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

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How do judicial institutions, such as sub-national courts, impact economic growth? I examine the effect of trial court capacity on local firms' performance by exploiting quasi-random variation in judge vacancies and mapping trial records for a third of such courts in India with court-level performance measures, bank lending, and firm outcomes. I find that reducing judge vacancy increases local firms' labor use, production, and profitability through improved access to bank credit arising from better enforcement of debt contracts. Addressing judge vacancy would generate at least 12:1 benefit-cost ratio. (*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 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 to markets and the economy.

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The judiciary across the world is constrained including in 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 is apposite in aiding 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 value added 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 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 rotation policy that is implemented

[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.

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 lending by banks, and firm outcomes. Therefore, I use judge occupancy 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 increases overall disposal rate as well as the disposal rate of debt related trials by about 1 percent. In other words, adding one additional judge - i.e. 7.2 percentage points reduction in vacancy - increases the rate of trial resolution by 200 more resolved trials per year. This is a large effect given the baseline annual disposal rate is only 14 percent of an average trial load of 20000 trials 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 0.3 and 0.23 disposal rate elasticities of district-level loan repayment from and lending to manufacturing firms, respectively, for public sector banks. In terms of vacancy, an additional judge increases repayment by 1.7 percent. Focusing on local credit market seems concordant with the fact that banks are heavy users of district courts relative to any other

[2]The respective 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.

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% 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 smaller firms that are typically credit constrained, and towards manufacturing and consumption uses relative to agricultural uses.[4]

Third, the disposal rate elasticities of wage bill, sales revenue, and value added for local firms are 0.27, 0.1, and 0.2 respectively. Putting it differently, an additional judge increases wage bill, sales, and value addition by 7, 2.5, and 4 percent respectively. Given the overall credit market effect, I also find a corresponding increase in firms' long term borrowing from banks by 3.6 percent per judge added. Isolating the channel of credit access from other potential channels, I find that these firms are typically credit constrained and an exogenous increase in long term borrowing from banks increases firms' investment in plants and machinery.

Further, I find that improved trial resolution increases access to bank credit among smaller firms but not larger firms, and lowers interest incidence across the average borrower firm. These findings are consistent with a simple lending model where the lender takes into account enforcement quality and borrower wealth in their lending decisions. They lower the wealth threshold when the courts function better. 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. Thus, this suggests that well-functioning courts aid credit circulation and plausibly improve credit allocation.

[4]Over 80 percent of all commercial banks are public sector banks in this period, 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.

Finally, I compute the benefit-cost ratio of reducing judge vacancy that implies benefits that are at least 12 times larger than the cost. Using the baseline median wage bill, the elasticity estimate suggests that an additional judge increases firm's wage bill by USD 18500 on average. With around 376 formal sector firms per district and an average income tax incidence on salaried individual of 7.3 percent, the state can earn 12 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 exit, and 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

[5] The calculation presented is an approximation to illustrate the magnitude of effects. The benefit-cost ratio using increase in value addition and associated corporate tax revenue generates an even larger number.

among district judge posts, this paper contributes to the growing literature on the personnel economics of the state (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; Burgess and Pande 2005; Banerjee and Duflo 2014; Nguyen 2019). This paper contributes to this literature by shedding 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.

[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 the approved capacities.

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, showing 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 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 Supreme Court at the apex followed by High Courts at the state level and finally the district or trial courts that are typically the first interface with the 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. Additionally, the district court is also the court of appeal over other courts of first instance within its jurisdiction.[7]

A. Court Variables

I web scraped the universe of 6 million publicly available trial records 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]

[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.

[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.

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 - 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 the trials. These are also significantly correlated with disposal rate but have 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 designation 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 designation is vacant depending upon the annual workflow observed for the designation. To illustrate, the courtrooms in a district court are numbered 1, 2, 3,... and the judge designations 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 designation is recorded as a trial resolution or as filing of a new trial. Therefore, I encode the specific judge designation as present if I observe non-zero workflow in a given year and as vacant, otherwise. Aggregating this at the level of the court presents the rate of vacancy, or conversely, occupancy measured in percentage terms. The calculated vacancies compare with the numbers mentioned in the Law Commission reports as well

[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 A3.

as media reports, and therefore provide a source of measuring judge vacancy in the absence of a centralized source of judicial personnel records.

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 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 "*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.

Of the 49202 firms, 13298 firms are registered within the jurisdiction of 161 of the 195 sample district courts.[10] 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

[10]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.

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.

Next, I merge the sample of firms in Prowess with the trial dataset using firm names flexibly 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 A3 describes the firm sample construction process in detail. [11]

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 are 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 outcomes. Banks make about 300,000 loans every year and have about USD 8.8 billion as outstanding loan. The summary on annual firm-level financials indicate that these are large firms, with USD 77 million in sales revenue, 3 billion in accounting profits, and about 2000 employees on average. They also routinely borrow from banks with long repayment duration. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

[11] 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 firm and a trial. About 300 firms appear as co-petitioners or co-respondents that I ignore at the moment.

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.[12] 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 3 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 their investment in 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

[12] Characteristics of firms in the trial microdata is presented in Table A2.

leads to default, which initiates debt recovery process through 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 subgame 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 more firms at lower 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. Therefore, this model suggests that production increases across board resulting in higher value addition from increased access to cheaper capital as well as transaction costs.

Empirical Tests This framework generates a few testable hypotheses in relation to an improvement in judicial capacity to empirically examine using the data:

- 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.

H4: Firm value added (net sales) increase, 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. ϕ_{st}, ϕ_d correspond to state-year and district fixed effects, and ϵ_{fdt+k} is the idiosyncratic error term.

However, D_{dt} is likely endogenous if courts process litigation faster using better management abilities in districts exhibiting better growth or could be slower if more dynamic districts also imply increasing new litigation workload. That is, there are likely omitted variable bias 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.

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

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 1 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 of an average trial load of 20000 trials per court.

To enable the 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 (Table 3). Binned regression by deciles of judge occupancy as well as by different case-types further support this assumption (Figure A6).

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. Empirical tests involve examining $\rho = 0$; and $\psi = 0$, $\psi' = 0$, and $\Omega = 0$ for $s < 0$ in the specifications below.

$$\begin{aligned} \Delta Pop_d &= \nu_s + \rho\overline{Occup}_d + \eta_d & (3) \\ D_{dt+s} &= \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X'}_f \Pi + \nu_{fdt} & (4) \\ \Delta D_{dt+s} &= \gamma'_d + \gamma'_{st} + \psi' \Delta Occup_{dt} + \mathbf{X'}_f \Pi' + \nu'_{fdt} & (5) \\ Y_{fdt+s} &= \kappa_d + \kappa_{st} + \Omega Occup_{dt} + \mathbf{X'}_f \Gamma + \epsilon_{fdt \pm k} \;; -4 \leq s \leq 4 & (6) \end{aligned}$$

The 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.[13] 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 A3.

"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 A of Figure 2, estimates (3), revealing that there is no correlation between population growth rate and judge occupancy rate. Panel B of Figure 2 plots the event coefficients from specifications (4) and (5). Figure 4, Figure 6, and Figure 5 present the correlations between judge occupancy and firm outcomes estimating (6).

Exclusion Restriction: Judge occupancy affects outcomes of interest only through court's trial resolution rate. Exclusion restriction may be violated, for example, if judge occupancy directly affects 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, certain type of criminal offense, particularly bailable crime, increases subsequent to an increase in judge occupancy as a downstream effect, i.e. via disposal rate. Bailable crime includes

[13] Figure A7 in the appendix shows that level of judge occupancy is relatively uniform across districts in any given calendar year. The structural problem of vacancy increases over time across all courts.

criminal charge for "bounced check" under Negotiable Instruments Act, which banks are known to use as a strategy to incentivize debt repayment (Daksh 2017). Further, increase in judge occupancy also increases 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 by addressing judge vacancy, which subsequently facilitates economic value addition by 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.

A. Litigation, debt recovery, and credit allocation

As discussed in the previous section, an increase in judge occupancy (converse of 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 pronouncing of judgement. For execution petitions, resolution leads to execution of the 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. This allows the bank to use law enforcement officials to take possession of property or assets owned by the debtor. Among litigation involving banks, a reduction in vacancy by adding a judge increases disposal rate by 5.6 percent or 0.8 percentage points. This implies that an additional judge is able to resolve close to one more percent of the existing caseload. Even if one in hundred ongoing cases are resolved marginally, the bank is able to recover unproductive capital from that specific

[14] These are seen in Figure A6 Panel B and Figure A11 depicting the role of judges in resolving bail petitions and effects on crime.

debt contract given that secured business loans and even personal loans such as education, home or vehicle loans are large. Further, encountering judge vacancy during its 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.

Loan recovery and overall lending I begin with district-level aggregate effects on public sector banks by examining total outstanding loan - reflecting the extent of repayment from, and total number of loans to manufacturing firms. Public sector banks account for 80 percent of total banking in the period of study and perhaps closer to 100 percent in non-metropolitan districts in the study sample. Since these capture the direct effects of litigation related delays, I weight the IV and reduced form specifications by total number of ongoing trials involving banks in a given district-year.

Table 4 presents the OLS, IV, reduced form, and the first stage estimates on outstanding loan amount (Panel A) and total number of loans (Panel B). Both IV and reduced form estimates imply that the outstanding loan amount declines as court capacity improves. From a reduced form point of view, adding one more judge reduces amount outstanding by 1.7 percent. The IV estimate implies a 0.3 repayment elasticity with respect to disposal rate. This large effect on repayment includes both overdue loans under litigation as well as timely payment of other loans, suggesting a disciplining effect on borrowers. Another strategy that banks deploy to encourage timely repayment is to evoke criminal offense for bounced checks under Negotiable Instruments Act. As discussed in the previous section, I find that an increase in judge occupancy increases total bailable crime in the district but otherwise has no significant effect on overall crime.

Panel B presents the estimates with log total number of loans in the district as the dependent variable. An additional judge increases total loans by over 1 percent. With respect to disposal rate, the loan elasticity is 0.23 percent. OLS estimates in both specifications are biased towards zero, suggesting the presence of omitted variables that are negatively correlated with disposal rate.

Table 5 shows that smaller delinquent borrowers are likely to settle instead of pursuing litigation and overall rate of litigation reduces as judicial capacity improves. This is because the judgement is typically in favor of the lender and improved capacity implies faster settlement. This also supports the first hypothesis in the credit model suggesting that initial wealth matters whether or not the delinquent borrower engages in litigation.

Local Firms' Credit Access Table 6 shows the corresponding effects on local firms' long term borrowing from banks. As per model propositions, I examine overall borrowing effect across all local firms as well as heterogeneous effects by their ex-ante asset size. Consistent with the proposition, smaller firms borrow more from banks as judicial capacity improves whereas there is muted and statistically insignificant effect on larger firms. The estimates imply that, on average, adding one more judge increases total borrowing by 3.6 percent. The average disposal rate elasticity is 0.26. The increase is larger and significant for smaller firms in the sample - one more judge increases total borrowing by 11 percent and implies a disposal rate elasticity of almost 1. These coefficients for larger firms are close to 0 and statistically insignificant. The event study graphs in Figure 4 present this more clearly, showing lagged effects of a reduction in judge vacancy, particularly among small firms, and no significant pre-trends.

Table 7 provides evidence on changes in interest incidence calculated as the percentage of interest expenditure of average borrowing as reported in the Prowess data. While the estimates are imprecise, it suggests that lenders are likely to charge lower interest rate on average as judicial capacity improves. Note that this is not exactly the interest rate on loan contracts from banks alone but a measure of aggregate interest burden. A positive incidence for small firms could suggest that these firms may borrow more from formal institutional lenders when courts function better, and less likely to use their own saving or retained earning for production.

This differential access to bank loans is also seen at a sectoral level where total lending increases by 3-4 times more for manufacturing and consumption loans relative to agricultural loans.[15] Together with the heterogeneity in firm level borrowing, this suggests that an improvement in court capacity also affects subsequent credit allocation by banks within the district. This is also consistent with the fact that the bank loan officers themselves are frequently rotated and therefore, any credit allocation is based on current capital availability and officer specific incentives.[16]

B. Firms' Production Outcomes

The comparative statics following the credit market implications of improvement in trial resolution as well as empirical evidence above shows that borrowing increases particularly for smaller, potentially credit constrained firms. This helps expand production by increasing input use. In addition, larger firms are likely to experience an increase in value added (net sales) from reduced transaction costs.

Table 8 presents local firms' production and input use effects of an improvement in court capacity. The effect on wage bill is stark, both statistically and economically. The estimates imply that an additional judge increases average firms' wage bill by 7 percent. This increase is present across the distribution of firms by size - both small and large firms expand their expenditure on labor between 3 and 7 percent. Measured disposal rate elasticities are between 0.11 and 0.27 across the distribution of firms. On the other hand, the estimates on plants and machinery is smaller and statistically insignificant, suggesting a plausibly modest increase between 1-2 percent per additional judge. The expansion in wage expenditure relative to investment in capital and equipment suggests that there may have been slack in their capacities, at least among larger firms.[17] Figure 5 present the event study graphs, showing this pattern

[15]See Table A6 for the estimates.

[16]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".

[17]All regressions are weighted by the number of firms in the district at the start of the study period. The results on wage bill continues to of similar magnitude with or without weights.

of effects on wage bill but relatively no effect on capital investment.

Overall production, measured as sales revenue, expands. Panel A Table 8 shows that revenue increases by 2.5 percent per additional judge, implying a 0.1 disposal rate elasticity. Much of the increase appear to be driven by small firms although the estimates on revenue for this subgroup is imprecise. Value added, measured as sales revenue net of expenditure on raw material and inputs, also increase by 4 percent per additional judge on average with 0.2 disposal rate elasticity. There is potentially substantial heterogeneity in value addition across firms: effects are positive and of similar magnitude among large firms whereas negative among small firms. A likely explanation is potential reduction in raw material and inventory by large firms, enabling them higher value addition. In contrast, small firms are likely to expand use of raw material and accumulate inventory, lowering their value addition. Event study graphs Figure 6 show this lagged effect and no significant pre-trend in these outcomes.

C. Robustness Checks

Alternate Construction of Judge Occupancy: I verify that the instrument is robust to variations in constructing the judge occupancy measure. For example, row 2 in Table 2 presents the first stage estimates when the total number of judge positions - denominator in the judge occupancy rate - is fixed as of a specific year. A second method tests whether the year when all judge positions are filled is strategically manipulated based on caseload. An absence of pre-trends in the disposal rate suggests that this is likely not the case.

Verification using judge tenure data: Lastly, I verify whether judge tenure is correlated with past measures of court performance as well as firm outcomes. 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 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 these courts do not remain without a head judge for long. Finally, I find that their tenure or "seniority" is uncorrelated with past outcomes, suggesting the independence of judge occupancy as an instrument.[18]

Alternate Identification: Event Study To verify the effects of the effect of well functioning courts on firm outcomes as estimated through the above mentioned IV strategy, I employ an alternate approach that relies on an event study design.

$$Y_{fdt} = \rho_d + \rho_{st} + \sum_{k=-5}^{k=5} \gamma_k \mathbb{1}\{t \geq k\} + \zeta_{fdt} \tag{7}$$

where event t 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.

Figure A12 shows the event study graphs using the above specification. The results are qualitatively similar to the IV or reduced form estimation using court disposal rate and judge vacancy respectively. Bank lending increases after experiencing a positive shock (10 percent increase) in judge occupancy. Firm estimates are noisier but also exhibit an increasing pattern after the district court experiences a positive judge shock for the first time. On the other hand, the effect on capital investment in the form of plant and machinery show no consistent pattern. Even with a different design and definition of "treatment", we continue to find similar qualitative effect of judicial capacity on bank lending and firm outcomes.

Visual IV Figure A13 presents binned scatter-plots of the relationship between residualized lending and firm outcomes and predicted court disposal

[18] 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 A8 presents the distribution of PDJ tenure, associated vacancy from rotations, and event study graphs of firm outcomes.

rate, after absorbing the fixed effects. These plots show positive relationship across these outcomes excluding capital investments. The plots also show goodness of fit and that the results are not driven by outliers.

D. Firm Borrowing as a Causal Channel

While I show an increase in long-run borrowing from banks, this may not be the only mechanism affecting firms' production outcomes. For example, improved court capacity may reduce hold up problem in labor disputes and therefore, may provide an improved environment for expanding production. In order to understand the causal effect through access to formal credit, we need to shut down these other channels. Following Imai et al. (2011), I estimate Average Causal Mediation Effect (ACME) through borrowing by instrumenting total long term bank borrowing by firms with a rural branch expansion shock in the district. The specification is as follows:

$$
\begin{aligned}
Y_{fdt+k} &= \psi_d + \psi_{st} + \omega_1 B_{fdt+k} + \omega_2 Occup_{dt} + \mathbf{X'}_f \Gamma_1 + \epsilon_{fdt+k} \qquad (8) \\
B_{fdt+k} &= \alpha_d + \alpha_{st} + \beta_1 Bank\ Shock_{dt+j} + \beta_2 Occup_{dt} + \mathbf{X'}_f \Gamma_2 \\
&+ \mu_{fdt+k}\ ;\ k \geq j \geq 0 \qquad (9)
\end{aligned}
$$

The idea behind ACME estimation is to establish the causal chain flowing through the credit channel. Interpreting coefficient ω_1 in (8) as the causal estimate through increased borrowing is problematic as B_{fdt+k} itself is affected by $Occup_{dt}$. One way to enable causal estimation of this mediation effect is to instrument Brw_{fdt+k} in (8) with a variable that is independent of judicial capacity and the functioning of judicial institutions. $Bank\ Shock_{dt}$ is one such instrument which is determined by national level committee on banking and central bank (RBI) policies and plausibly independent of the capacities of district judiciary (Burgess and Pande 2005).

The $Bank\ Shock_{dt}$ variable is defined as follows. I use RBI data on new bank branch opening in the study districts post 2005. The shock is 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. This design is akin to the alternative research design proposed by Imai et al. (2011). Consistent with this, I do not find any significant correlation between bank shock and judge vacancy in Column 1 Table 9. Column 2 presents the first stage estimation with amount borrowed as the dependent variable. The coefficient on judge occupancy is similar to the reduced form estimate of judge occupancy on bank borrowing in Table 6, suggesting plausible independence between judge occupancy and bank shock. The coefficient on bank shock implies that borrowing increases by 12 percent when the district experiences a large number of rural bank branch openings relative to the overall trend.

Table 10 presents the ACME estimates that I calculate by scaling the 2SLS estimate of ω_1 with the reduced form estimate of judge vacancy on firm borrowing. I compute the standard errors using the individual standard errors on each component, assuming independence between the random variables.[19] While the ACME estimates are imprecise, the similarity in the magnitude on sales and value addition with the reduced form estimates suggest that an improved access to credit plays an important role. The ACME estimate for plant and machinery implies that the increase in borrowing is used for expanding firms' capital investment, implying a 0.4 borrowing elasticity on capital investment. This is in contrast with the small and insignificant reduced form estimate, and the large reduced form effect of judge occupancy on wage expenditure.

Taken together, this analysis suggests that improved court capacity has a significant effect on local firm production through credit market channel as well as potentially through other channels such as reducing hold up problems during labor disputes and a general improvement in contracting environment.

[19] Table A9 presents the 2SLS estimates corresponding to ω_1 in (8).

E. Benefit-cost analysis

The analysis suggests that addressing judge vacancy in district courts translates into significant improvements in local firm production and value addition. Expansion on wage expenditure suggests that either formal sector employment increases or the labor employed by these firms experience a gain in their compensation. Evidence also supports an increase in sales revenue and value addition. 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 11, I calculate the benefit-cost ratio using the estimates from the above analysis and simple assumptions. I use median values of net sales and wage bill to compute the overall increase in value addition and salaried income at the level of a district, by aggregating across 376 firms per district. Since both enterprise and salaried individual pays 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. 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. Finally 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 12:1 considering only an increase in income tax revenue from salaried individuals hired by formal sector firms. Considering overall value addition in the local economy and the corresponding increase in corporate tax in addition to increase in salaried employment suggests a much larger benefit-cost ratio. Since provincial governments are responsible for district judge salaries, the increase in local economic output should provide sufficient incentives to address judge vacancies.

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 increased use of inputs, and increases value addition 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.

Comparing the estimated elasticities on borrowing from banks with those reported in Ponticelli and Alencar (2016) in the context of Brazilian trial courts reveals substantial similarity. The authors estimate the elasticity of borrowing with respect to court congestion as 0.178, similar to the estimated elasticity of 0.26 in this paper.[20] The elasticities of sales are also similar: they estimate 0.083 congestion elasticity of output whereas I estimate a 0.098 elasticity of revenue from sales. Though these estimates are comparable, this paper underlines the importance of judge vacancies in improving the rate of trial resolution in ordinary trial courts as a measure of state capacity, complementing the role played by the size of the court jurisdiction discussed in the Brazilian context. Further, 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.

Lastly, the sample districts in this study cover most industrial districts in India with the exception of Delhi NCR and Mumbai areas. The fraction of manufacturing firms and banking firms with registered office location in these

[20] The authors' measure congestion as log backlog per judge. On the other hand, I compute the fraction of backlog that is resolved in a given year as a measure of court capacity. Despite the differences in construction, the estimates are in the same ballpark.

districts is similar to the fraction of such firms in other districts not included in the study. The heterogeneity in the first stage estimates by underlying district population implies that addressing judge occupancy will likely have a strong effect in improving trial resolution for the large majority of non-metropolitan districts in India.

V Conclusion

To conclude, I present the first 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. Increasing judge occupancy by reducing vacancy substantially increases the rate of trial resolution. This paper demonstrates that judge occupancy is an important factor determining courts' capacity in enforcing credit contracts, freeing tied-up capital, and enabling credit circulation that has important ramifications for local economic development.

The importance of courts in facilitating credit markets is concordant with the observation that banks litigate intensively 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 in the district experience an increase in long term borrowing from banks, relaxing credit constraints and expanding production. Results suggest an increase in value addition on average, and an expansion in labor use across the entire distribution of firms. Causal mediation analysis helps isolate the role of credit channel from other mechanisms to establish the relative importance of access to credit for firm growth.

This paper highlights the problem of judge vacancy in district courts, that has meaningful economic repercussions. This is also consistent with the current demand by legal experts to address the issue of vacancy and strengthening 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 judge from increased tax collection and an expansion in employment.

The scope of this paper is limited to the outcomes of firms in the formal sector, whereas a large share of production and employment in India is in the informal sector. It is likely that the effects of courts may be heterogeneous depending on informality, including selection into informality. Further, informal sector firms may use extra-legal justice institutions for contract enforcement and protection of private property. More research is required to examine the interplay between judicial capacity and selection into formal sector production. This provides motivation for exploring this question in subsequent research using this dataset and context.

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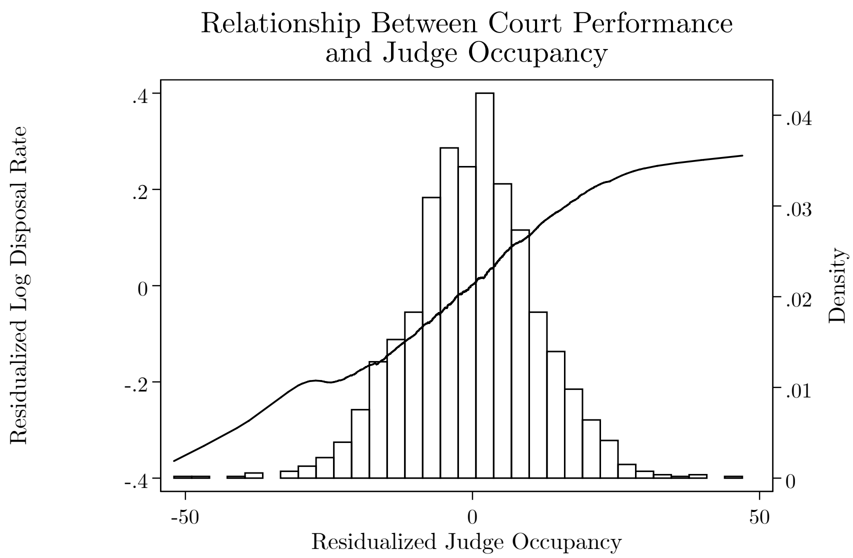
VI Figures

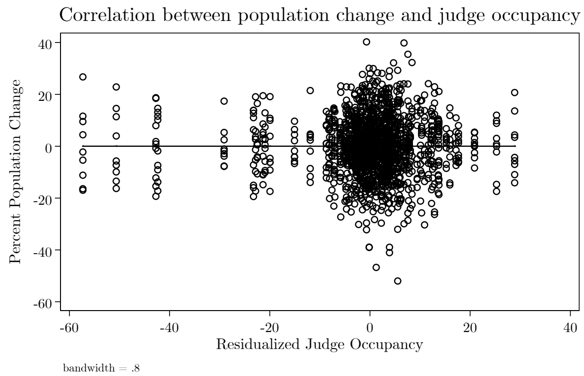
Figure 1: Disposal Rate and Judge Occupancy: First Stage



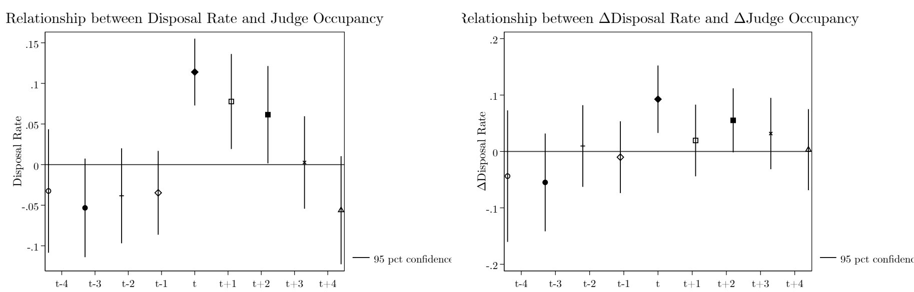
Notes: Above graph shows the relationship between disposal rate and judge occupancy, after controlling for district, year, and state-year fixed effects, using flexible lowess specification between disposal rate and judge occupancy. All standard errors are clustered by district-year.

Figure 2: Exogeneity of Judge Occupancy

Panel A:



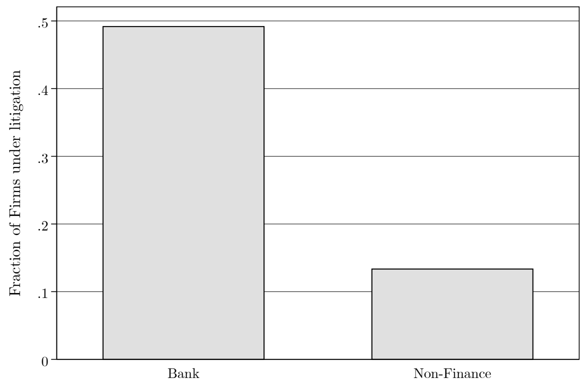
Panel B:



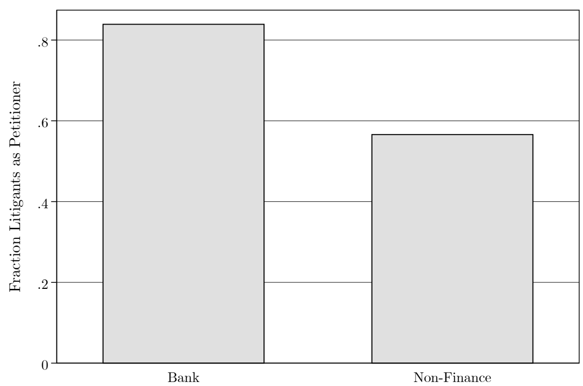
Notes: Panel A is a scatter-plot regressing judge occupancy after residualizing district and state-year fixed effects and the percent change in population between 2001 and 2011 census enumeration of the district. The figures in Panel B plot the relationship between both levels and changes in judge occupancy at time t with respect to levels and changes in leads and lags of disposal rate, respectively, after accounting for district and state-year fixed effects and firm specific controls. That is, 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 $t-4$ presents the regression coefficient when disposal rate measured 4 years prior is regressed on the current period judge occupancy. Similarly, value at $t+4$ presents the regression coefficient regressing disposal rate measured 4 years later on the current period judge occupancy. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure 3: Litigation Intensity by Firm Type

Panel A

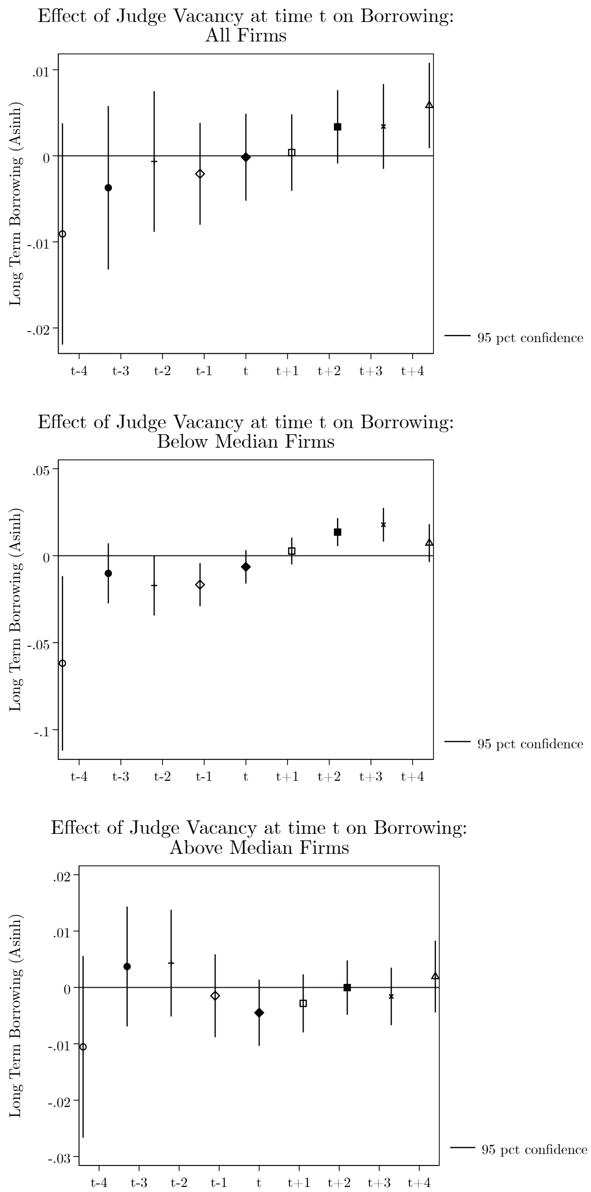


Panel B



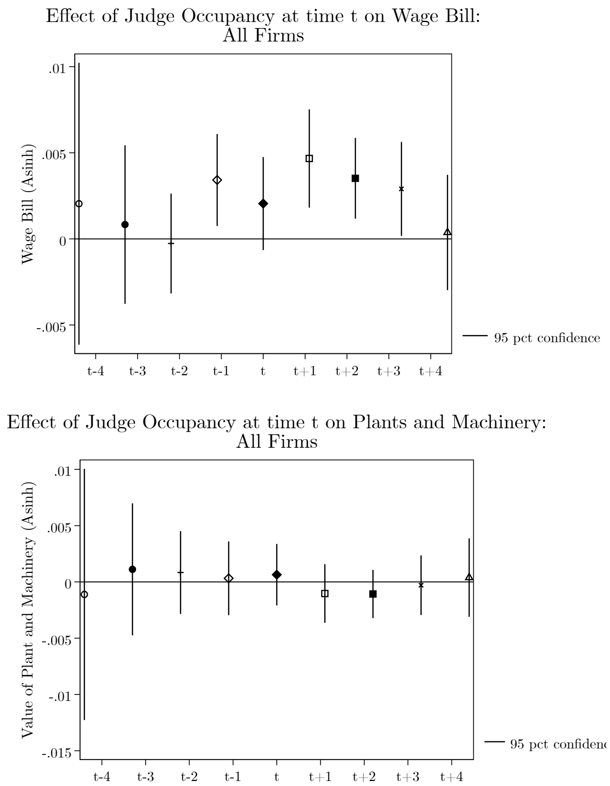
Notes: Panel A shows what fraction of firms in the study sample are also found as a litigant in the trial microdata, grouped by whether they are banking sector firm or belong to non-financial sector. Panel B shows what fraction of the cases that the litigant firm appears as a petitioner (plaintiff), grouped by whether the firm belongs to banking sector or non-financial sector.

Figure 4: Effects on Firm's Borrowing from Banks



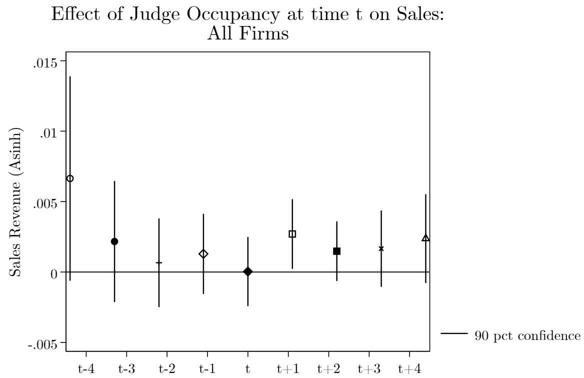
Notes: The graphs present the reduced form effect on borrowing across all firms, borrowing by small firms, and borrowing by large firms, respectively. Firms are classified as small or large depending on whether they are below or above median based on their ex-ante asset size distribution. The x-axis presents the time difference between the year the dependent variable is measured and the year judge occupancy is measured. For example, the value at $t-4$ presents the regression coefficient when borrowing measured 4 years prior is regressed on the current period judge occupancy. Similarly, value at $t+4$ presents the regression coefficient regressing borrowing measured 4 years later on the current period judge occupancy. 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.

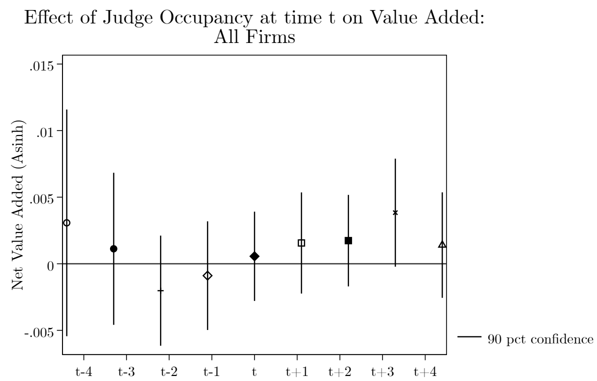
Figure 5: Reduced Form Effects of Judge Occupancy on Factor-Use



Notes: The graphs above plot the RF coefficients from regressing lags and leads of wage bill and value of plant and machinery. 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 $t-4$ presents the regression coefficient when wage bill/plant value measured 4 years prior is regressed on the current period judge occupancy. Similarly, value at $t+4$ presents the regression coefficient regressing wage bill/plant value measured 4 years later on the current period judge occupancy. 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.

Figure 6: Reduced Form Effects of Judge Occupancy on Sales and Value-Added





Notes: The graphs above plot the RF coefficients from regressing lags and leads of sales revenue (top) and value-added (bottom) on judge occupancy, 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 $t-4$ presents the regression coefficient when sales/value-added measured 4 years prior is regressed on the current period judge occupancy. Similarly, value at $t+4$ presents the regression coefficient regressing sales/value-added measured 4 years later on the current period judge occupancy. 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, million USD)	195	1746	8843	20486	33	264336
Panel C: Firm Variables						
Long Term Borrowing (real terms, million USD)	2460	9313	26	131	0	3546
Revenue from Sales (real terms, million USD)	4189	20029	77	332	0	11244
Value Added (in real terms, million USD)	2483	12905	44.8	183	-1921	5802
Accounting Profits (in real terms, million USD)	4618	24010	3	57	-2037	2234
Wage Bill (in real terms, million USD)	4454	21847	6	30	0	993
No. of Workers ('000)	1095	4075	2	7	0	154
Plant value (real terms, million USD)	3580	18124	41	236	0	12396

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	0.750	0.790	0.750	0.69	0.69

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 measured towards the start of the study period. All specifications include district and state-year fixed effects. Standard errors in Columns 1-3 are clustered at the district-year level, Column 4 by state-year, and Column 5 by district.

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	15.13	3.370
Adj R-Squared	0.700	0.740	0.680	0.710	0.710	0.600	0.780
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: Banks' Lending Behavior

	(1)	(2)	(3)	(4)
	OLS	2SLS	RF	Log Disp (First Stage)
Panel A: Asinh Outstanding Loan				
Log Disposal (t-1)	-0.00516	-0.296**		
	(0.0233)	(0.138)		
Judge Occupancy (t-1)			-0.00230**	0.0078***
			(0.000977)	(0.002)
Observations	4279	4279	4279	4279
Adj R-Squared	0.96	0.96	0.96	0.58
Wald F-Stat (First Stage)				18.29
Panel B: Asinh No. Loans				
Log Disposal (t-1)	-0.0129	0.225**		
	(0.0164)	(0.110)		
Judge Occupancy (t-1)			0.00175**	0.0078***
			(0.000765)	(0.002)
Observations	4279	4279	4279	4279
Adj R-Squared	0.940	0.93	0.940	0.58
Wald F-Stat (First Stage)				18.29
District FE	Yes	Yes	Yes	Yes
Case Type FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes

Standard errors in parentheses

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

Notes: Results presented in this table focuses on public sector banks' lending towards manufacturing firms, using RBI data. These banks are either partially or completely owned by the state and represent 80% of the formal banking sector. Panel A reports specifications using log outstanding loan amount and Panel B reports using log number of loans as dependent variables, respectively. Regressions are weighted by number of litigations involving banks within a court-year. All standard errors are clustered at the district-year level.

Table 5: Potential Defaulter' Litigation Behavior

	Ever Litigate (Among Defaulters)	Litigate this year (Among Defaulters)
Small Firms x Judge Occupancy		0.0000863
		(0.000390)
Judge Occupancy		-0.000912**
		(0.000378)
Small Firms	-0.120***	-0.0439
	(0.0156)	(0.0351)
Observations	18536	5669
Adj R-Squared	0.290	0.100

Standard errors in parentheses

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

Notes: Dependent variable in Columns 1 is a binary variable, coded as 1 if a firm has ever appeared as a respondent/defendant in the trial microdata. Dependent variables in Columns 2 is a binary variable coded as 1 for each year in the sample dataset if a litigating firm appeared as a respondent 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 6: Firms' Borrowing

	(1) OLS	(2) 2SLS	(3) RF	(4) Log Disp (First Stage)
Panel A: All Firms				
Log Disposal (t-2)	0.024	0.255*		
	(0.035)	(0.136)		
Judge Occupancy (t-2)			0.005**	0.0183***
			(0.002)	(0.005)
Observations	9405	9421	9405	9421
Adj R-Squared	0.14	0.15	0.14	
K-P Wald F-Stat				11.25
Panel B: Small Firms				
Log Disposal (t-2)	0.074	0.91**		
	(0.051)	(0.374)		
Judge Occupancy (t-2)			0.0151***	0.0166**
			(0.0038)	(.007)
Observations	1530	1530	1530	1530
Adj R-Squared	0.28	0.23	0.285	
K-P Wald F-Stat				5.57
Panel C: Large Firms				
Log Disposal (t-2)	-0.006	0.045		
	(0.026)	(0.122)		
Judge Occupancy (t-2)			0.00085	0.0188***
			(0.0023)	(0.0054)
Observations	7891	7891	7891	7891
Adj R-Squared	0.20	0.20	0.20	
K-P Wald F-Stat				12.19

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

Notes: The table above reports OLS, IV, and reduced form estimates with firms' long term borrowing from banks as dependent variable. Panel A presents the estimates on all firms, Panel B for below median firms, and Panel C reports for above median firms. The explanatory variable trail the dependent variables by 2 years. 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 7: Change in Firms' Interest Incidence

	(1) OLS	(2) 2SLS	(3) RF	(4) Log Disp (First Stage)
Panel A: All Firms				
Log Disposal (t-2)	-0.0197	-0.099		
	(0.031)	(0.124)		
Judge Occupancy (t-2)			-0.002	0.020***
			(0.0024)	(0.0053)
Observations	7282	7282	7282	7282
Adj R-Squared	0.044	0.044	0.044	
K-P Wald F-Stat				14.19
Panel B: Small Firms				
Log Disposal (t-2)	-0.069	0.104		
	(0.059)	(0.34)		
Judge Occupancy (t-2)			0.0016	.0152**
			(0.0052)	(.0069)
Observations	1424	1424	1424	1424
Adj R-Squared	0.067	0.063	0.067	
K-P Wald F-Stat				4.83
Panel C: Large Firms				
Log Disposal (t-2)	-0.0052	-0.16		
	(0.041)	(0.17)		
Judge Occupancy (t-2)			-0.00296	0.0187***
			(0.003)	(0.0057)
Observations	4020	4020	4020	4020
Adj R-Squared	0.068	0.065	0.068	
K-P Wald F-Stat				10.59

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

Notes: The table above reports OLS, IV, and reduced form estimates with change in interest incidence as the dependent variable. Panel A presents the estimates on all firms, Panel B for below median firms, and Panel C reports for above median firms. 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 8: Firms' Production Outcomes

	Asinh Sales	Asinh Value Added	Asinh Wage Bill	Asinh Plants-Machinery
	Panel A: All Firms			
OLS	0.052***	0.048**	0.064**	0.0207
	(0.014)	(0.02)	(0.02)	(0.014)
IV	0.097**	0.19*	0.268**	0.068
	(0.043)	(0.11)	(0.087)	(0.058)
RF	0.0034**	0.0058**	0.0099***	0.0021
	(0.0016)	(0.0025)	(0.0017)	(0.0017)
FS	0.035**	0.0303**	0.037**	0.031**
	(0.013)	(0.0146)	(0.013)	(0.014)
Observations	20179	12896	21867	18299
Adj R-Squared	0.29	0.10	0.33	0.22
K-P Wald F-Stat	7.06	4.29	8.18	4.67
	Panel B: Small Firms			
OLS	0.066***	-0.042	0.022	0.015
	(0.018)	(0.06)	(0.014)	(0.023)
IV	0.11	-0.25	0.106*	0.0802
	(0.0695)	(0.22)	(0.057)	(0.088)
RF	0.004	-0.0079	0.0042**	0.00265
	(0.0027)	(0.0053)	(0.0019)	(0.0025)
FS	0.037**	0.0317*	0.0394**	0.033**
	(0.0157)	(0.018)	(0.0147)	(0.0166)
Observations	4375	2126	5388	3464
Adj R-Squared	0.3	0.21	0.32	0.23
K-P Wald F-Stat	5.6	3.10	7.19	3.94
	Panel C: Large Firms			
OLS	0.0397**	0.061**	0.076**	0.033**
	(0.014)	(0.028)	(0.0295)	(0.0155)
IV	0.0102	0.16	0.253***	-0.045
	(0.048)	(0.11)	(0.079)	(0.084)
RF	0.00037	0.0051	0.00965***	-0.0015
	(0.0018)	(0.0035)	(0.00225)	(0.0025)
FS	0.036**	0.0317**	0.038***	0.033**
	(0.012)	(0.0126)	(0.012)	(0.0127)
Observations	15788	10754	16461	14812
Adj R-Squared	0.28	0.11	0.29	0.24
K-P Wald F-Stat	9.96	6.37	10.65	6.9

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

Notes: The explanatory variables trail the dependent variables by 2 years. The regressions are weighted by the number of firms in the district at the start of the study period and 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: Effect of Bank Expansion Shock on Firms' Borrowing

	(1) Bank Shock (t-1) Exogeneity Test	(2) Amount Borrowed First Stage
Judge Occupancy (t-3)	-0.002	
	(0.0021)	
Judge Occupancy (t-2)	-0.0039	0.0053**
	(0.0025)	(0.0025)
Judge Occupancy (t-1)	-0.000025	
	(0.0025)	
Bank Shock (t-1)		0.116**
		(0.047)
Observations	25300	8601
Joint Test p-value	0.13	
Wald F-Stat (First Stage)		53.15
Adj R-Squared	.62	.13

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

Notes: The regressions include district and state year fixed effects. Column 1 tests whether past period judge occupancy is correlated with observed bank shock. The sample of firms in Column 2 include all those that were incorporated before 2010. Additional controls include firm age, age-squared, and sectoral dummies. All standard errors are clustered at the district-year level.

Table 10: Mediation Effect through Credit

Outcome	**RF**	**Mediation**
Sales	0.202*	0.295
	(0.12)	(0.20)
		[0.14]
Value Added	0.14	0.325
	(0.2)	(0.45)
		[0.48]
Wage Bill	0.45***	0.052
	(0.12)	(0.1)
		[0.63]
Plant	-0.06	0.41*
	(0.12)	(0.24)
		[0.089]

Notes: Column 1 represents the unweighted reduced form coefficients on judge occupancy on firms' production outcomes scaled by a factor of 100 as occupancy is measured in percentage points. Column 2 scales the independent direct effect of an increase in borrowing from bank expansion shock on the same set of outcomes with the reduced form effect of judge vacancy on borrowing. Standard errors on the mediation effect (Col 2) are computed analytically as product of variances of two independent random variables.

Table 11: Cost-Benefit Calculation

Parameter	**Value**	**Units**	**Units**
Median Value Added	8.2	Million USD	Prowess
Median Wage bill	0.57	Million USD	Prowess
Median No. Firms	376	per district	Prowess
Value Added ϵ	0.14x 7.2 = 1.01	% change per judge	Estimation
Wage Bill ϵ	0.45 x 7.2 = 3.25	% change per judge	Estimation
Δ District Value Added	$\frac{1.01}{100}$ x 8.2 x 376 = 31.14	Million USD	Calculation
Δ District Wage Bill	$\frac{3.25}{100}$ x 0.57 x 376 = 6.96	Million USD	Calculation
Corporate Tax Rate	15	Percent	Govt. of India
Income Tax Rate	7.3	Percent	LiveMint 21st Oct 2019
Discount Rate	10	Percent	Assumption
Annual Judge Salary + Other costs	0.035	Million USD	Personal Interviews
Benefit-cost Social	$\frac{\frac{31.14+6.96}{1.1^2}}{0.035} \approx 900$	Ratio	Calculation
Benefit-cost Δ Tax on Wage Bill	$\frac{\frac{0.073 \text{ x } 6.96}{1.1^2}}{0.035} \approx 12$	Ratio	Calculation

Notes: Adding one judge in a court with 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 using unweighted firm level regressions with 7.2 to obtain the corresponding elasticities with respect to adding one more judge. 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.

Appendix

A1 Data Appendix

A. Representativeness of District Courts Sample

Figure A2 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 A1 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

[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.

terms. [2]

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. Value added (sales net of input expenditure): I generate this variable by subtracting total sales revenue and total expenditure on raw material and cost of other goods and services used as inputs.

3. Total 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, and other parts of the contract with employees.

[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.Area and production statistics from the Ministry of Agriculture and Farmers Welfare available here: https://aps.dac.gov.in. National Crime Records Bureau annual crime statistics available on their website.

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 Case Data

I follow the steps below to match firms with 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 petitioner, or as a 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 that involve a firm.

2. Create a set of unique firms appearing in above subset of case data. I note that same firm appears as a litigator in more than one district, both as a petitioner or as a respondent. 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. Ensure not to categorize cases as belonging to firms when firm names are used as landmark in the addresses of individual litigants. To do this, I detect words such as "opposite to" "above", "below", "near", and "behind". These adverbs are often used in describing landmarks. I excludes were firm names are preceded by such adverbs.

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. In future, I plan to modify my algorithm to allow these types of scenarios.

A2 A Simple Model of Credit Markets with Enforcement Costs

In order to create a framework to base the core economic rationale behind the importance of timely adjudication through courts on firm growth, I follow and extend the credit contract model in Banerjee and Duflo (2010). Specifically, I consider a 2 player sequential game with the lender's choice to enforce the contract through litigation, which is similar to the role of social sanctions in the group liability model discussed in Besley and Coate (1995). The solution to the game gives the optimal contract that details the interest rate schedule and requires a minimum threshold of wealth (collateral) for borrowing. I show that the optimal contract varies with court disposal rate, which then affects all firms in the local credit markets through changes in the credit constraints they face. The overall effect on production and firm profits, consequently, depends on whether or not firms were credit constrained.

I consider a representative lender-borrower game where borrower needs to invest, K, in a project with returns $f(K)$, where K is the total capital expenditure. Her exogenous wealth endowment is W. She needs an additional $K_B = K - K_M$ to start the project, where K_M is the amount she raises from the market whereas K_B is met in the form of borrowing from the lender (bank) on the basis of her wealth, W, as collateral. The lender earns a return $R > 1$. The project meets with success with probability s, upon which the borrower decides to repay or evade. Evasion is costly, where the borrower needs to pay an evasion cost ηK in the process, with remaining payoff at $f(K) - \eta K$. 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 under failure, in which case the lender chooses to litigate or not to monetize borrower's assets to recover their loan. The game is depicted in Figure A4. Under default, the lender can choose to litigate, incurring a cost $C_L(\gamma) > 0$, $\frac{\partial C_L}{\partial \gamma} < 0$, where γ is disposal rate of the corresponding district court. The borrower can either choose to accept the trial or settle out of court. Once the lender chooses to litigate and borrower accepts, lender mostly win as seen in the data. [3]

Borrower chooses to litigate rather than settling if her payoffs are better under litigation. In particular, when the production fails, the borrower litigates only if she has sufficient wealth to cover the litigation costs. Under production failure, the lender monetizes part of her wealth, δW, to recover the loan. If the borrower settles, she allows this monetization. On the other hand, engaging in litigation, the outcome of which mostly favors the lender, earns the lender a payoff of $\Gamma\delta W - C_L(\gamma)$, where $\Gamma < 1$ is the fraction of the disputed amount that the court is able to help recover. I assume Γ to be high and close to 1. The borrower faces a payoff $\Gamma\delta W - E[C_B(\gamma)]$, where her litigation costs $C_B(\gamma)$ is unknown ex-ante. As in the case of lender litigation costs, $C_B(\gamma) > 0$, $\frac{\partial C_B}{\partial \gamma} < 0$. Therefore, the condition for the borrower to accept litigation instead of opting to settle under production failure is

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

This gives a distribution of borrowers likely to litigate, based on their wealth. That is, the fraction $1 - F(\tilde{W})$ will litigate. Using backward induction, litigation under production 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.

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

This gives a minimum wealth threshold, W^*, that the lender imposes so that they are able to recover the amount lent through litigation even when production under the borrower's project fails. Under production success, the borrower can choose to default if she can successfully evade. However, default again leads the lender to initiate litigation, which the borrower can either accept and continue with the litigation or settle (i.e. repay). Borrower litigates if

$$f(K) - \Gamma RK_B - E[C_B(\gamma)] \geq f(K) - RK_B$$
$$\implies RK_B \geq \frac{E[C_B(\gamma)]}{(1-\Gamma)} = \delta\tilde{W} \tag{3}$$

This gives a distribution of firms who would litigate, based on their total repayment. Since K_B only depends on the project, where the project size distribution in the population is given by CDF, $G(.)$, fraction $1 - G(\tilde{W})$ borrowers will litigate. Therefore, by backward induction, litigation will be lender's dominant strategy if

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

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^*, as discussed above and setting the interest rate schedule. The returns from lending to ensure adequate recovery of loan under default gives the following schedule:

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

Next, the dominant strategy for the borrower would be to repay if the project is successful and the credit contract ensures that litigation would be the dominant strategy for the lender. This again is dependent on the distribution of borrowers that accept litigation. Specifically, the fraction of borrowers that will repay is $G(\tilde{W})$.

Finally, lender's participation constraint is given by

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

The timing of the game where the lender and borrower decide on their strategies are as follows, which is depicted as an extensive form game in Figure A4.

T0 Lender decides to lend or not lend. If they do not lend, then the payoffs to the lender and borrower, respectively, are $(\phi B, 0)$, where the lender earns returns from the external capital market while the borrower cannot start their project.

T1a Borrower invests in their project, which succeeds with probability, s. If successful, she decides to repay or default. If repays, the payoffs are $(RK_B(W), f(K) - RK_B(W))$, and the game ends.

T2a If the borrower defaults, the lender decides to litigate or not, i.e. whether to file a complaint against the borrower for default in the court of relevant jurisdiction. If the lender chooses not to litigate, the payoff is $(-K_B, f(K) - \eta K)$, where η is fraction of capital used to evade.

T3a The borrower then decides to accept and litigate, or settle. If they litigate, then the lender almost certainly wins (or has a relatively high probability of winning) but incurs a cost $C_L(\gamma)$. Borrower also incurs litigation costs, that is unknown ex-ante. The payoff in this situation is $(\Gamma RK_B - C_L(\gamma), f(K) - \Gamma RK_B - E[C_B(\gamma)])$. If lender chooses to settle, the payoffs are $(-K_B(W), f(K) - RK_B)$.

T1b If the project fails, the borrower automatically defaults.

T2b The lender decides whether to litigate to be able to monetize the collateral/seize borrower's assets. If they choose to litigate, again, the lender almost certainly wins but incurs litigation costs. If the lender does not litigate, the payoff would be $(-K_B(W), 0)$.

T3b The borrower decides to accept and litigate, or settle. As explained before, she also incurs ex-ante unknown litigation costs. Payoff under litigation is $(\Gamma\delta W - C_L(\gamma), -\Gamma\delta W - E[C_B(\gamma)])$. Payoff under settling is $(\delta W, -\delta W)$.

Constraint (1) provides conditions under which the borrower would litigate. Specifically, borrowers with wealth above a threshold, $\tilde{W}$, will litigate.

Proposition 1: Litigation Response of Borrowers As the disposal rate, γ, increases, the wealth threshold for litigation decreases. That is, $\frac{\partial\tilde{W}}{\partial\gamma} < 0$.

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

Constraints (2) and (5) define the credit contract. Additionally $R \geq \phi$ else the lender would rather invest in external markets than engaging in lending. This gives the relationship between returns, R, borrowing, K_B, and the threshold wealth, W^* required to borrow, as depicted in Figure A5.

Proposition 2: Credit Market Response to Court Performance As the disposal rate, γ, increases, the credit market response varies as follows:

1. Effect on W^* is negative. That is, an increase in court disposal rate 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: Credit Market Response to Court Performance Differentiating (2) and (5) with respect to γ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as follows:

$$\frac{\partial R}{\partial \gamma} = \frac{\overbrace{\frac{\partial C(\gamma)}{\partial \gamma}}^{\text{-ve}}}{K_B(W)} < 0$$

$$\frac{\partial W^*}{\partial \gamma} = \underbrace{\frac{\partial W^*}{\partial C_L}}_{+\text{ve}} \underbrace{\frac{\partial C_L}{\partial \gamma}}_{\text{-ve}} + \underbrace{\frac{\partial W^*}{\partial F(\tilde{W})}}_{+\text{ve}} \underbrace{\frac{\partial F(\tilde{W})}{\partial \gamma}}_{\text{-ve}} < 0$$

A. Firm Production

In this section, I model the production effects of credit market response to changes in court disposal rate. Additionally, the model also accounts for alternate channels of effects, for example through transaction costs - m, incurred by the firm. 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 is a function of inverse court congestion γ, with $\frac{\partial m_i}{\partial \gamma} \leq 0$. i represents whether the firm is a small firm based on ex-ante asset size, denoted by S, or a large firm L. 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. W is the exogenous initial level of assets or wealth. Firm that can borrow from banks have $K_i = K_M + K_B$, which is the total borrowing from market as well as banks. This only depends on project size and hence considered exogenous to the firm's decision problem. Firms of type S with assets just below the initial lending threshold W^*, rely mainly on market capital as banks are unwilling to lend. As court quality, γ, improves, the banks lower the threshold wealth for lending so that these firms experience an increase in borrowing. The interest rate on bank lending, $R(\gamma, .)$, is determined as in the Lender-Borrower set-up above. Finally, I assume that firms are credit constrained as shown in Banerjee and Duflo (2014).

Proposition 3: Effects of Court Congestion on Firm Production As the inverse court congestion, γ, increases, the firm responds as follows:

1. Lending from banks becomes available for firms of type S, i.e. those with less assets.

2. Optimal input use X_1, X_2 increases on an average.

3. Increase in γ increases production output and profits on an average.

4. Heterogeneity in effects are as follows:

   (a) For large firms, L, optimal inputs and profits increase if decrease in monitoring costs more than offsets the increase in input expenditure.

   (b) For marginal small firms, S, optimal inputs and profits increase if the increase in borrowings 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.

5. For credit unconstrained firms, if any, profits increase through a decrease in monitoring costs.

Proof for Proposition 3: Effects on Firm Production In this set-up, court performance affects the firms' optimization problem through both credit availability and monitoring costs - for example, monitoring labor or input vendors. I assumed a fixed monitoring cost as a decreasing function of court performance, γ, i.e. $\frac{\partial m_i}{\partial \gamma} < 0$, $i \in \{S, L\}$. From the discussion above, borrowing increases with an increase in court performance 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:

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

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

$$\frac{\partial \mathcal{L}}{\partial \lambda} = K_i - w_1 X_1 - w_2 X_2 - m_i(\gamma) = 0$$

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

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

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, γ. Specifically:

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

$\frac{\partial g^*}{\partial \gamma} > 0$ if marginal benefits from an improvement in institutional quality exceeds marginal cost, in which case, the value of the objective increases. If the condition is not true, then the welfare effects is potentially ambiguous. For firms across asset size distribution, the prediction is as follows:

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 due to higher optimal input use under better institutional quality, then the 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 the profits for such firms will increase.

3. For inframarginal small firms, $i = S$ and $W << W^*$, neither their optimal inputs nor their profits change under improved institutional quality since $(\underbrace{\frac{\partial K_S}{\partial \gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial \gamma}}_{\approx 0}) \approx 0$.

A3 District Judge Assignment Policy

The procedure for 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. 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.

2. Each district judge is asked to list 3-4 preferred locations they would like to be transferred to and rank them based on their order of preference.

3. Districts where the judges have already worked in the past, either in the capacity of a judge or a lawyer are dropped.

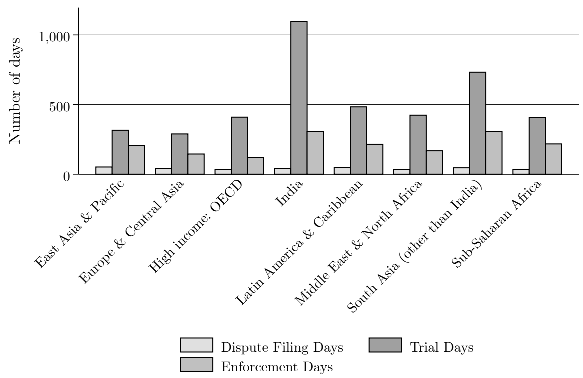
4. The judges are then matched to a district court based on this ranking, taking into consideration others' preferences, vacancies, and seniority.

5. District court judges are senior law professionals. Recruitment to this post requires a minimum number of years of experience as a trial lawyer and in some states, requires to pass a competitive examination. This implies that their age at entry is generally advanced ("mid-career") and consequently, they witness few number of transfers before their retirement. Given the average tenure at any given seat is less than the average trial duration and the procedure of frequent transfers, it is unlikely that the judges cover all of their preferred locations or stay in their preferred location for a long time. For example, the average tenure of the PDJ, for whom I was able to get tenure data, is about 18 months whereas the average trial duration is close to 21 months.

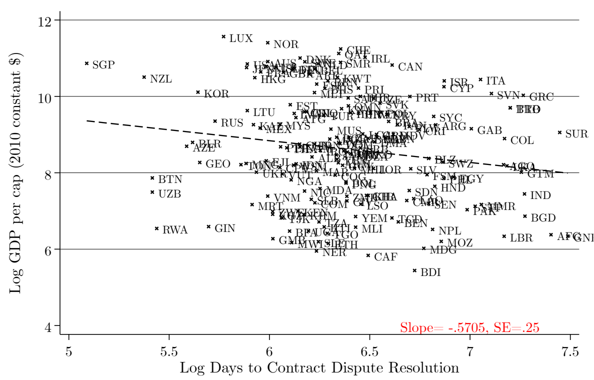
A4 Appendix: Figures

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: Sample District Courts

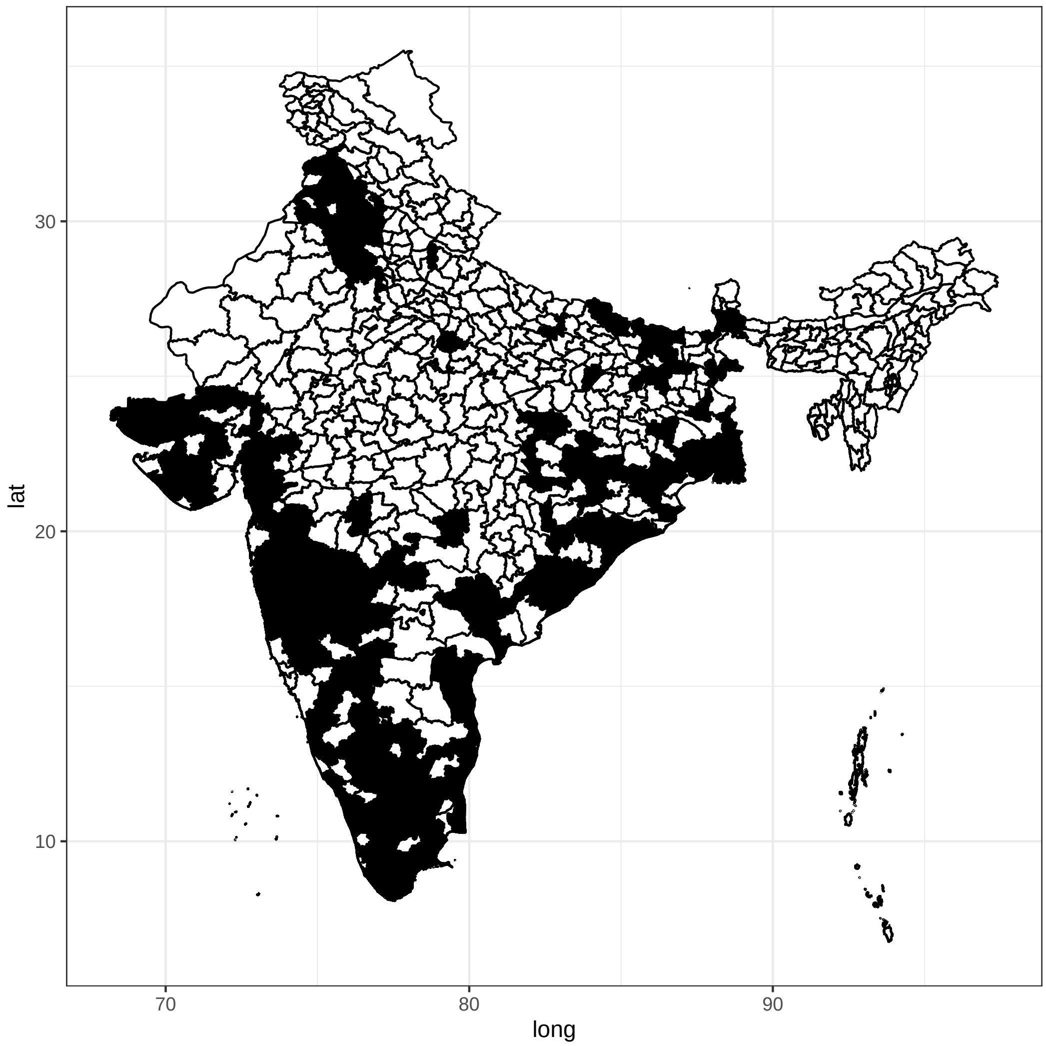


Figure A3: Construction of Firm Sample

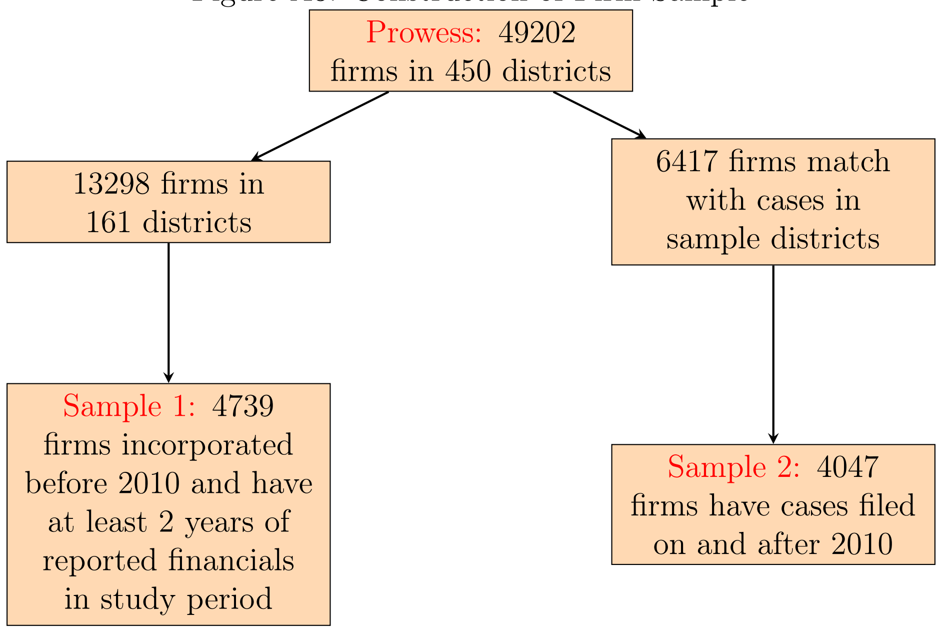


Figure A4: Model: Lender-Borrower Game

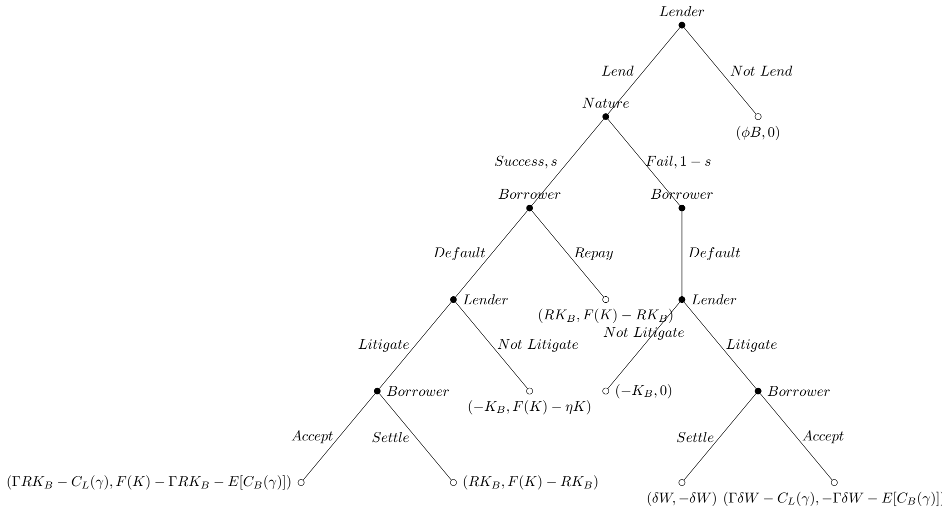


Figure A5: Model: Credit Contract

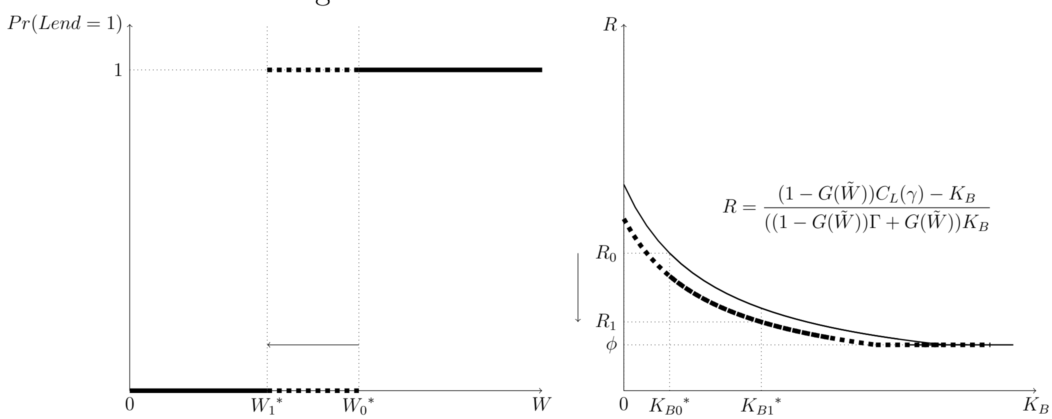
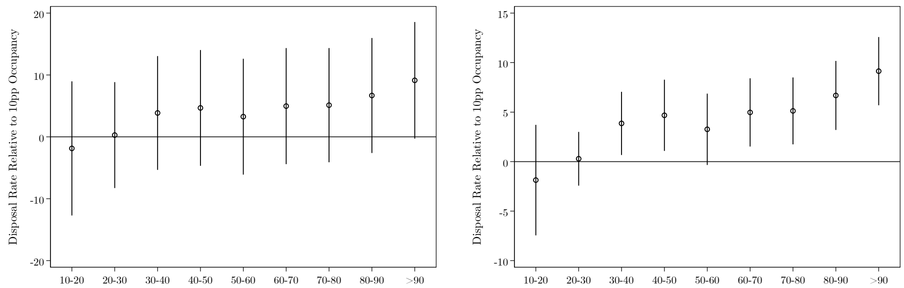
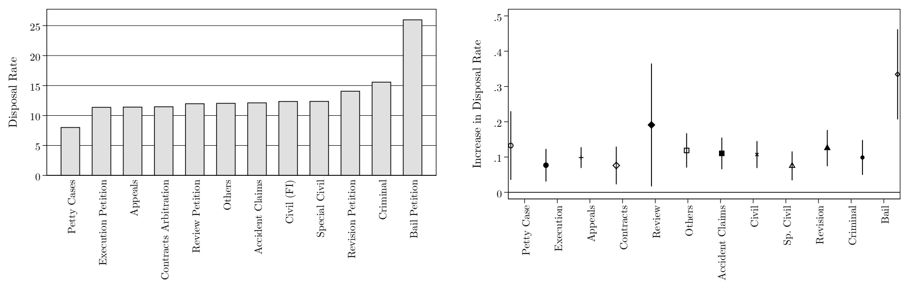


Figure A6: Heterogeneous effects of judge occupancy on disposal rate



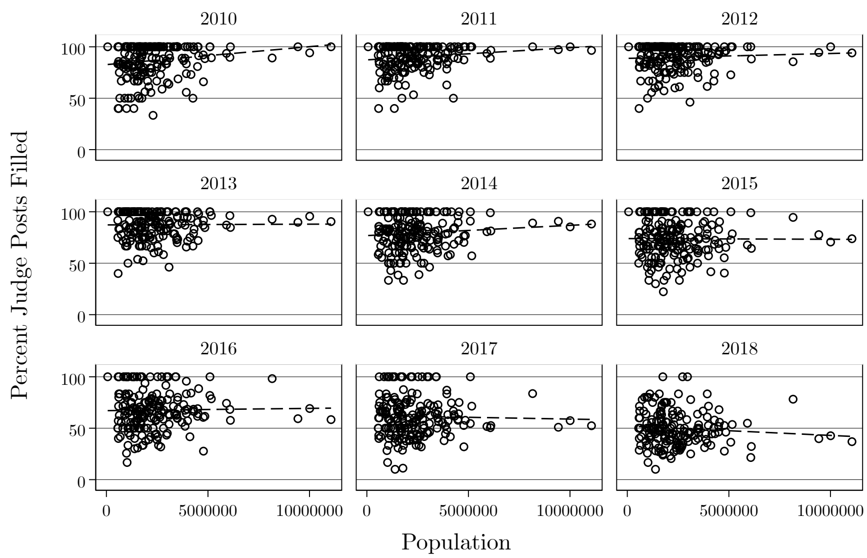
Panel A: By Judge Occupancy Bins



Panel B: By Case-Type

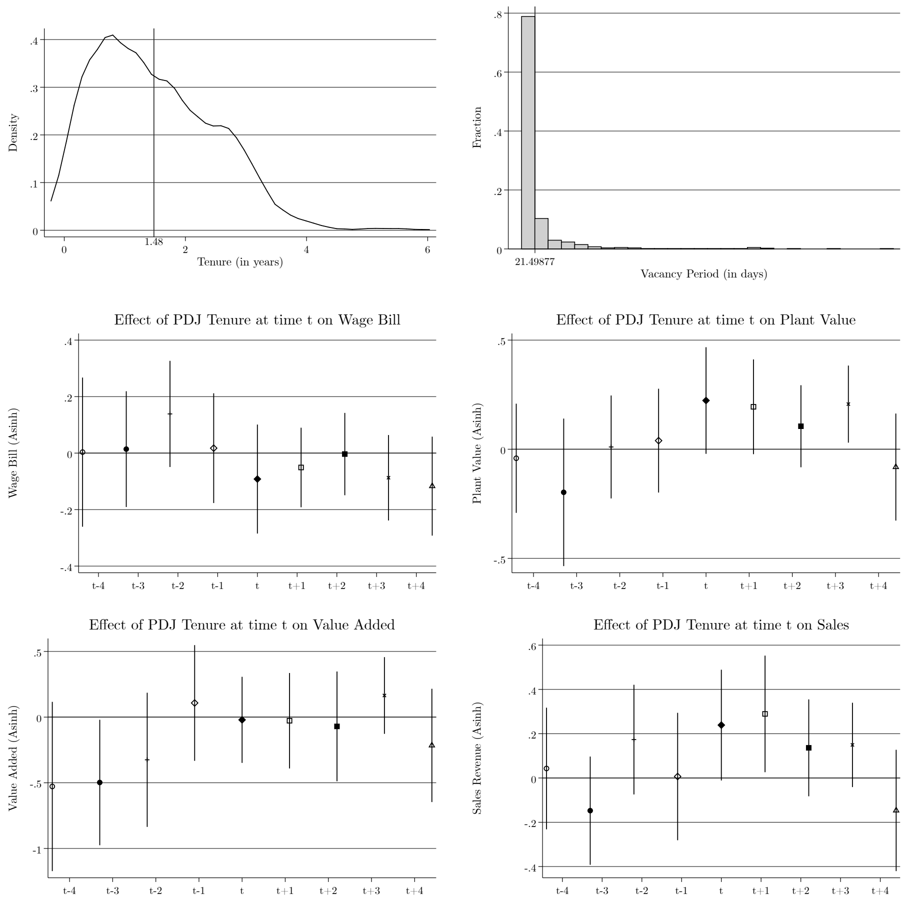
Notes: Panel A presents the regression coefficients on judge occupancy, binned by decile, with disposal rate as the dependent variable. The leave-out group is judge occupancy bin 0-10. Standard errors are clustered by district-year on the left and by district on the right. Panel B presents average disposal 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 A7: Exogeneity: Judge occupancy similar across districts over time



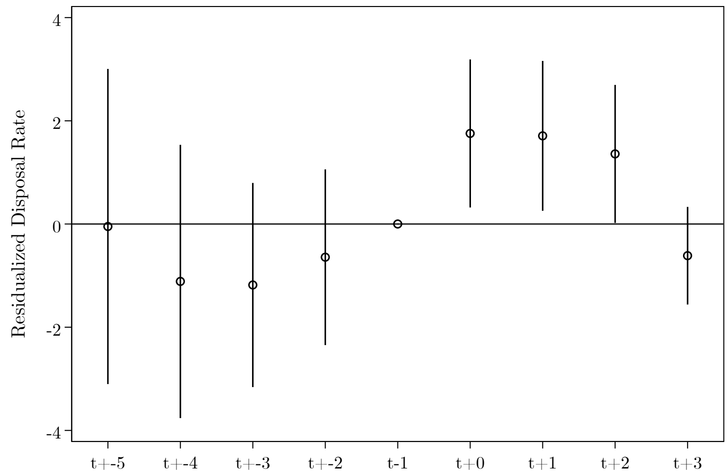
Notes: Judge occupancy plotted against 2011 census population of the district court jurisdiction over the entire study period.

Figure A8: Judge Tenure: An Example of Principal District Judge



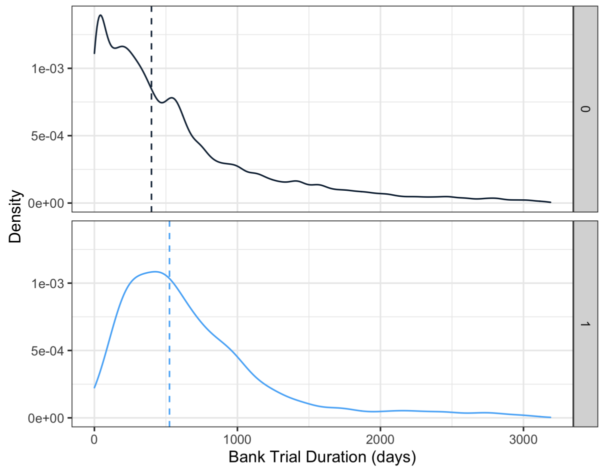
Notes: I use data on judge start date and end date in a given district court, available mainly for the Principal District Judge (PDJ) from court websites. Using this, I construct the tenure period at the end of each stay, gap between the tenure of two consecutive judges for the same position, and measure correlations between leads and lags of firm level outcomes and tenure length. These graphs show that the average tenure of district court judges is short and the timing of rotation - that affects the tenure length - is uncorrelated with firm-level outcomes from the preceding periods. The rotations also generate vacancy arising from the joining delay of the incoming judge. Standard errors are clustered by district-year.

Figure A9: First Stage: Robustness



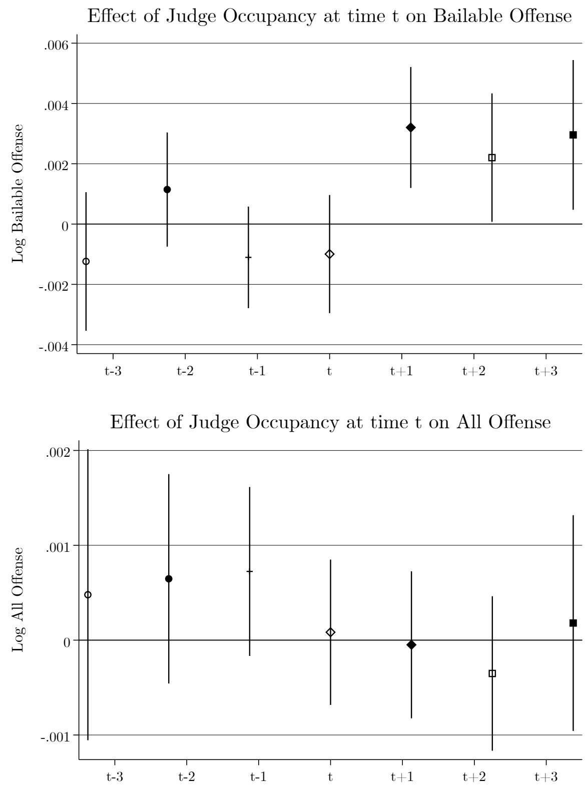
Notes: Event year ($t = 0$) is defined as the calendar year where I observe 100 occupancy rate of district court judges. That is, the event year corresponds to the calendar year with maximum observed number of judges in a given court, that I use as the denominator in constructing judge occupancy. Each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

Figure A10: Median trial duration involving banks increases with vacancy



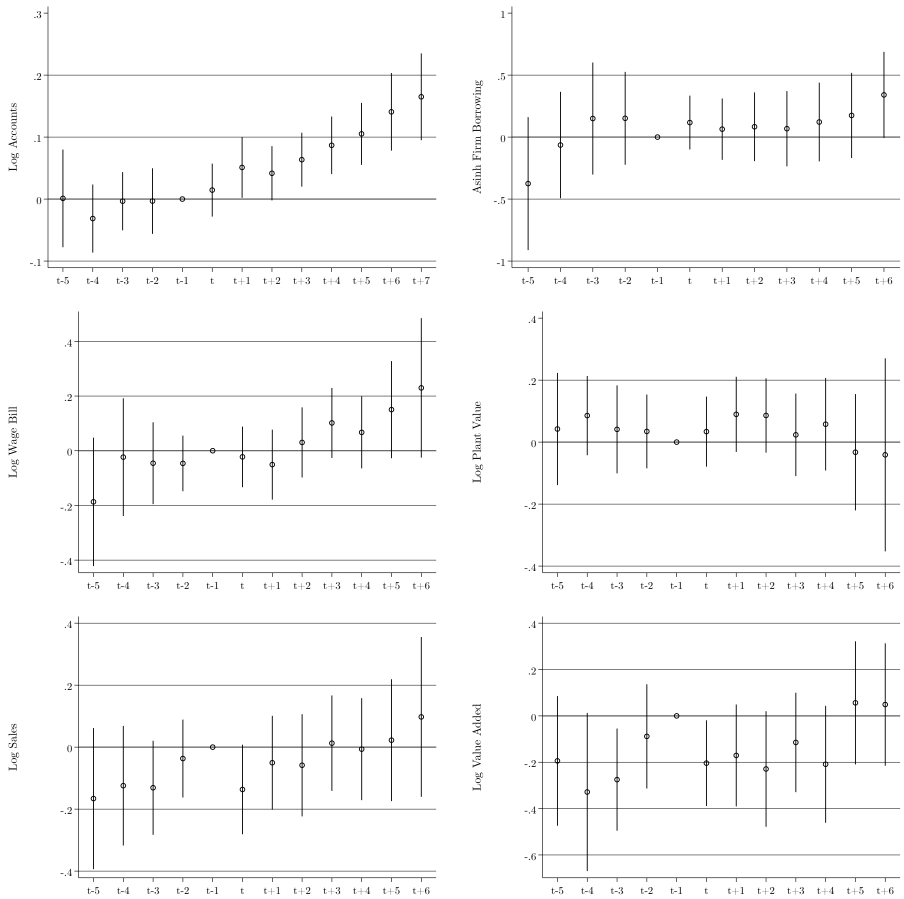
Notes: Above figure presents the density of trial duration for litigation involving banks by whether or not such a litigation experiences judge vacancy during its lifetime. The median duration of litigation encountering judge vacancy is 525 days compared to 399 days for those that do not, reflecting 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 A11: Banks also file criminal petition for debt recovery



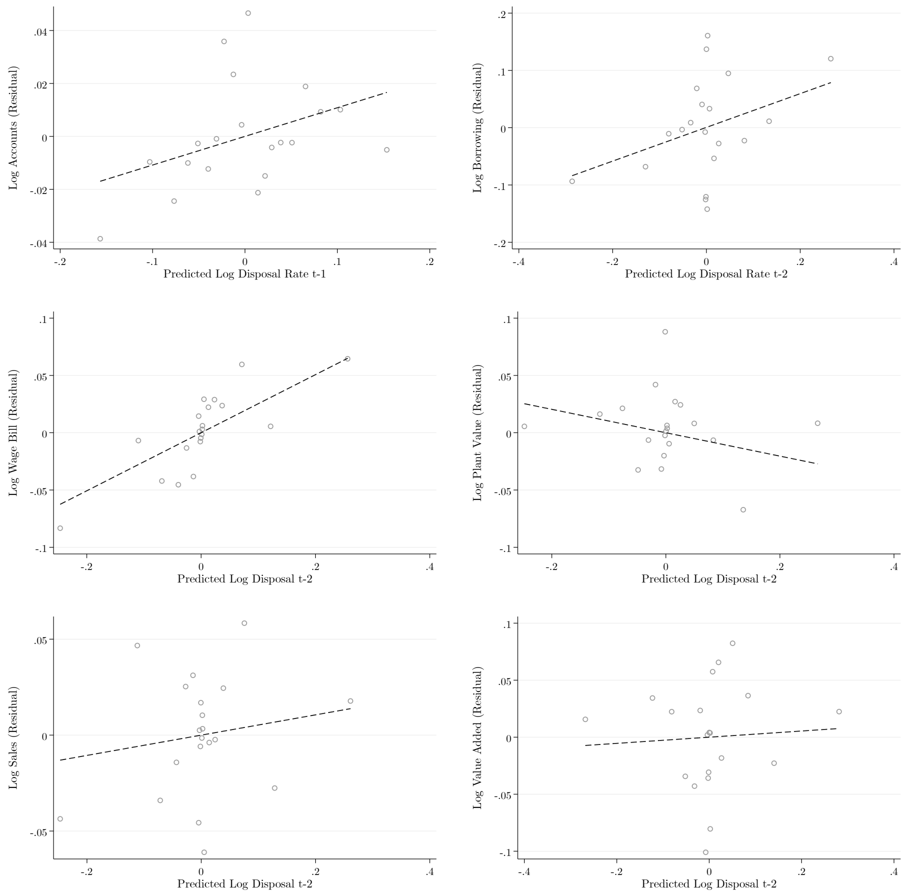
Notes: The graphs presents the effect of judge vacancy on bailable crime as well as all crime outcomes, respectively. Important bailable offenses include banks filing criminal petition when the debtor's check is dishonored citing insufficient balance in their checking account. This is a bailable criminal 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. The IV estimate on log disposal rate with bailable crime and total crime as dependent variables are 0.068 (0.023) that is statistically significant at 5%, and -0.0069 (0.009) that is not statistically significant. Standard errors are clustered at the district-year level.

Figure A12: 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. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district-year.

Figure A13: Visual IV Results



Notes: The figures present binned scatters-plots depicting the relationship between predicted log disposal rate and outcomes including bank lending, firm borrowing, value-added, sales, wage bill, and value of plant and machinery, respectively, after residualizing fixed effects and control variables.

A5 Appendix: Tables

Table A1: 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.

Table A2: Description of Firms with Cases in Sample Court Districts

	(1)				
	Not in Court Mean	Not in Court SD	In Court Mean	In Court SD	Difference p-val
Firm Age (yrs)	24.375	15.598	33.346	20.943	0.0000
Entity Type:					
Private Ltd	0.396	0.489	0.279	0.448	0.0000
Public Ltd	0.593	0.491	0.704	0.457	0.0000
Govt Enterprise	0.001	0.025	0.001	0.026	0.9425
Foreign Enterprise	0.004	0.059	0.002	0.048	0.1202
Other Entity	0.007	0.084	0.015	0.120	0.0000
Ownership Type:					
Privately Owned Indian Co	0.709	0.454	0.632	0.482	0.0000
Privately Owned Foreign Co	0.026	0.159	0.043	0.204	0.0000
State Govt Owned Co	0.009	0.094	0.033	0.179	0.0000
Central Govt Owned Co	0.009	0.094	0.029	0.166	0.0000
Business Group Owned Co	0.247	0.431	0.263	0.441	0.0060
Finance vs. Non-Finance:					
Non Finance Co	0.782	0.413	0.844	0.363	0.0000
Non Banking Finance Co	0.215	0.411	0.137	0.343	0.0000
Banking Co	0.003	0.053	0.019	0.137	0.0000
Broad Industry:					
Trade, Transport, and Logistics	0.150	0.357	0.165	0.371	0.0015
Construction Industry	0.082	0.275	0.100	0.300	0.0000
Business Services	0.338	0.473	0.226	0.418	0.0000
Commercial Agriculture	0.020	0.142	0.025	0.155	0.0339
Mining	0.023	0.150	0.035	0.184	0.0000
Manufacturing	0.386	0.487	0.450	0.497	0.0000
No. Firms	43064		6138		

Notes: All firms in the table above are those registered in any of the sample court districts. Firms can be involved in cases either in its home district or in any other district based on the case jurisdiction.

Table A3: 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 A4: Balance on district and firm time-varying characteristics

	(1) Judge Occupancy (t)	(2) Judge Occupancy (t)	(3) Judge Occupancy (t)
Disposal Rate (t-1)	0.00646		
	(0.0251)		
Disposal Rate (t-2)	-0.0361		
	(0.0282)		
Num Filed (t-1)	-6.695		
	(4.273)		
Num Filed (t-2)	-6.595		
	(4.075)		
Num Resolved (t-1)	-5.265		
	(6.573)		
Num Resolved (t-2)	-8.816		
	(6.806)		
Borrowing (t-1)		-0.00758*	
		(0.00441)	
Borrowing (t-2)		-0.000903	
		(0.00522)	
Sales (t-1)			0.000451
			(0.00156)
Sales (t-2)			0.00103
			(0.00159)
Profit (t-1)			0.00229
			(0.00371)
Profit (t-2)			0.00210
			(0.00373)
Wage Bill (t-1)			0.00307**
			(0.00126)
Wage Bill (t-2)			-0.0000648
			(0.00125)
Employees (t-1)			-0.0000317
			(0.00154)
Employees (t-2)			-0.000454
			(0.00169)
P-value(joint test)	0.580	0.66	0.46

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

Notes: This table presents estimates of regressing lagged court, district, and firm variables on judge occupancy. In each of the specification, the standard errors are clustered at the district-year level. Reported p-values are from F-tests of joint null test for each family of dependent variables, allowing for correlations in the error structure across the dependent variables.

Table A5: Banks' Loan Behavior

	(1) OLS	(2) 2SLS	(3) RF	(4) Log Disp (First Stage)
		Panel A: Log Outstanding Loan		
Log Disposal Rate (t-1)	0.0178*	-0.0383		
	(0.00927)	(0.0569)		
Judge Occupancy (t-1)			-0.000297	0.00780***
			(0.000435)	(0.0018)
Observations	4279	4279	4279	4279
Wald F-Stat				18.3
Adj R-Squared	0.980	0.985	0.980	0.590
		Panel B: Log Loan Accounts		
Log Disposal Rate (t-1)	0.00754	0.109**		
	(0.00752)	(0.0476)		
Judge Occupancy (t-1)			0.000848**	0.00780***
			(0.000329)	(0.0018)
Observations	4279	4279	4279	4279
Wald F-Stat				18.3
Adj R-Squared	0.980	0.97	0.980	0.590

Standard errors in parentheses

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

Notes: Results presented in this table focuses on all banks governed by the RBI. Panel A reports specifications using log total number of loan accounts as the dependent variable whereas Panel B reports specifications using log outstanding loan as depending variable. Column 4 reports the first stage. All standard errors are clustered at the district-year level.

Table A6: Banks' Lending Behavior: Sectoral Allocation

	(1) OLS	(2) IV	(3) Reduced Form	(4) First Stage
Panel A: Manufacturing				
Log Disposal (t-1)	-0.0327*	0.286**		
	(0.0185)	(0.140)		
Judge Occupancy (t-1)			0.00222**	0.00777***
			(0.000933)	(0.00182)
Observations	4279	4279	4279	4279
Adj R-Squared	0.93	0.91	0.93	0.58
Wald F-Stat				18.29
Panel B: Consumption				
Log Disposal (t-1)	0.0278**	0.167***		
	(0.0123)	(0.063)		
Judge Occupancy (t-1)			0.00130***	0.00777***
			(0.000452)	(0.00182)
Observations	4279	4279	4279	4279
Adj R-Squared	0.97	0.99	0.97	0.58
Wald F-Stat				18.29
Panel C: Agriculture				
Log Disposal (t-1)	0.00417	0.0594		
	(0.00851)	(0.0489)		
Judge Occupancy (t-1)			0.000461	0.00777***
			(0.000383)	(0.00182)
Observations	4279	4279	4279	4279
Adj R-Squared	0.98	0.99	0.98	0.58
Wald F-Stat				18.29

Standard errors in parentheses

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

Notes: Results presented in this table focus on all banks governed by the RBI. Panel A reports specifications using log total number of loan accounts allocated to the manufacturing sector as the dependent variable. Panel B reports the estimates using log total number of loans allocated for consumption, i.e. individual housing or vehicle purchase loans whereas Panel C reports the estimates using log total number of loans allocated for agriculture. All standard errors are clustered at the district-year level.

Table A7: Robustness Check: By Levels of Clustering of Standard Errors

	(1) OLS	(2) 2SLS	(3) Reduced Form
		Panel A: Cluster by State-Year	
Asinh Borrowing	0.024	0.255*	0.005**
	(0.038)	(0.138)	(0.0025)
Asinh Sales	0.052***	0.097**	0.0034*
	(0.014)	(0.045)	(0.0018)
Asinh Value-Added	0.048**	0.19*	0.0058**
	(0.02)	(0.11)	(0.0029)
Asinh Wage Bill	0.064**	0.268**	0.0099***
	(0.022)	(0.087)	(0.00202)
Asinh Plant Value	0.0207	0.068	0.0021
	(0.015)	(0.059)	(0.0019)
		Panel B: Cluster by District	
Asinh Borrowing	0.024	0.255	0.005*
	(0.046)	(0.17)	(0.003)
Asinh Sales	0.052**	0.097**	0.0034*
	(0.018)	(0.044)	(0.0017)
Asinh Value-Added	0.048**	0.19**	0.0058**
	(0.022)	(0.079)	(0.0029)
Asinh Wage Bill	0.064**	0.268**	0.0099***
	(0.026)	(0.089)	(0.0023)
Asinh Plant Value	0.0207	0.068	0.0021
	(0.022)	(0.075)	(0.0025)

Standard errors in parentheses

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

Notes: The row headers indicate the dependent variable and the columns 2 - 3 provide the coefficients on disposal rate from OLS and 2SLS estimations respectively, and column 4 provides the reduced form coefficients on judge occupancy. All standard errors are clustered at the state-year level.

Table A8: Firms' Production Outcomes: Unweighted Regressions

	Asinh Sales	Asinh Value Added	Asinh Wage Bill	Asinh Plants-Machinery
Panel A: All Firms				
OLS	0.0202	0.039	0.0396**	0.0013
	(0.018)	(0.026)	(0.017)	(0.014)
IV	0.098*	0.074	0.206***	-0.0303
	(0.057)	(0.102)	(0.056)	(0.063)
RF	0.00202*	0.0014	0.0045***	-0.0006
	(0.0012)	(0.002)	(0.0012)	(0.0012)
FS	0.0206***	0.0187***	0.0216***	0.031**
	(0.005)	(0.005)	(0.005)	(0.014)
Observations	20187	12900	21875	18303
Adj R-Squared	0.24	0.125	0.28	0.24
K-P Wald F-Stat	15.35	12.93	16.05	13.53
Panel B: Small Firms				
OLS	0.028	-0.02	0.004	0.003
	(0.025)	(0.04)	(0.0156)	(0.022)
IV	0.033	0.0386	0.06	-0.103
	(0.11)	(0.24)	(0.068)	(0.11)
RF	0.0006	0.0006	0.0012	-0.0018
	(0.002)	(0.0037)	(0.0014)	(0.0018)
FS	0.0188**	0.0148**	0.0207***	0.0171**
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	4375	2126	5388	3464
Adj R-Squared	0.32	0.185	0.36	0.27
K-P Wald F-Stat	9.74	5.80	11.53	8.14
Panel C: Large Firms				
OLS	0.011	0.044	0.042**	0.0027
	(0.018)	(0.029)	(0.019)	(0.015)
IV	-0.0062	-0.044	0.153**	-0.144*
	(0.056)	(0.12)	(0.053)	(0.081)
RF	-0.00013	-0.00085	0.0033**	-0.0029**
	(0.0012)	(0.0022)	(0.0013)	(0.0013)
FS	0.0211***	0.0194***	0.0219***	0.0203***
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	15812	10774	16487	14839
Adj R-Squared	0.28	0.15	0.27	0.3
K-P Wald F-Stat	16.63	14.59	16.91	14.74

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

Notes: The explanatory variables trail the dependent variables by 2 years. 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 A9: Effect of increased borrowing from bank expansion on firms' production

	(1)	(2)	(3)	(4)
	Asinh Sales	Value Added	Asinh Wage Bill	Asinh Plant Value
Percent Judge Occupancy (t-2)	-0.0023	-00016	0.0006	-0.0024
	(0.0021)	(0.004)	(0.0016)	(0.0019)
Asinh Borrowing	0.59*	0.65	0.104	0.817**
	(0.304)	(0.806)	(0.19)	(0.327)
Observations	7805	5788	7986	7662
Adj R-Squared	.41	.17	.35	.50

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

Notes: The above results report estimates from 2SLS estimation, instrumenting borrowing with bank shock. The explanatory variables trail the dependent variables by 2 years. 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.