State Govt Owned Co	0.015	0.122	0.019	0.136	0.017
Central Govt Owned Co	0.008	0.091	0.012	0.108	0.003
Business Group Owned Co	0.201	0.401	0.226	0.418	0.000
Finance vs. Non-Finance:					
Non Finance Co	0.789	0.408	0.831	0.375	0.000
Non Banking Finance Co	0.208	0.406	0.166	0.372	0.000
Banking Co	0.003	0.053	0.003	0.050	0.675
Broad Industry:					
Trade, Transport, and Logistics	0.150	0.357	0.139	0.346	0.011
Construction Industry	0.054	0.226	0.086	0.280	0.000
Business Services	0.300	0.458	0.282	0.450	0.001
Commercial Agriculture	0.031	0.173	0.025	0.157	0.006
Mining	0.033	0.179	0.028	0.165	0.014
Manufacturing	0.432	0.495	0.439	0.496	0.194
No. Firms	13298			15042	

Notes: “Not in Sample” excludes Delhi and Mumbai, which are the two largest cities in India and also account for over 35% of all formal sector enterprises. For better comparison, firms in my study sample need to be compared with those registered in similar districts not in my sample. Finally, all firms considered for analysis are those incorporated before 2010.