# Judicial Capacity Increases Firm Growth Through Credit Access: Evidence from Clogged Courts of India

*By* MANASWINI RAO*

How do judicial institutions, such as sub-national courts, impact local markets and firms' production decisions? I examine this relationship by exploiting quasi-random variation in judge vacancies and mapping trial records for a third of district courts in India with court-level performance measures, bank lending, and local firms' outcomes. I find that reducing judge vacancy increases firms' wage bill, production, and profitability through access to bank credit arising from improved rates of trial resolution and better enforcement of debt contracts. Addressing judge vacancy would generate orders of magnitude larger benefit relative to its cost. (*JEL* O16, O43, K41, G21)

Courts play a central role in enforcing contracts and property rights (North 1986; La Porta et al. 1998; Anderson 2018), which supports the development of the formal financial sector, investment, and economic growth (Coase 1960; Glaeser et al. 2001; Johnson et al. 2002; Acemoglu and Johnson 2005; Nunn 2007). Long lags in trial resolution can increase uncertainty and transaction costs that prevent effective contracting and weaken *de facto* rights (Djankov et al. 2003). Even more immediately, this constrains factors of production - particularly bank capital stuck under litigation - from being put to productive use. Therefore, the capacity

*Contact: manaswini.rao@gmail.com, Dept. of Economics, UC San Diego. I am indebted to Aprajit Mahajan, Elisabeth Sadoulet, Frederico Finan, Emily Breza, Arun Chandrasekhar, and Karthik Muralidharan for their guidance and feedback. I thank Abhay Aneja, Sam Asher, Prashant Bharadwaj, Johannes Boehm, Benjamin Bushong, Decio Coviello, Alain de Janvry, Ernesto Dal Bo, Giacomo De Giorgi, Marco Gonzalez-Navarro, Rema Hanna, Sean Higgins, Supreet Kaur, Erin Kelley, Ben Krause, Ethan Ligon, John Loeser, Jeremy Magruder, Ted Miguel, Paul Niehaus, Yusuf Neggers, Matthew Pecenco, Jeffery Perloff, Gerard Roland, Vaishnavi Surendra, and all participants at seminars and workshops at UC Berkeley, NEUDC, Pacdev, SIOE, and Barcelona GSE. Importantly, thanks to Kishore Mandyam, Harish Narasappa, Surya Prakash, and members of the Indian judiciary for help with court data extraction and insightful discussions. Special thanks to S.K. Devanath, Suhrid Karthik, and Vinay Venkateswaran for thoughtful discussions. I acknowledge the generous funding support from International Growth Centre (IGC), State Effectiveness Initiative, and UC Berkeley Library. This paper was previously circulated as "Judges, Lenders and the Bottom Line: Court-ing Firm Growth in India". All errors are my own.

of courts with respect to its ability to resolve contractual disputes in a timely fashion likely has a large implication not just for the litigants but also for markets and the economy.

The judiciary across the world is constrained including in the OECD countries (Dimitrova-Grajzl et al. 2012; Coviello et al. 2014) such as Italy and Greece and more severely in developing economies, generating long lags in trial resolution. For example, 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 States.[1] This is exacerbated by low levels of investment in local state capacity and public goods (Kapur 2020). Given this, I seek to estimate the benefits from improving judicial capacity on market and economic outcomes. Further, in the context of weak revenue capacity, calculating the cost effectiveness from investing in state capacity improvements such as hiring more district judges would benefit policy deliberations.

In this paper, I exploit quasi-random variation in district judge vacancy in India to investigate the causal effects of judicial capacity - measured as the annual rate of trial resolution or disposal rate in district courts - on two sets of outcomes. First, I examine the consequences on local credit market outcomes including loan repayment rates and subsequent bank lending using district-level data from the Reserve Bank of India. Second, I estimate the effect on local firms' production outcomes including long term borrowing, wage bill, value of capital, sales revenue, and net profits to examine its real economic implications, using annual balance-sheet data for a sample of formal sector firms registered within the district.

To study this, I generate a novel dataset on judicial capacity for a sample of 195 district courts by assembling the universe of six million trial-level microdata between 2010 and 2018. The main identifying variation is driven by annual variation in district judge vacancy that arises due to a combination of existing undersupply of judges, short tenure, and a judge ro-

[1] Ordinary 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.

tation policy that is implemented centrally by the respective state high courts.[2] This creates a within-court variation in judge occupancy that is likely orthogonal to credit and firm-level outcomes, serving as a plausibly exogenous shock to judicial capacity. Consistent with this, I find no evidence of pre-trends or strategic manipulation of judge vacancies in relation to court-level rate of trial resolution, lending by banks, and firm outcomes. Therefore, I use judge occupancy - $(100 - \%vacancy)$ - as an instrument for judicial capacity to study its subsequent effect on credit and firm-level outcomes. In such an instrumental variables (IV) estimation strategy, both the first stage result on judicial capacity and second stage results on credit market and firm level outcomes 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 0.978 and 0.8 percent, respectively. In other words, adding one additional judge - i.e. 7.2 percentage points reduction in vacancy - increases the rate of trial resolution by about 200 more resolved trials (including dismissals) 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 registered cases per court per year. Disposal rate, defined as the percentage of total caseload that is resolved in a given year, 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 depends on the fraction of trials that are resolved in a given 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 1.7 and 2 percent,

[2]The state high courts are responsible for judge assignment, following a policy of avoiding the judge's hometown and location of her past legal experience either as a lawyer or as a judge.

[3]I also show that judge vacancy increases the median duration of debt related trial. However, from the point of view of freeing capital, how many such cases are resolved in a year with specific court directive on recovery matters. 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.

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 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. The credit market response suggests that courts also alter the incentives for subsequent lending, where banks circulate freed up capital towards more productive uses, including expanding access to otherwise credit constrained firms.[4]

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 long term borrowing. Since these are large firms that borrow heavily from banks, an increase in repayment from such firms brings back more credit into subsequent circulation. While the quanta of all long term borrowing from banks drops among existing borrowers, there is a suggestive decline in their overall interest burden as well. 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 also correspond to a declining value of plants and machinery owned by firms following an increase in judge occupancy. However, at the same time, I observe an increase in unsecured borrowing (without any collateral) by these firms on average. Taking these different effects on access to credit including the cost of credit, I find a positive effect on wage bill, sales revenue, and profit on average, with respect to improved judicial

[4] Over 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.

capacity. 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.

To further explore whether this reflects an efficiency gain, I examine heterogeneous treatment 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. This also squares with the fact that the loan officers allocate credit based on available capital rather than future repayment as they themselves get rotated on a frequent basis. This suggests that well-functioning courts aid credit circulation and plausibly improve credit allocation.

Finally, I compute the benefit-cost ratio of reducing judge vacancy that implies benefits that 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 the addition of a judge.[5]

This paper contributes to several 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 institutions. 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

[5]The 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.

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, coupled with plausibly exogenous variation in annual judge vacancy enables me to overcome these limitations to credibly show that daily functioning of trial courts matter for the economy.

Second, this paper emphasizes that judge vacancy is an important state capacity constraint, resulting in the observed large trial backlog. As detailed in the review paper by Dal Bo and Finan (2016), research examining the judiciary is relatively scant. By examining the role of persistent vacancies among district judge posts, this paper contributes to the growing literature on state capacity (Muralidharan et al. 2016; Dhaliwal and Hanna 2017; Finan et al. 2017). I show that high levels of vacancy undermines the functioning of the judicial institutions and consequently, social welfare.[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 firm growth (La Porta et al. 1998; von Lilienfeld-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;

[6]The 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.

Burgess and Pande 2005; Banerjee and Duflo 2014; Nguyen 2019). This paper sheds light on 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 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 discuss the results, concluding in Section V.

## I 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 A1 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]

[7] The 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.

## 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 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 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

[8]E-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.

[9]For 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 A1.

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]

## 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 ($\approx$ 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

[10]The 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, there is likely to be minimum measurement error.

"*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 A2 describes the firm sample construction process in detail.[12]

[11] Matching 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.

[12] Note 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.

### C. Summary statistics

Panel A of Table 1 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, resolution takes 420 days on average, with a standard deviation of 570 days.

Panels B and C describe credit market and firm-level outcomes. Banks make about 300,000 loans every year and have about USD 9.4 billion worth outstanding loans. 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).

### D. A descriptive analysis of litigation behavior

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 to the borrower's location.

Panels A and B in Figure 1 show that banks litigate intensively with close to 50 percent of all banks in the firm sample having matched with the trial microdata. Further, they engage as plaintiffs, i.e. initiator of the litigation, in over 80 percent of the litigation. 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.

## II 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: 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.
- H4: Firm profits increase with judicial capacity, particularly for larger firms.

## III Estimation and identification strategy

The main estimating equation of interest is the relationship between disposal rate and outcomes of interest, given in (1) below.

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

$Y_{fdt+k}$ 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. $\phi_{st}$, $\phi_d$ correspond to state-year and district fixed effects, and $\epsilon_{fdt+k}$ 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:

$$Y^m_{dt+k} = \phi^m_d + \phi^m_{st} + \theta^m D_{dt} + \epsilon^m_{dt+k} \text{ };k \geq 0$$

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.

$$D_{dt} = \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X'}_f \Pi + \nu_{fdt+k} \text{ };k \geq 0 \tag{2}$$

**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:** Panel A Figure 2 and Table 2 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 3). Binned regression by deciles of judge occupancy as well as by different case-types further support this assumption (Figure A3).

**Independence:** 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 two pieces of evidence in support of this claim. First, I provide empirical evidence on pre-trends using Event-Study approach (implemented as a distributed lag model).

$$\begin{aligned}
\Delta Pop_d &= \nu_s + \rho \Delta Occup_d + \eta_d &(3)\\
D_{dt} &= \gamma_d + \gamma_{st} + \sum_{s=-3}^{s=3} \psi_s Occup_{dt+s} + \nu_{dt} &(4)\\
\Delta D_{dt} &= \gamma'_d + \gamma'_{st} + \sum_{s=-3}^{s=3} \psi'_s \Delta Occup_{dt+s} + \nu'_{dt} &(5)\\
Y_{fdt} &= \kappa_d + \kappa_{st} + \sum_{s=-3}^{s=3} \Omega_s Occup_{dt+s} + \mathbf{X'}_f \Gamma + \epsilon_{fdt} &(6)
\end{aligned}$$

Equation 3 tests for correlation between judge occupancy rate 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, $\rho$, would be non-zero. Equation 4 and Equation 5 presents the event-study specification with levels and changes in court-level disposal rate as the dependent variable, respectively. Equation 6 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. 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.

A second piece of evidence arises from the 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 term 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 Appendix A2.

**"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 2, estimates (3), revealing that there is no correlation between population growth rate and judge occupancy rate.[13] Panels C and D of Figure 2 plots the event coefficients from specifications (4) and (5). Figure 3 and Figure 4 present the

[13]Further, judge occupancy exhibits no correlation with the underlying district population in any year in the study period as seen in Figure A4. The structural problem of vacancy increases over time across all courts.

correlations between judge occupancy and credit-market, firm-level outcomes - district-level lending, firm borrowing from banks, factor use, sales and profit - estimating (6), 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 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]

## IV Results

In this section, I discuss empirical evidence supporting the role of improved trial resolution in district courts through a reduction in judge vacancy, which subsequently affects 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 that in-turn influences how banks reallocate credit across borrowers.

[14] These are seen in Figure A3 Panel B and Figure A6 depicting the role of judges in resolving bail petitions and effects on crime.

### A. Litigation, debt recovery, and credit allocation

As discussed in the previous section, a reduction in judge vacancy increases the fraction of resolved cases relative to existing workload. Resolution indicates either a settlement between the litigating parties or completion of a full trial with judgement. For execution petitions, resolution results in directions to implement a judgement order passed previously. 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 petition allows the bank to use law enforcement officials to take possession of property or assets owned by the debtor.

Table 4 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 implies faster settlement.

The first stage 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 5). 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/consumption loans such as vehicle, education, or home loans.[15]

[15] The 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.

**Loan recovery and overall lending:** Table 5 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 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 billion, this implies that reducing judge vacancy by one judge brings back about USD 188 million for recirculation.[16]

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 consumption loans (see Table A2). The event-study results depicted in Panels A and B, Figure 3, shows that while the number of loans - particularly for manufacturing - initially decline, they increase after a lag.

**Local firms' credit access:** Commensurate to the findings at the overall credit market level, total borrowing among local formal sector firms declines initially whereas unsecured borrowing (i.e. without any collateral) increases, as seen in the event study results in Panels C and D, Figure 3.

Total borrowing declines by approximately 1 percent per one percent improvement in disposal rate or by 12 percent per judge (Column 1 Table 6). A caveat is that these results are applicable among firms reporting bank borrowing in the past. As seen in the number of observations in Table 6, not all firms either borrow or report borrowing in their annual bal-

[16]Since 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.

ance sheet. However, this "attrition" or selection of firms in the data does not systematically vary with judge vacancy.

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 6). 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 7).

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 7).

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.[17]

### 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 inputs and production outcomes (Figure 4).

Columns 3-6 of Table 6 reports the effects of judicial capacity improvement on firms'

[17] 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".

sales, profit, wage bill, and value of plants and machinery following the specification in Equation 1. 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 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.[18] 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 7). On the other hand, 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

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

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.

### C. Credit access as a causal channel

In order to show the relationship between firms' long term borrowing from banks and the value of plants and machinery as an important mechanism, I include borrowing, $B_{fdt+k}$, as an explanatory variable on the RHS of Equation 1 as shown in Equation 7. However, because judicial capacity 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 given district to instrument for firm's borrowing. This first stage is presented in Equation 8. This approach is similar to one proposed by Imai et al. (2011) to enable correct estimation of mediation effects.

$$Y_{fdt+k} = \psi_d + \psi_{st} + \omega_1 B_{fdt+k} + \omega_2 Occup_{dt} + \mathbf{X'}_f \Gamma_1 + \epsilon_{fdt+k} \quad (7)$$

$$B_{fdt+k} = \alpha_d + \alpha_{st} + \beta_1 Bank\ Shock_{dt} + \beta_2 Occup_{dt} + \mathbf{X'}_f \Gamma_2 + \mu_{fdt+k}\ ;\ k \geq 0 \quad (8)$$

$Bank\ Shock_{dt}$ is determined by national level committee on banking and central bank (RBI) policies (Burgess and Pande 2005) and 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 A8).

Table 8 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 typically 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.

### D. Robustness Checks

**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 2 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.

A second method to test the robustness of judge occupancy employs an event-study approach by using the year of full occupancy as the event of interest (Panel A Figure A9). This enables an examination of both pre-trends that could violate the exogeneity of the constructed judge occupancy, as well as post event outcomes.

Lastly, I use an index of court performance constructed as the first principal component using Principal Component Analysis instead of disposal rate (Column 2 Table 2). The point estimate is of similar magnitude as the main 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 outcomes, suggesting exogeneity of judge occupancy as an instrument.[19]

**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.

$$Y_{fdt} = \rho_d + \rho_{st} + \sum_{k=-7}^{k=7} \gamma_k \mathbb{1}\{|t - E_d| = k\} + \zeta_{fdt} \tag{9}$$

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 A11 shows the event study graphs using the above specification. The results are qualitatively similar to the main reduced form estimation using continuous judge occupancy

[19] Currently, 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 A10 presents the distribution of PDJ tenure, associated vacancy from rotations, and event study graphs of other court performance measures.

measure.

**Accounting for heterogeneity in two-way fixed effects:** 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_multiplegt) laid out by de Chaisemartin and D'Haultfœuille (2020).

Panel B Figure A9 presents the adjusted estimates for the first stage. The adjustment procedure returns the first stage coefficient similar in magnitude and sign as the main estimate. Table A3 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 judicial capacity on borrowing, interest rate, sales, and wage bill is relatively robust to heterogeneity of firms. 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 A4). 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.[20] Therefore, I also estimate the specifications by clustering at district-level instead of district-year (Panel B Table A4). The coefficients continue to remain statistically significant even after clustering at these different levels.

[20] Judge 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.

### E. Benefit-cost analysis

The analysis suggests that addressing judge vacancy in district courts translates into significant improvements in local credit markets and firms' productivity. Expansion in wage expenditure suggests that either formal sector employment increases or the labor employed by these firms experience a gain in their compensation (with higher wages 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 9, I calculate the benefit-cost ratio using the estimates from the 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 average individual income tax.[21] 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 her 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 $25^{th}$ 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 address judge vacancies.

[21] These assumptions are motivated by articles in the news media, with sources mentioned in Table 9. 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.

## F. 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 from 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 heterogeneity 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 A5), the results are likely to be valid for the majority of non-metropolitan India.

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 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.

## V 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 firm growth, the state will be able to more than recover the costs of hiring additional judges from increased tax collection and an expansion in employment.

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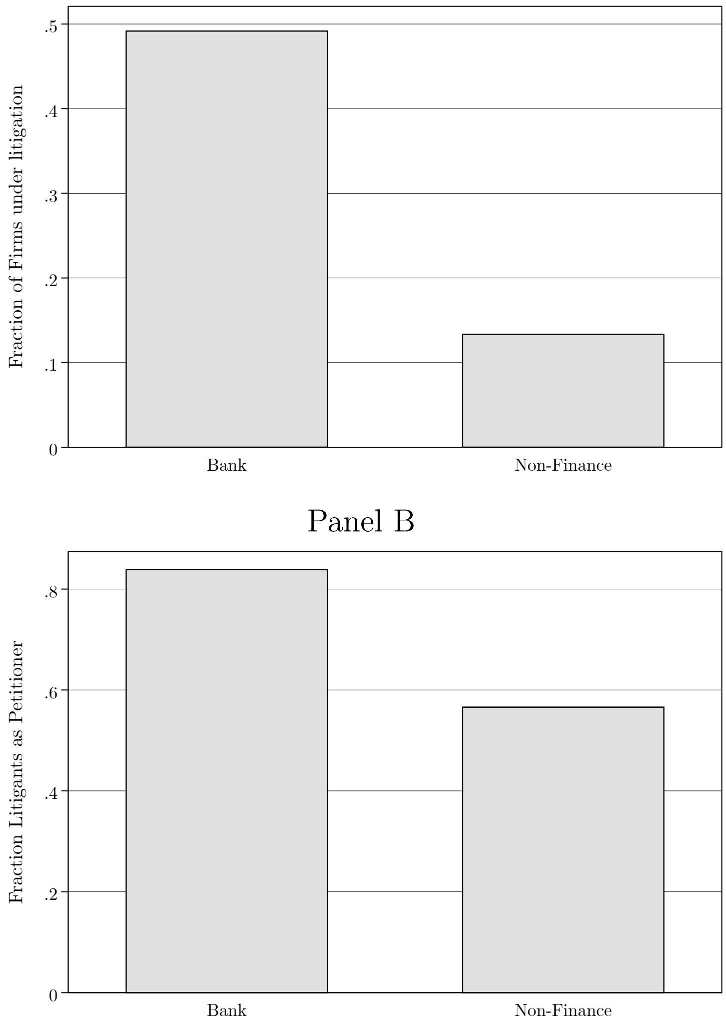
## VI Figures

Figure 1: Litigation intensity by firm type

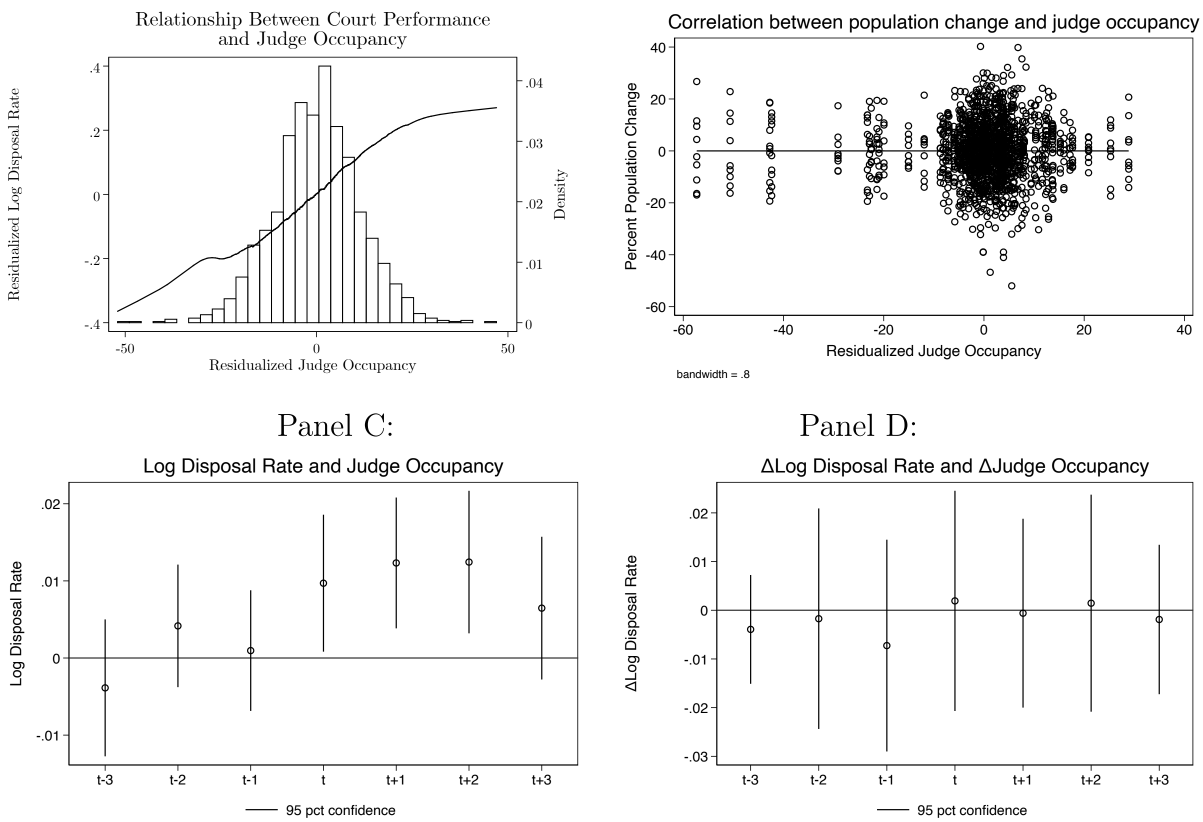
Panel A




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.

Figure 2: Disposal rate and judge occupancy: First stage

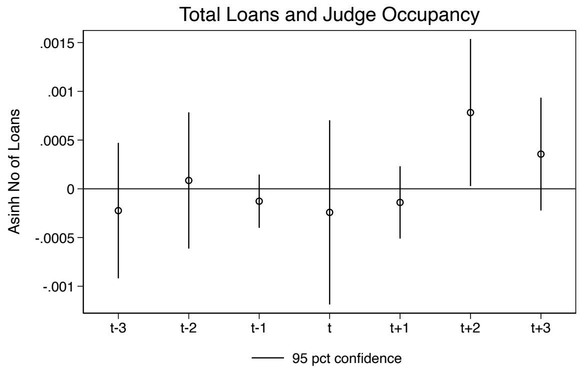
Panel A: Panel B:



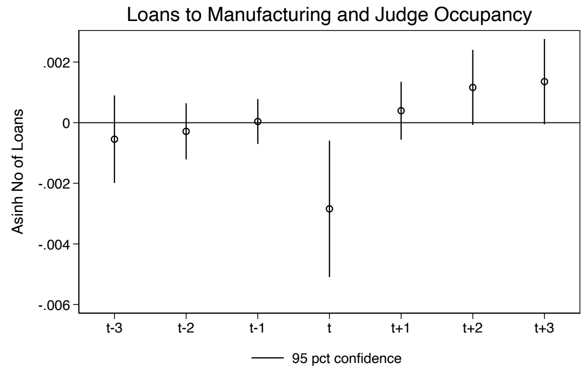

Notes: Panel A above shows the relationship between disposal rate and judge occupancy, after controlling for district, year, and state-year fixed effects, using flexible lowess specification between log disposal rate and judge occupancy. Panel B is a scatter-plot regressing percent change in district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

Figure 3: Credit: Market-level and firm-level outcomes

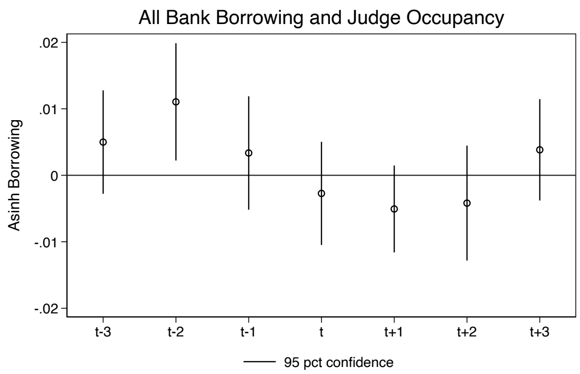
Panel A:



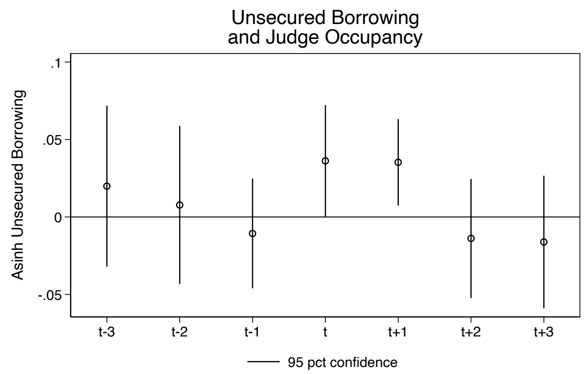

Panel B:




Panel C:

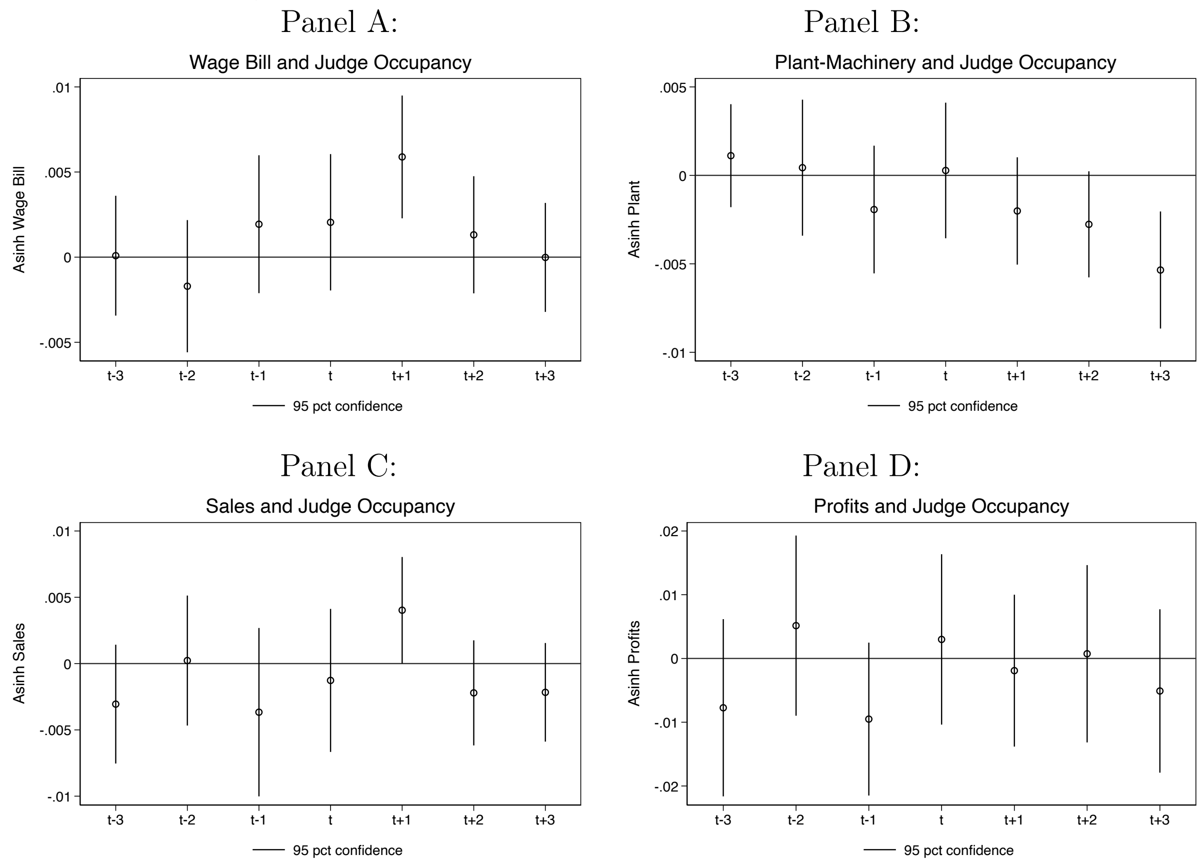



Panel D:




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 6).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 6). 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 4: 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 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 - 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.

## VII Tables

Table 1: 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 2: 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*** | 0.00745*** | | 0.00978*** | 0.00978*** |
| | (0.00182) | (0.00231) | | (0.00216) | (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.

Table 3: First stage: By sub-groups of district courts

| | (1) All | (2) Court Size tercile 1 | (3) Court Size tercile 2 | (4) Court Size tercile 3 | (5) Pop. Density tercile 1 | (6) Pop. Density tercile 2 | (7) Pop. Density tercile 3 |
|---|---|---|---|---|---|---|---|
| Judge Occupancy | 0.00978*** | 0.0118*** | 0.0112*** | 0.00701** | 0.00895*** | 0.0151*** | 0.00607* |
| | (0.00182) | (0.00324) | (0.00272) | (0.00351) | (0.00239) | (0.00389) | (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 4: 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*** | -0.0415 |
| | (0.0156) | (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. Standard errors are clustered by district-year.

Table 5: 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 | -0.03 | | |
| | (0.0149) | (0.048) | | |
| Judge Occupancy | | | -0.000237 | 0.00791*** |
| | | | (0.000374) | (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 | -0.352** | | |
| | (0.031) | (0.139) | | |
| Judge Occupancy | | | -0.00278** | 0.0079*** |
| | | | (0.000945) | (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 | -0.243** | | |
| | (0.0275) | (0.111) | | |
| Judge Occupancy | | | -0.00192** | 0.0079*** |
| | | | (0.0008) | (0.0017) |
| Observations | 4620 | 4611 | 4611 | 4611 |
| Adj R-Squared | 0.97 | -0.27 | 0.97 | |
| Wald F-Stat | | | | 21.62 |
| Panel D: Consumption Loans | | | | |
| Log Disposal | 0.0288*** | 0.0365 | | |
| | (0.009) | (0.038) | | |
| Judge Occupancy | | | 0.00029 | 0.0079*** |
| | | | (0.0003) | (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 | 0.057 | | |
| | (0.0086) | (0.048) | | |
| Judge Occupancy | | | 0.00045 | 0.0079*** |
| | | | (0.00037) | (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 standard errors are clustered at the district-year level.

Table 6: Firms' production outcomes

| | Asinh $\Delta$Borrowing | Asinh $\Delta$Interest | Asinh Sales | Asinh Profit | Asinh Wage Bill | Asinh Plants-Machinery |
|---|---|---|---|---|---|---|
| OLS | 0.173 | 0.0484 | 0.0457* | 0.0827 | 0.0386** | -0.0156 |
| | (0.113) | (0.039) | (0.0241) | (0.0589) | (0.0177) | (0.019) |
| IV | -0.92** | -0.217 | 0.181 | 0.655** | 0.265** | -0.224** |
| | (0.44) | (0.15) | (0.113) | (0.318) | (0.111) | (0.112) |
| RF | -0.0163** | -0.0041 | 0.00257 | 0.0096** | 0.0037** | -0.0032** |
| | (0.0071) | (0.0027) | (0.00158) | (0.00388) | (0.00133) | (0.00132) |
| FS | 0.0178*** | 0.0187*** | 0.0142*** | 0.0146*** | 0.014*** | 0.0144*** |
| | (0.0033) | (0.0034) | (0.004) | (0.004) | (0.004) | (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 1. 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 7: Firms' production outcomes: Heterogenous effects

| | Asinh $\Delta$Borrowing | Asinh $\Delta$Interest | Asinh Sales | Asinh Profit | Asinh Wage Bill | Asinh Plants-Machinery |
|---|---|---|---|---|---|---|
| **Panel A: By Asset Size** | | | | | | |
| Small Firm x Judge Vacancy | -0.00313 | -0.00459 | -0.00414 | 0.000809 | 0.000911 | 0.00310 |
| | (0.00727) | (0.00363) | (0.00375) | (0.00494) | (0.00285) | (0.00331) |
| Percent Judge Occupancy | -0.0153** | -0.00307 | 0.00374** | 0.00930** | 0.00340** | -0.00386** |
| | (0.00759) | (0.00283) | (0.00168) | (0.00432) | (0.00141) | (0.00160) |
| Small Firm | 0.432 | 0.290 | -2.170*** | -0.801* | -2.228*** | -2.755*** |
| | (0.639) | (0.323) | (0.338) | (0.445) | (0.262) | (0.304) |
| Observations | 10475 | 7696 | 20133 | 21055 | 20139 | 17845 |
| Adj R-Squared | 0.233 | 0.037 | 0.31 | 0.05 | 0.19 | 0.20 |
| **Panel B: By Credit Rating** | | | | | | |
| High Credit Rating x Judge Vacancy | 0.0285 | 0.00766 | -0.00355 | -0.00734 | 0.00718* | 0.00317 |
| | (0.0182) | (0.00484) | (0.00421) | (0.0164) | (0.00368) | (0.00428) |
| Percent Judge Occupancy | -0.0709*** | -0.0105* | 0.00310 | 0.0212 | -0.00486 | -0.00466 |
| | (0.0188) | (0.00541) | (0.00349) | (0.0153) | (0.00297) | (0.00368) |
| High Credit Rating | -2.208 | -0.437 | 1.459*** | 2.240 | 0.672** | 0.874** |
| | (1.563) | (0.424) | (0.368) | (1.439) | (0.338) | (0.380) |
| Observations | 3246 | 2522 | 5343 | 5392 | 5326 | 5188 |
| Adj R-Squared | 0.17 | 0.061 | 0.15 | 0.05 | 0.19 | 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 8: 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 | 0.004 | 0.00898 | 0.00423 | -0.000343 |
| | (0.0025) | (0.003) | (0.0112) | (0.0026) | (0.0043) |
| Asinh Borrowing (t+1) | | 0.83 | -0.075 | 0.555 | 0.997* |
| | | (0.54) | (2.38) | (0.396) | (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 9: 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 $\epsilon$ | 0.96 x 7.2 = 6.9 | % change per judge | Estimation |
| Wage Bill $\epsilon$ | 0.37 x 7.2 = 2.66 | % change per judge | Estimation |
| $25^{th}$ pctile Firm $\Delta$Profit | $\frac{6.9}{100}$ x 9.9 = 0.68 | Million USD | Calculation |
| $75^{th}$ pctile Firm $\Delta$Profit | $\frac{6.9}{100}$ x 51.5 = 3.56 | Million USD | Calculation |
| $25^{th}$ pctile Firm $\Delta$Wage Bill | $\frac{2.66}{100}$ x 6.4 = 0.17 | Million USD | Calculation |
| $75^{th}$ pctile Firm $\Delta$Wage Bill | $\frac{2.66}{100}$ x 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 | $\frac{\frac{(0.073 \text{ x } 0.17)+(0.15 \text{ x } 0.68)}{1.1^2}}{0.035} \approx 2.7$ | Ratio | Calculation |
| (Tax Revenue) | $\frac{\frac{(0.073 \text{ x } 4.22)+(0.15 \text{ x } 3.56)}{1.1^2}}{0.035} \approx 20$ | | |

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.

# For Online Appendix

## A1 Data Appendix

### A. Representativeness of district courts sample

Figure A12 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 A5 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]

### 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]

[1] Scraping 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.

[2] All 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.

## C. Outcome variables

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

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.

## 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.

## A2 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.

## A3 A model of credit market with enforcement costs

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 suceeds with probability $s$, upon which the borrower decides to repay or evade. Evasion is costly as the borrower incurs an evasion cost $\eta K_B$ 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 A13. 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, $\gamma$. 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, $\delta W$, to recover the loan, where $\delta$ 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

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

This gives a distribution of borrowers, $1 - F(\tilde{W})$, likely to litigate, where $F(.)$ 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

[3] Introducing a probability of winning, $p >> 1-p$ 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.

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

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

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

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, $G(.)$, 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

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

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:

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

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

$$s\Big(G(\tilde{W})RK_B + (1 - G(\tilde{W}))(\Gamma RK_B - C_L(\gamma))\Big) + \tag{6}$$
$$(1 - s)\Big((1 - F(\tilde{W}))(\Gamma\delta W - C_L(\gamma)) + F(\tilde{W})\delta W\Big) \geq \phi K_B$$

The timing of the game where the lender and borrower decide on their strategies are depicted as an extensive form game in Figure A13.

**Proposition 1: Litigation response from borrower** As judicial capacity, $\gamma$, 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 $\gamma$ 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 A14.

**Proposition 2: Credit market response to judicial capacity** As judicial capacity, $\gamma$, 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 $\gamma$ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as below. For the distribution functions, I assume $g(\tilde{W}), f(\tilde{W}) \to 0$ since only large firms engage in litigation.

$$\frac{\partial R}{\partial \gamma} = \frac{\overbrace{\frac{\partial C_L(\gamma)}{\partial \gamma}}^{\text{-ve}} \overbrace{(1 - G(\tilde{W}) - C_B g(\tilde{W}))}^{\text{+ve}}}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} - \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{(((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B)^2} \left( \overbrace{g(\tilde{W}) \frac{\partial C_B}{\partial \gamma}(K_B - \Gamma)}^{\approx 0} \right)$$

$$\implies \frac{\partial R}{\partial \gamma} < 0$$

$$\frac{\partial W^*}{\partial \gamma} = \frac{\overbrace{(1 - F(\tilde{W}))\frac{\partial C_L}{\partial \gamma} - C_L f(\tilde{W})\frac{\partial C_B}{\partial \gamma}}^{\text{-ve}}}{((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta} - \frac{(1 - F(\tilde{W}))C_L(\gamma) - K_B}{(((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta)^2} \underbrace{f(\tilde{W}) \frac{\partial C_B}{\partial \gamma}(\delta - \Gamma)}_{\approx 0}$$

$$\implies \frac{\partial W^*}{\partial \gamma} < 0$$

**Firm Production**

Consider a representative firm with production function $Q = Q(X_1, X_2)$ where $Q(.)$ is twice differentiable, quasi-concave, and cross partials $Q_{X_1X_2} = Q_{X_2X_1} \geq 0$. Further assume that the firm is a price taker. The firm's problem is to maximize their profits as follows:

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

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

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, $\gamma$, improves, banks begin to lend to smaller firms and the overall interest rate on bank lending, $R(\gamma, .)$ drops.

**Proposition 3: Effects of judicial capacity on firm production** As judicial capacity, $\gamma$, 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:**

$$\mathcal{L} = pQ(X_1, X_2) - w_1 X_1 - w_2 X_2 - m_i(\gamma) + \lambda\big(K_i - w_1 X_1 - w_2 X_2 - m_i(\gamma)\big)$$

FOC:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial X_1} &= pQ_{x_1} - w_1 - w_1\lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial X_2} &= pQ_{x_2} - w_2 - w_2\lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial \lambda} &= K_i - w_1 X_1 - w_2 X_2 - m_i(\gamma) = 0
\end{aligned}$$

To examine how the optimal production choices vary with exogenous variation in the institutional quality parameter, $\gamma$, I use Implicit Function Theorem where $X_1, X_2, \lambda$ are endogenous variables and $\gamma$ 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 $\gamma$ increases. For $i = L$, $\frac{\partial K_i}{\partial \gamma} = 0$. Applying Cramer's Rule:

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

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, $\gamma$:

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

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

$\frac{\partial g^*}{\partial \gamma} > 0$ 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.

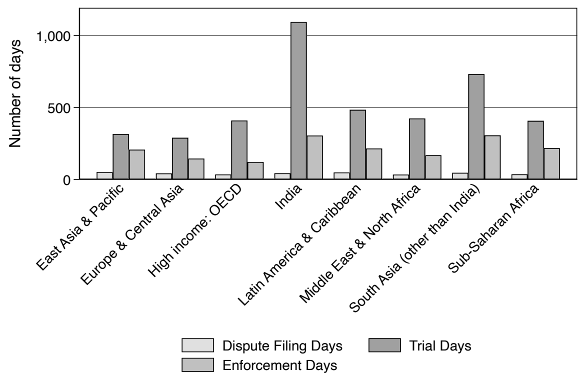
2. For marginal small firms, $i = S$ and $W \approx W^* - \epsilon$, the marginal benefit $K_B - \frac{\partial m_S}{\partial \gamma}$ is due to both availability of borrowing from banks $K_B$ as well as a reduction in monitoring costs. I assume that the monitoring costs for small firms do not decrease 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 $W << W^*$, neither their optimal inputs nor their profits change since $(\underbrace{\frac{\partial K_S}{\partial \gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial \gamma}}_{\approx 0}) \approx 0$.

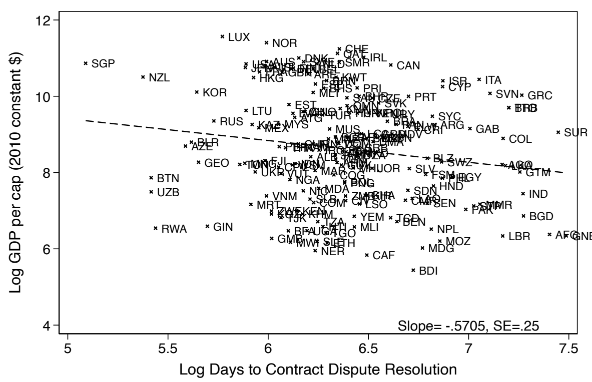
## A4 Appendix: Figures

Figure A1: 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 A2: Construction of firm sample

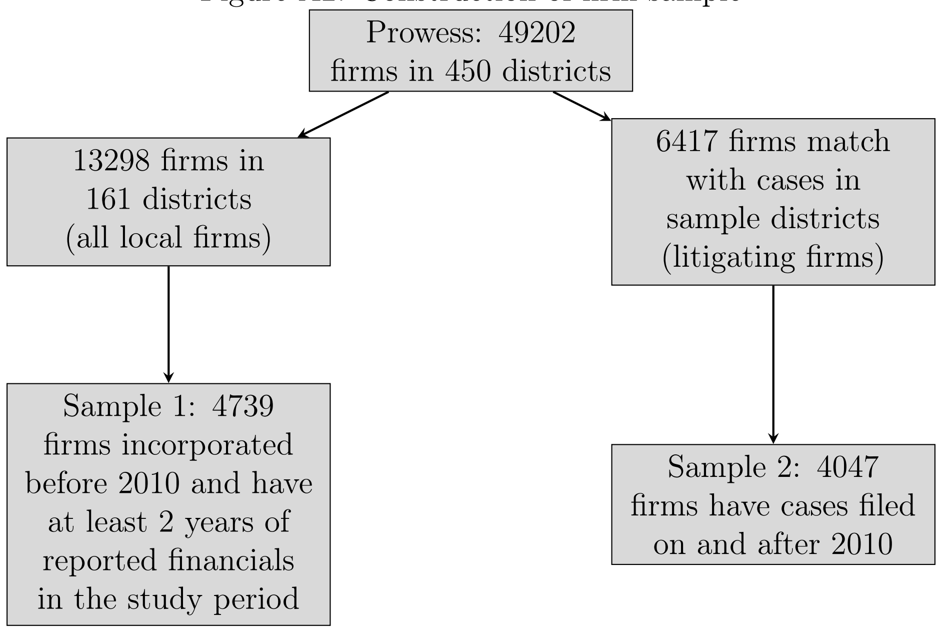
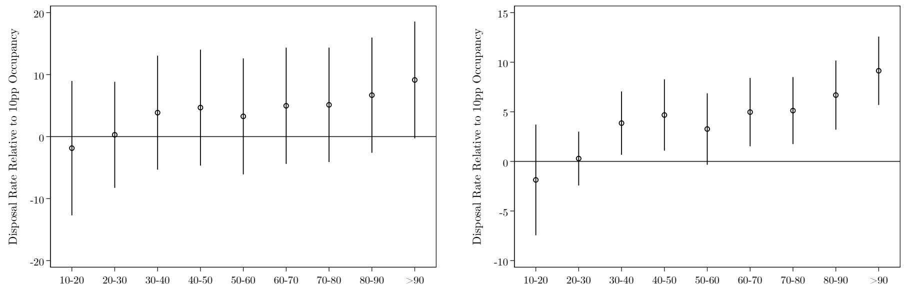
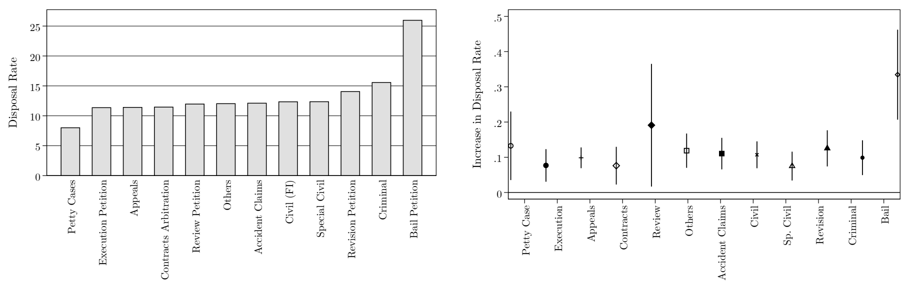


Figure A3: Heterogeneous effects of judge occupancy on disposal rate



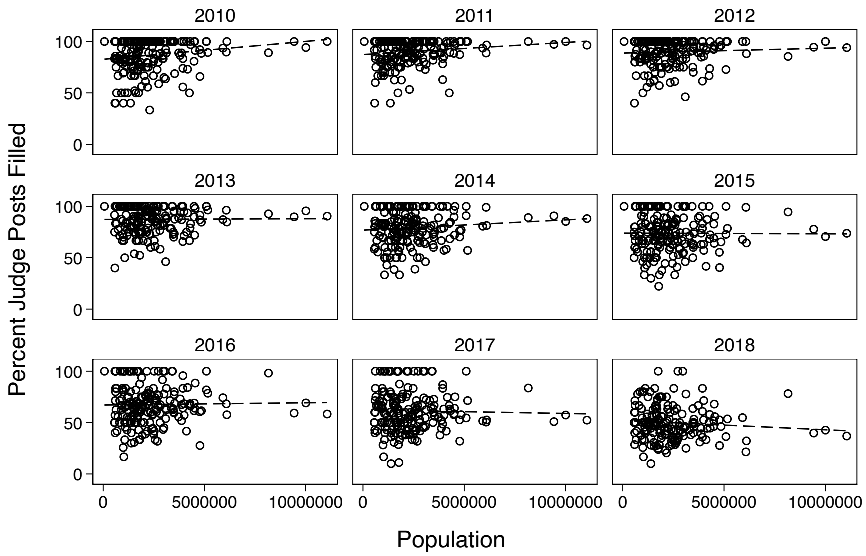

Panel A: By Judge Occupancy Bins




Panel B: By Case-Type

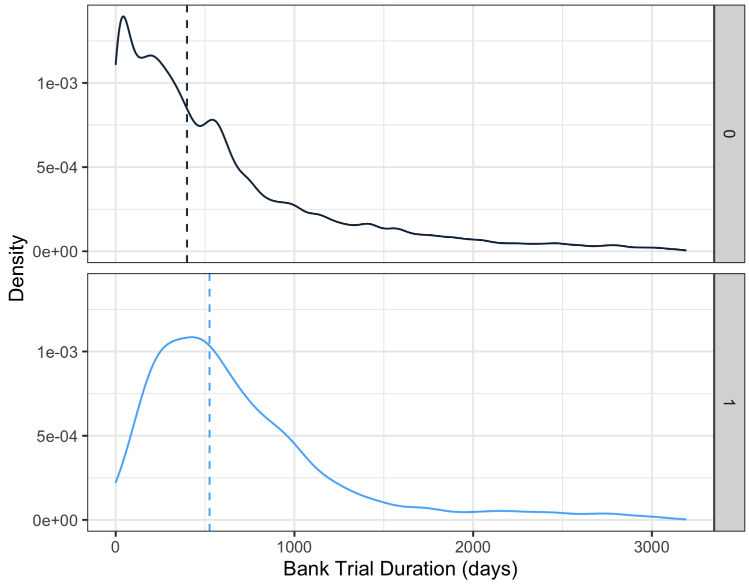
Notes: Panel A presents the regression coefficients on judge occupancy, binned by decile, with disposal rate as the dependent variable. The leave-out group is judge occupancy bin 0-10. Standard errors are clustered by district-year on the left and by district on the right. Panel B presents average disposal 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 A4: Exogeneity: Judge occupancy similar across districts over time



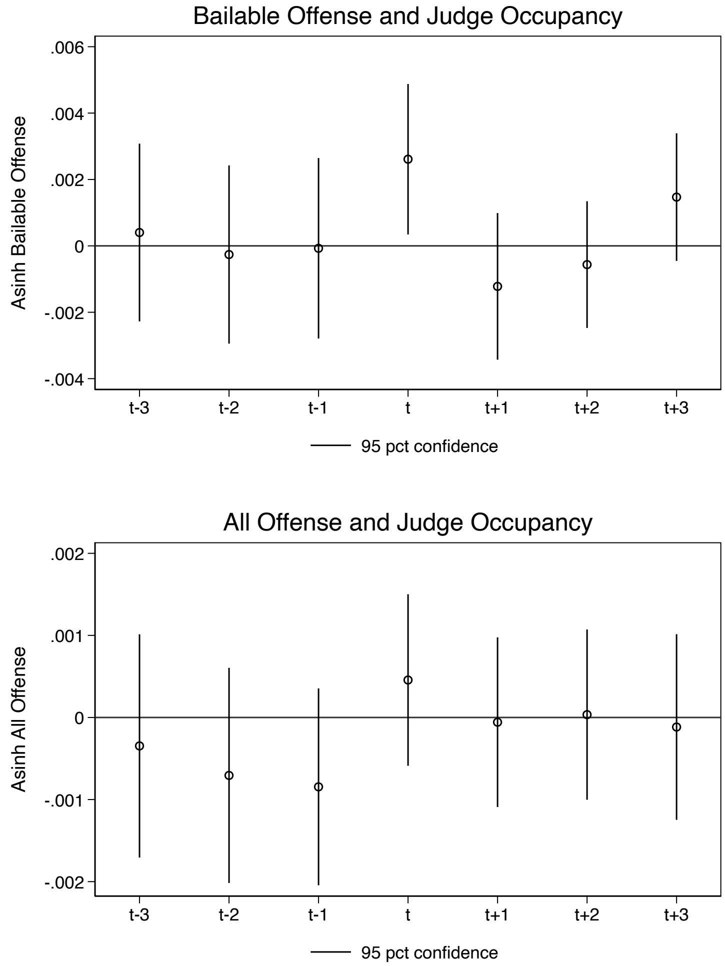

Notes: Judge occupancy plotted against 2011 census population of the district court jurisdiction over the entire study period.

Figure A5: Median trial duration involving banks increases with vacancy



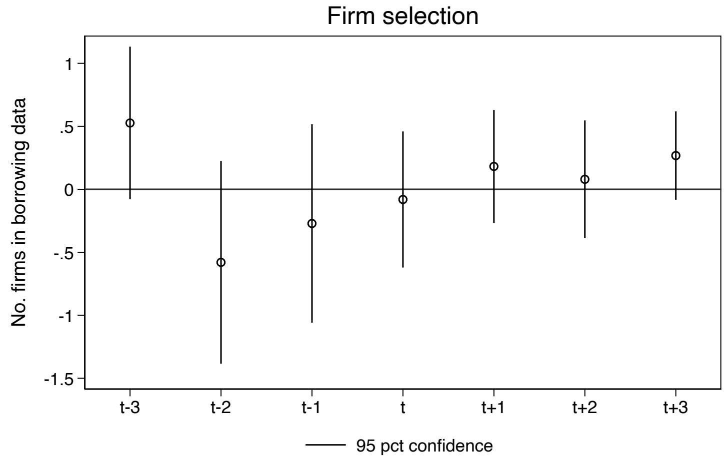

Notes: Above figure presents the density of trial duration for litigation involving banks by whether or not such a litigation experiences judge vacancy during its lifetime. The median duration of litigation encountering judge vacancy is 525 days compared to 399 days for those that do not, reflecting 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.

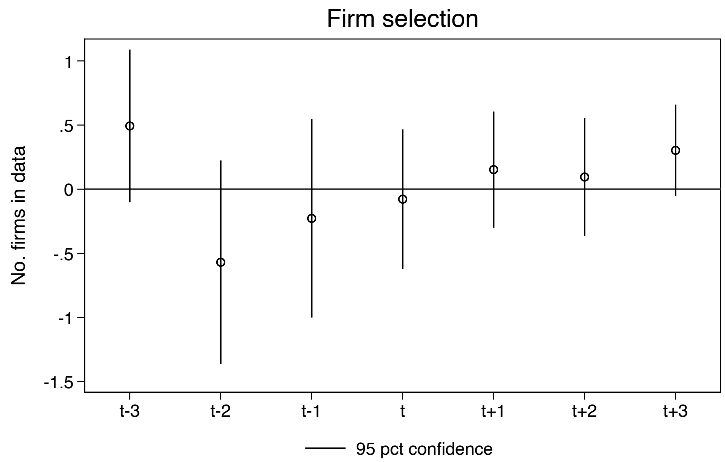
Figure A6: Banks also file criminal petition for debt recovery




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.

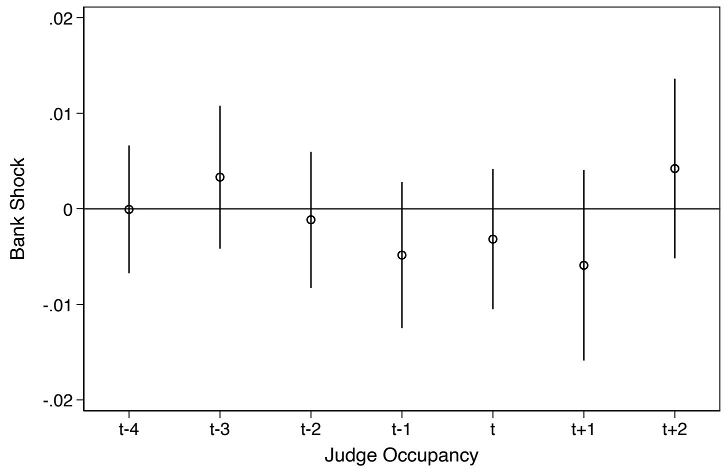
Figure A7: Firm attrition in Prowess data




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.

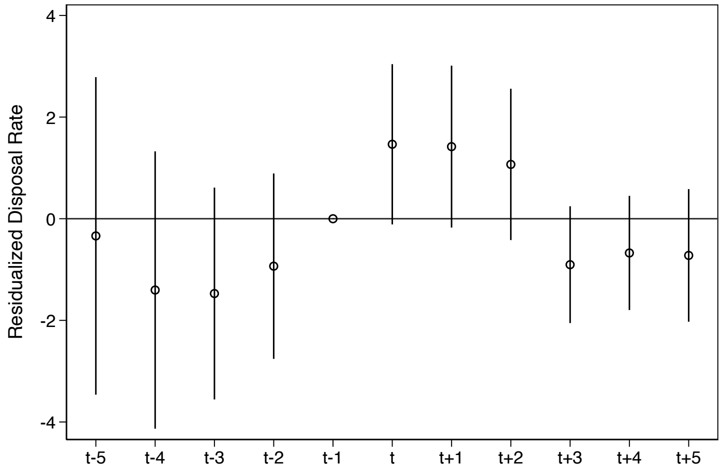
Figure A8: Exogeneity of bank-shock instrument



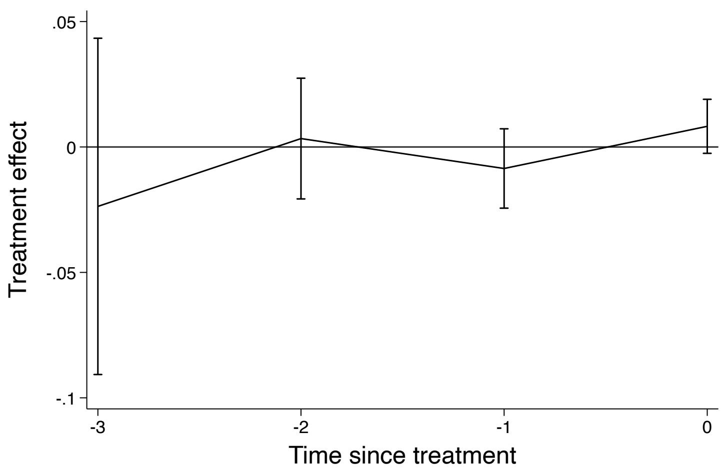

Notes: The graphs present the coefficients on leads and lags of judge occupancy variable with bank shock as the dependent variable. The x-axis presents the time difference between the year the dependent variable is measured and the year judge occupancy is measured. For example, the value at $t-2$ presents 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 A9: First stage: Robustness

Panel A:

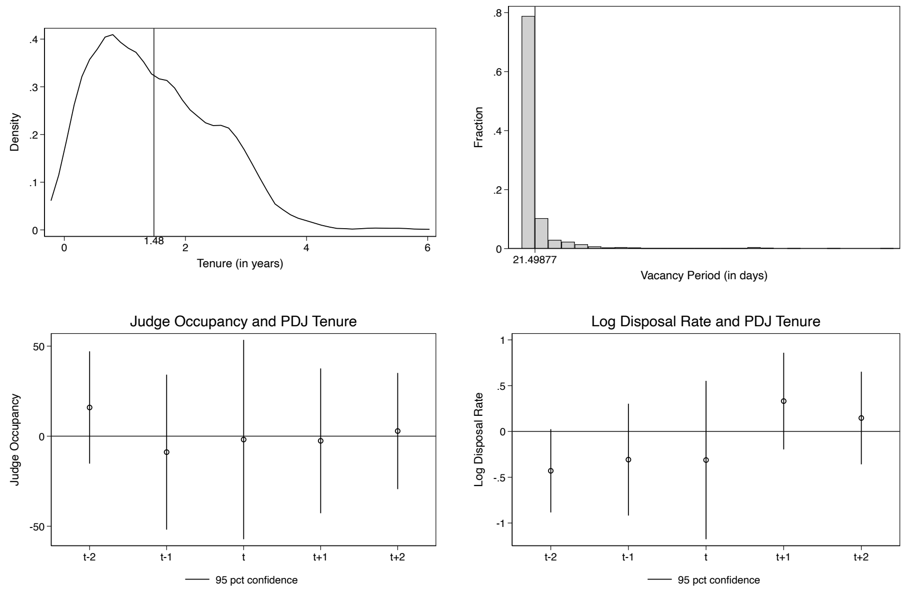



Panel B:



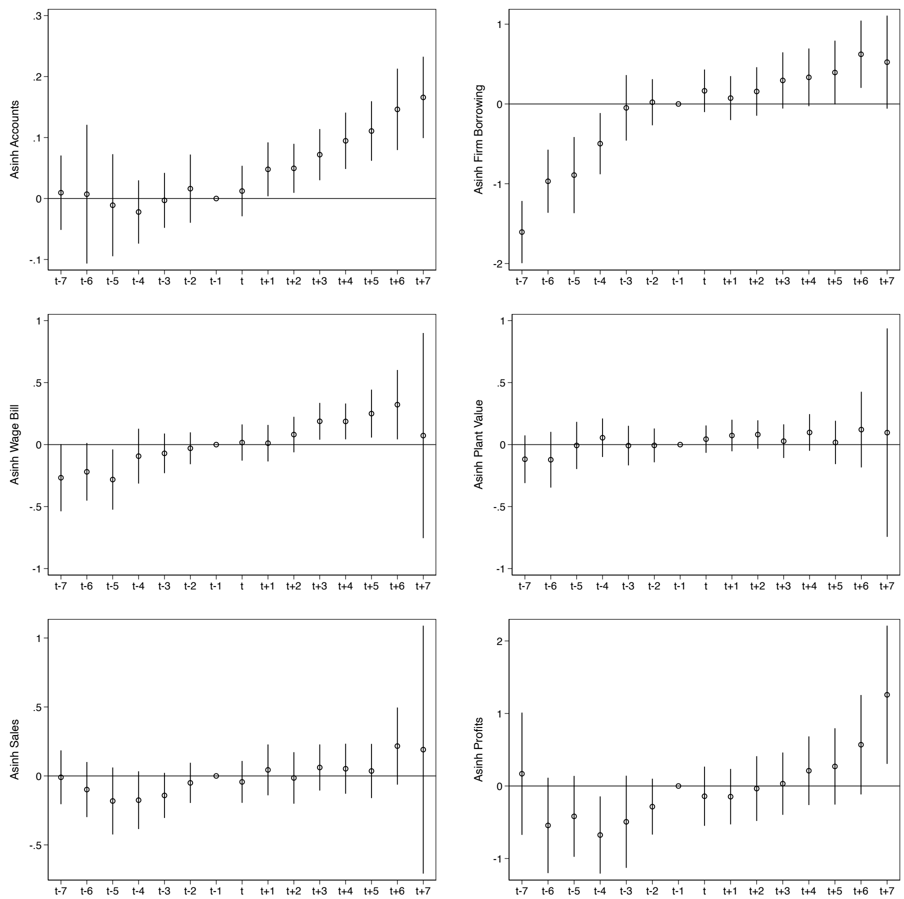

Notes: In Panel A, event year ($t = 0$) is defined as the calendar year where I observe 100 occupancy rate of district court judges. That is, the event year corresponds to the calendar year with maximum observed number of judges in a given court, that I use as the denominator in constructing judge occupancy. 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 2. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure A10: 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 A11: 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 A12: Sample district courts

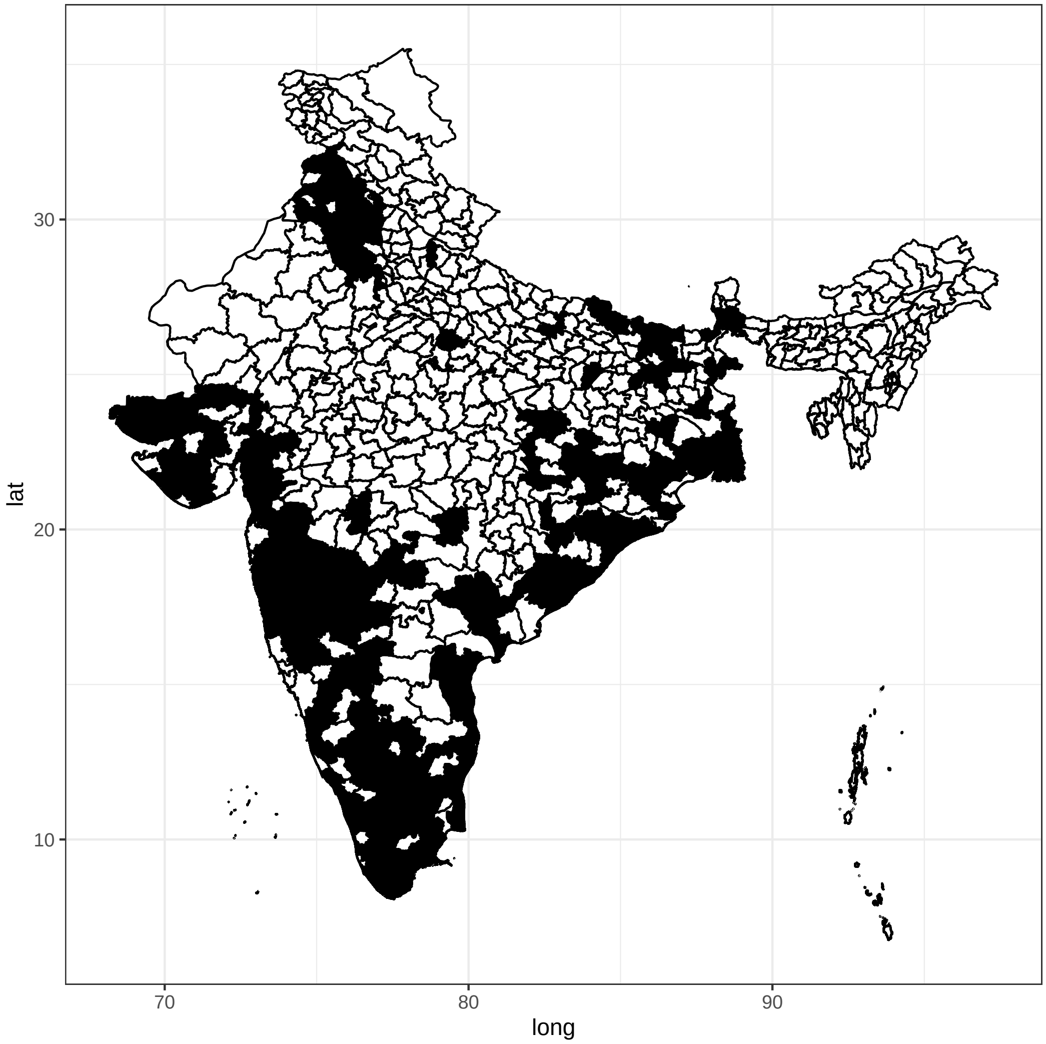


Figure A13: Model: Lender-borrower game

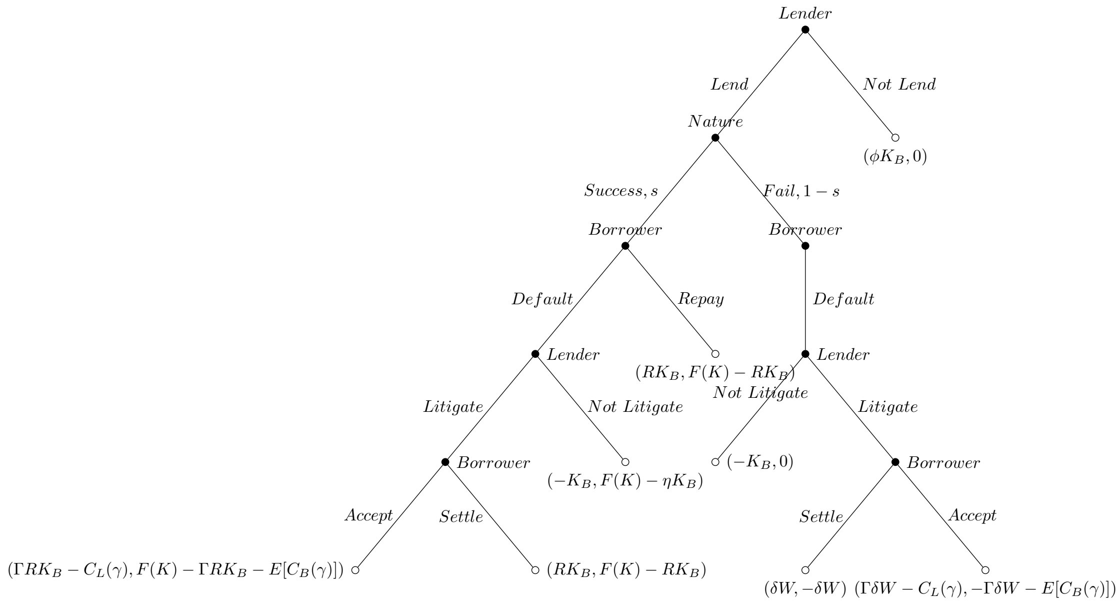
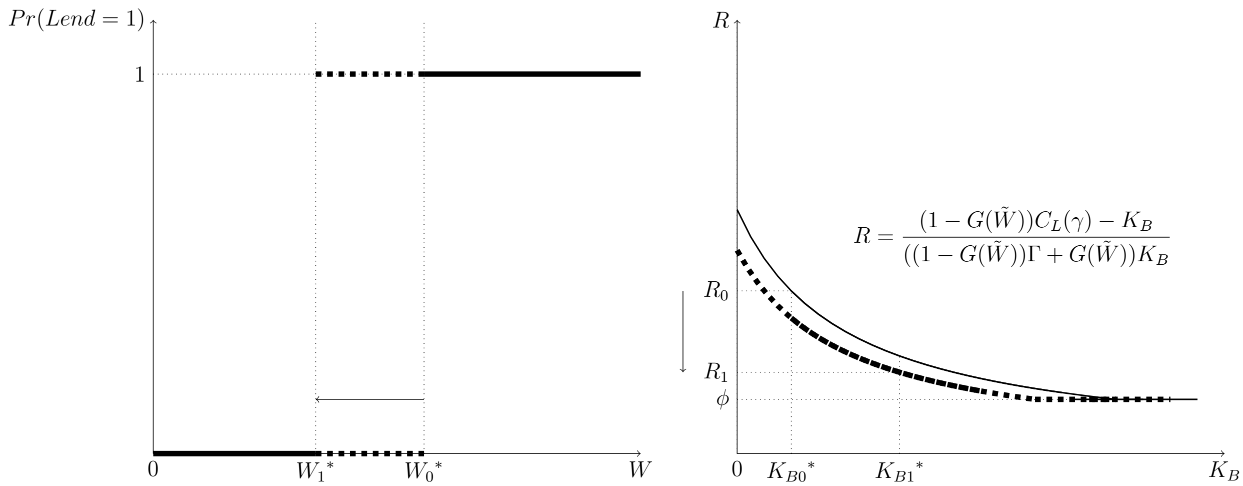



Figure A14: Model: Credit contract



## A5 Appendix: Tables

Table A1: 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 A2: District-level total number of loans

| | (1) OLS | (2) 2SLS | (3) RF | (4) Log Disp (First Stage) |
|---|---|---|---|---|
| Panel A: All Banks | | | | |
| Log Disposal Rate | 0.00044 | 0.067* | | |
| | (0.00675) | (0.04) | | |
| Judge Occupancy | | | 0.000528* | 0.00791*** |
| | | | (0.000297) | (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 | 0.053 | | |
| | (0.0163) | (0.086) | | |
| Judge Occupancy | | | 0.00042 | 0.0078*** |
| | | | (0.00067) | (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** | -0.051 | | |
| | (0.0163) | (0.099) | | |
| Judge Occupancy | | | -0.0004 | 0.0079*** |
| | | | (0.00078) | (0.0017) |
| Observations | 4620 | 4611 | 4611 | 4611 |
| Adj R-Squared | 0.92 | -0.062 | 0.92 | |
| Wald F-Stat | | | | 21.66 |
| Panel C: Consumption Loans | | | | |
| Log Disposal | 0.0262** | 0.175** | | |
| | (0.0106) | (0.062) | | |
| Judge Occupancy | | | 0.00139*** | 0.0079*** |
| | | | (0.00043) | (0.0017) |
| Observations | 4620 | 4611 | 4611 | 4611 |
| Adj R-Squared | 0.97 | -0.228 | 0.97 | |
| Wald F-Stat | | | | 21.66 |
| Panel C: Agriculture Loans | | | | |
| Log Disposal | -0.0057 | -0.0191 | | |
| | (0.0079) | (0.0426) | | |
| Judge Occupancy | | | -0.00015 | 0.0079*** |
| | | | (0.00033) | (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 A3: Robustness check: Coefficients adjusted for TWFE heterogeneity

| | (1)<br>DID-M | (2)<br>Reduced Form |
|---|---|---|
| Asinh $\Delta$Borrowing | -0.143 | -0.0163 |
| Asinh $\Delta$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'Haultfœuille (2020) that accounts for treatment effect heterogeneity and Column 2 reports coefficients from the main reduced form two-way fixed effect specification.

Table A4: Robustness check: By levels of clustering standard errors

| | (1) | (2) | (3) |
|---|---|---|---|
| | OLS | 2SLS | Reduced Form |
| Panel A: Cluster by State-Year | | | |
| Asinh ΔBorrowing | 0.173 | -0.92** | -0.0163** |
| | (0.113) | (0.43) | (0.00646) |
| Asinh ΔInterest | 0.0484 | -0.217 | -0.0041 |
| | (0.0412) | (0.161) | (0.0028) |
| Asinh Sales | 0.0457 | 0.181 | 0.0026 |
| | (0.0323) | (0.144) | (0.002) |
| Asinh Profit | 0.083 | 0.655** | 0.0096** |
| | (0.0636) | (0.224) | (0.003) |
| Asinh Wage Bill | 0.0386** | 0.265** | 0.0037** |
| | (0.0183) | (0.115) | (0.0014) |
| Asinh Plant Value | -0.0156 | -0.224* | -0.0032** |
| | (0.0216) | (0.119) | (0.0015) |
| Panel B: Cluster by District | | | |
| Asinh ΔBorrowing | 0.173 | -0.92* | -0.0163** |
| | (0.124) | (0.528) | (0.0078) |
| Asinh ΔInterest | 0.0484 | -0.217 | -0.0041 |
| | (0.0436) | (0.162) | (0.0027) |
| Asinh Sales | 0.0457 | 0.181 | 0.0026 |
| | (0.0337) | (0.152) | (0.0021) |
| Asinh Profit | 0.083 | 0.655 | 0.0096* |
| | (0.0692) | (0.436) | (0.0051) |
| Asinh Wage Bill | 0.0386 | 0.265* | 0.0037* |
| | (0.0261) | (0.147) | (0.0019) |
| Asinh Plant Value | -0.0156 | -0.224* | -0.0032* |
| | (0.027) | (0.132) | (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 A5: 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.