# Judges, Lenders, and the Bottom Line: Court-ing Firm Growth in India

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October 18, 2019

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**Abstract**

Courts are considered as an important institution in the functioning of markets. Yet, there is limited causal evidence showing this relationship. This paper estimates the causal effects of court performance on formal sector firm growth in India. I construct a robust measure of court performance using novel data comprising of the universe of 6 million case records over 9 years across 195 district courts and then match it to a dataset on registered, formal sector firms. For causal inference, I exploit plausible exogenous variation in judge supply, arising out of a system of judge rotations and existing vacancies, to instrument for the potentially endogenous court performance. I show that higher court performance positively affects lending behavior in local credit markets. This is because timely resolution of litigation supports lenders and acts as a deterrent against non-repayment to borrower firms. This, in turn, relaxes the credit constraints firms face, expanding production and improving profits.

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# 1 Introduction

At the heart of the Coase theorem (Coase (1960)) is well defined property rights and effective enforcement of contracts that enable welfare enhancing trade. Comparing cross-country institutions, Acemoglu and Johnson (2005) show that enforcement of property rights have strong implications on long run growth and investment, whereas timely contract enforcement promotes financial intermediation and development of formal financial sector. Practically, this requires seamlessly functioning third party enforcers, such as the courts, and well written laws to enable clear interpretation of rights (Kornhauser and MacLeod (2010)). North (1986) states that as organizations grow in complexity, third party enforcement becomes dominant in comparison to self-enforcement or social norms. This involves not just ensuring that the terms of the contract are adhered to or rights are clearly defined *de jure*, but doing so in a timely fashion. Timely enforcement reduces uncertainty, the absence of which adds to transactions costs preventing effective contracting and weakening *de facto* rights. The implications of delayed justice administration are large, eroding the sense of basic rights and trust in markets. Given the importance of the issue, an examination of the causal effects of timeliness of justice administration through courts on socio-economic outcomes is warranted. With access to detailed data on trial proceedings and a natural experiment affecting the supply of judges, this paper is among the first to study the effects of court performance on firm growth along the entire causal chain.

As of July 2019, over 11 million cases (3 million civil cases) have been pending over 3 years across the district courts in India and close to 1.6 million cases pending in state High Courts (NJDG Dashboard [1]). In contrast, the United States has only about 60,000 civil cases pending as of March 2019 (FCMS, 2019 [2]). This implies that there are 10 times more pending civil cases per capita[3] in India relative to the United States. These delays imply potentially large losses for the litigators, in addition to the overall market and economy-wide effects.[4] The World Bank's Doing Business indicators rank India below most countries, including neighboring South Asian nations, in the area of contract enforcement. A cross-country correlation between time to enforce contracts through courts and GDP per capita shows strong negative relationship, indicating plausible costs of court delays.[5]

[1] `https://njdg.ecourts.gov.in/njdgnew/index.php`

[2] `https://www.uscourts.gov/federal-court-management-statistics-march-2019`

[3] Population in India and the United States was 1.339 billion and 325.7 million respectively in 2017 as per the World Bank and the United States Census Bureau.

[4] An anecdote presented in Dutta et al. (2019) describes how one single instance of delay in concluding litigation in India's highest court costed the public purse over USD 2.6 million towards payment of damages along with an additional USD 84000 towards litigation expenses in a suit between a foreign company and an Indian firm.

[5] Figure 1 and Figure 2 in the appendix show these patterns.

In this paper, I present the causal effects of district court [6] performance on the growth of formal sector firms in India, showing the role of credit markets as an important channel linking the two. I define court performance, reflecting the timeliness of the dispute resolution process, as a ratio between the number of cases resolved in a year and total workload, including the backlog of unresolved cases. The performance varies across district courts as well as over time, primarily due to fluctuations in judge supply, defined as the share of judge posts that are filled in a year that I refer to as judge occupancy throughout. Since judges are a key input of the court production function, variation in judge occupancy strongly determines court performance.[7] Specifically, this variation arises from a combination of judge rotation policy and existing undersupply that are likely orthogonal to firm growth. These judges typically have a short tenure of under 2 years on an average and are transferred to districts where they haven't worked in the past. This assignment policy is determined centrally in each state by the respective state high court. Existing vacancies in any given district thus get shifted to a different district with annual rotations. This creates potentially exogenous variation in the judge occupancy within a district court over time, which I use as an instrument for court performance in an instrumental variables estimation strategy.

I construct a panel on annual court performance using a unique dataset on the universe of 6 million trial proceedings[8] active between 2010 and 2018 across 195 district courts in India. I then match it with incumbent[9] firms in Prowess dataset, with registered office location in the corresponding court's territorial jurisdiction, as also done 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 involving the firm as the respondent are filed (Code of Civil Procedure, 1908).[10] This creates a sample of firms for which the institution of courts matter, irrespective of whether or not they actually use the court for litigation. However, examining the correlation between firm level outcomes and court performance as defined above is unlikely to provide a causal estimate if the latter is correlated with unobserved district specific time varying characteristics or is affected by firm specific dynamics. For example, districts that are high growth markets may mechanically increase litigation as conflicts are more likely to occur in such a setting than in one with lower interactions, adding to the court's backlog. On the other hand, judge occupancy is mainly determined by the administrative procedures within the judiciary, and therefore, serves as an ap-

[6] I focus on the District and Sessions Court, which is the court of first instance for commercial cases, civil cases with large monetary values, as well as, heinous criminal cases.

[7] Both from a statistical sense in terms as $R^2$ as well as from discussions with former members of the judicial and legal experts.

[8] These records contain granular detail including the court where the case is filed, various case-flow time stamps, nature of dispute, and litigant details.

[9] Incorporated before 2010, the period of study.

[10] In most contractual disputes, the location of the court for filing the trial is the one mapping to the respondent's registered office. The relevant court may vary for other types of disputes, which is determined by the Code of Civil Procedure, 1908. Overall, there is no scope for "forum shopping" in India as suits filed in wrong courts are simply dismissed without being adjudicated.

propriate instrument for court performance. In addition to plausible exogeneity, the first stage relationship between the two is strong, where a 1 standard deviation increase in judge occupancy increases court performance by 0.25 of a standard deviation, or one percentage point increase in judge occupancy increases court performance by 1 percent. Considering continuous "treatment" of judge occupancy and low baseline levels of court performance at 14 percent, the effect of improved judge occupancy is likely large.

In order to shed light on the mechanisms behind the reduced form effects and explore the causal chain, I also match firms at the level of individual trials in the court dataset, wherever the firm appears as either the petitioner or the respondent. [11] This allows me to estimate the direct effects of litigation delays specific to such firms, again using judge occupancy as an instrument to shock the timeliness of the adjudication process specific to the litigating firm. I define the latter as an index comprising of the number of subsequent cases filed and resolved. This matching process reveals that close to 50 percent of the banks in the firm sample[12] find a match in the trial dataset whereas the match rate is much lower for other non-financial firms, which is about 13 percent. Further, banks initiate litigation (filing plaints) in 80% of the trials involving them. About 20 percent of cases initiated by banks and other external financiers are execution petitions, which are petitions to bring past judgements into force, indicating that these firms are clear winners in the associated litigation. A positive judge supply shock - a one percentage point increase in judge occupancy - occurring once a case is filed, increases banks specific court performance index by 0.4 percent. Using district-wise summary of bank lending by the Reserve Bank of India, I show that the reduced form effects of a 1 standard deviation increase in judge occupancy increases the number of bank lending accounts in the corresponding district by nearly 2 percent, which are mainly directed towards manufacturing (4.4 percent) and consumption loans (2.3 percent) with a 1-2 year lag. This is large considering that banks have around 350,000 loan accounts in a district on an average. The IV estimate, which can be interpreted in terms of elasticity with respect to improvement in bank specific court performance index, indicates that a 1 percent improvement increases the number of loan accounts by 0.25 percent.

An increase in lending by banks in the local credit markets, especially in favor of firms, likely relaxes some of the credit constraints faced by them. This motivates me to examine the subsequent effects on all incumbent firms in the corresponding local economy on three sets of outcomes within a window of 0-2 years from the year of the judge shock. First, I show that firms' borrowing from banks increase with court performance. There is also an increase in lending by other local lenders (i.e. Non-Banking Financial Corporations or NBFC) as well as inter-firm lending.[13] The

[11] Petitioners are also called as plaintiff and respondents as defendants in different countries.
[12] This dataset contains the universe of all scheduled commercial banks in India.
[13] Firms typically engage in mutual lending via trade credit, subsidiary support, and other debt investments.

results indicate an elasticity of 0.39, 0.98, and 1.2 for borrowing from banks, inter-firm lending, and lending by NBFCs respectively. Second, I show that labor use in firm production process, measured as total labor expenditure and number of employees, increase with court performance with an elasticity of 0.2 and 0.04, respectively. Finally, I examine annual sales revenue and profits net of taxes, which also exhibit a positive improvement resulting from improved court performance with elasticities 0.1 and 0.26 respectively. To illustrate the credit channel, I present heterogeneous effects based on ex-ante wealth, i.e. asset size prior to 2010, as a proximate measure of credit constraints faced by firms in external borrowing from the formal financial sector. This analysis supports a theory of credit contracting, where external lenders have favorable terms for borrowers with larger assets. However, an improvement in the contract enforcement environment lowers the threshold of assets required for borrowing and increases borrowing among those that were credit constrained.

Putting a monetary value to these estimates translates to gains by INR 0.48 million ($\approx$ USD 7000) in profits and INR 5.5 million (USD 78 K) in sales revenue over an average baseline profit of approximately INR 184 million (USD 2.6 million) and sales revenue of INR 5452 million (USD 76.6 million). Adding one more judge in a district court increases judge occupancy by 5-6 percentage points, [14] which translates to a 5-6 percent increase in court performance. Therefore, one additional judge in a court increases profits by about INR 2.6 million (USD 37 K). With an average of $\approx$ 1000 formal sector firms in a given district and a value added tax rate of 18 percent on basic manufacturing and services, the state could potentially earn close to INR 0.5 billion (USD 7 million) in taxes[15] in the short run from each district. Judges cost much less than this. The average annual salary of a district judge is under INR 1 million per annum, including all non-pecuniary benefits. Given that the annual budgetary outlay for law and justice is less than a tenth of a percent of total expenditure in 2019 [16], there is a justifiable reason for increasing the outlay to address the problem of judge vacancy.

Since I use an IV strategy for causal identification, the results must be interpreted as Local Average Treatment Effects (Angrist and Imbens (1995)) in the presence of heterogeneous treatment effects. While the complier population is spread across the terciles of district court sizes and district population density, the complier share is relatively lower in the top tercile of both groupings. This implies that in large courts and districts with high population densities, adding one more judge may not induce a large improvement in court performance relative to medium sized and small courts or in districts with modest population densities. Therefore, the solution to improve

[14] A district court, on an average, has about 18 judge posts, of which about 77 percent is occupied.

[15] This is an approximate back of the envelope calculation to illustrate the magnitude of effects. The VAT system in India has provisions for input tax credit that may alter this figure.

[16] `https://www.theweek.in/news/india/2019/07/05/budget-2019-drastic-cut-in-allocation-for-law-and-justice html`

court performance in large courts may require complementary policy interventions in addition to improving judge occupancy, warranting further research.

This paper makes four contributions to the academic literature. First, it adds to the literature on institutions and economic development by using detailed micro-data, data science techniques, and causal inference to bridge the gap between cross-country literature and the emerging, micro-empirical literature on courts that was data constrained until recently. Economists have long been interested in understanding the role of institutions in promoting economic development (e.g. North (1991), Williamson (1998) with roots in theoretical work from earlier), some specifically examining legal and judicial institutions, including Djankov et al. (2003), Besley and Burgess (2004), Acemoglu and Johnson (2005), Nunn (2007). Many of these view legal and judicial institutions together as a bundle. Though they are the two sides to a coin, there are important differences. These stem from the fact that legal institutions pertain to the rule of law which are created by the legislature in a democracy, whereas judicial institutions pertain to administering justice as per the laws. The latter encompasses the formal judiciary, i.e. the system of courts, that adjudicate within the ambit of the laws. As detailed in the review paper by Dal Bo and Finan (2016), research examining the judiciary, including sub-national courts, are relatively scant. This paper aims to address this gap by studying district courts across a large number of states in India.

Second, the paper examines the role of judge occupancy as one of the primary drivers of court performance. There are many reasons why court performance varies across space and time. A burgeoning literature examines its determinants, including procedural formalism as in Djankov et al. (2003), co-existence of traditional and formal statutory courts as in Anderson (2018), and an increase in demand for court services as in Dimitrova-Grajzl et al. (2012). With the exception of Yang (2016), who studies the effects of judge vacancy in the US federal district courts as a resource constraint in criminal trials,[17] this paper is the first, to my knowledge, to examine the effect of judge occupancy, as a resource constraint, on overall court performance. Judges are central to the functioning of courts since they are the main actors who resolve trials by interpreting applicable laws in light of the issue under dispute and evidence presented. Therefore, any constraints limiting judge supply likely has large implications on court functioning.

Third, this paper is one of the first attempts to study a large part of the causal chain linking performance of courts with firm growth. While I cannot preclude other channels, I show that credit

[17]A vast literature examines the role of judicial inputs on crime outcomes in the United States. This literature relies on random assignment of cases to judges for identification, which is not the case in India or in most developing countries. However, none have examined the effects of judicial institutions, particularly courts on firms, as per my knowledge. Detailed case level data is also becoming available in the developed countries to interested researchers only recently and I am not aware of an equivalent large scale public data source as the Indian e-courts database elsewhere.

expansion from timely adjudication encourages labor intensive production, leading to higher sales and profits among firms in the local credit markets (i.e. district). This complements the growing literature examining the reduced form effects of judicial institutions on the aggregate economy (Chemin (2009a), Chemin (2009b), Chemin (2012)) lending behavior (Visaria (2009), Ponticelli and Alencar (2016)), and firms (von Lilienfeld-Toal et al. (2012), Ahsan (2013), Ponticelli and Alencar (2016), Amirapu (2017), Boehm and Oberfield (2018), and Kondylis and Stein (2018)). Due data limitations, these papers are able to study the effects of one-time cross-sectional differences in judicial capacity on the outcomes as mentioned. However, these institutions are not static but dynamic where time specific variations on both supply and demand side may determine the outcomes differently than when studied under a static lens. Using a panel on court performance and judge occupancy, I show that there are substantial short run effects. How these short run effects translate into long run outcomes is left for future research.

Finally, the paper adds to the vast literature on the development of credit markets, especially in the context of developing countries. Rajan and Zingales (1998), Banerjee (2003), Burgess and Pande (2005), and Banerjee and Duflo (2014) show that access to external finance through borrowing from formal/institutional lenders is important for firm growth. I show that timely adjudication enables lenders to expand credit supply in the short run, in particular to firms that were likely credit constrained. Therefore, this paper highlights the institutional barriers to the development of local credit markets.

This paper has a strong and actionable policy implication. The current policy debate in India has mainly focused on the issue of large pendency of trials in courts without exploring the economic cost of court delays. Access to Justice Surveys by Daksh (2017) reports substantial costs borne by private individual litigants - around INR 500 per day on travel to courts and INR 850-900 in the form of forgone wages. I provide the numbers for formal sector firms by translating the causal estimates of the court performance into its monetary equivalent. The choice of instrument - judge occupancy - also indicates that these results are in line with popular clamor for filling vacancies.

The rest of the paper is organized as follows. In section 2, I provide the context and describe the data, including patterns of litigation behavior. Section 3 lays down a theoretical framework linking court performance as a measure of institutional quality and firm growth through the credit market channel. In section 4, I detail the identification strategy and discuss the assumptions to establish causal inference. Section 5 and 6 present results from estimating the reduced form and IV specifications on the sample of litigating firms and all firms, respectively. Section 7 examines the interplay between court output and legal reforms. Finally, I present the conclusions in section 8.

# 2 Measuring Court Performance and Matching Outcomes

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 court system with first instance courts for civil and criminal trials. Our research question concerns with the performance of courts called the District and Sessions Court (hereinafter called district court), which are typically the first point of contact for filing cases involving firms and oversee the functioning of all other courts within the district. [18] The district court is headed by the Principal District Judge (PDJ), who along with Additional District Judges (ADJ) preside over all litigation filed in the court. This court also acts as the court of appeal for all matters originating in lower levels of the district court system. The High Courts and the Supreme Court serve mostly appellate functions in the case of most civil and criminal suits with original jurisdiction mainly over constitutional matters or when representing organs of the government. 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.

India has consistently ranked low in the World Bank's Doing Business ranking as well as ranking within contract enforcement. Even as its overall ranking has jumped from 142 in 2014 to 77 in 2018, the ranking under contract enforcement continues to remain poor at 163 in 2018. Figure 1 compares India with the rest of the world across various Doing Business indices, showing dispute resolution through courts as a key bottleneck. A simple cross-country correlation between log GDP per capita and log trial duration shows a significant negative association (Figure 2). This serves as a strong motivation to explore the causal relationship between the effectiveness of courts as an institution on firm growth using trial-level data from the district courts in India.

## 2.1 E-Courts Data

I construct the dataset on court variables by scraping publicly available case level records from 195 administrative districts from the E-Courts website. [19] Each record details case level meta data as well as proceedings from each hearing.[20] These districts were selected to ensure an overlap with registered formal sector firms in predominantly non-metropolitan districts.[21] Appendix Table A.27 illustrates the sample states and the fraction of districts from each of these states covered

[18] This is determined by monetary and geographic jurisdiction of the case.

[19] 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 web-portals - www.ecourts.gov.in and https://njdg.ecourts.gov.in - went live in late 2014.

[20] 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. See sample case page in the appendix.

[21] Scraping resources and funding limited assembling the dataset for the entire country. However, the districts are representative of non-metropolitan and rural districts across major industrial states in India.

in the dataset. Appendix Figure A.17 shows the availability of data through histograms on year of filing and year of resolution. 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[22] between these years.

**Constructing Court Performance Measures** From the case-level data, I construct court-level annual performance panel data. I define the main measure of annual court performance as the ratio between number of cases resolved in a calendar year and total active workload during that year, which I call the "disposal rate". 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 definition have been used by Ponticelli and Alencar (2016) and Amirapu (2017) with minor variations based on their data. I also calculate other ways of measuring court performance reflecting timeliness of the adjudication process. These include what I call "speed", constructed as the ratio between number of cases resolved and number of new filings in a given year. I also consider the logarithmic transformation of the volume of new cases filed and resolved by court-year as measures of court demand and output, respectively. For the set of cases that have been resolved within the study period, I calculate the trial duration until resolution. However, this measure only accounts for the select cases that were resolved in the study period. Additional measures include the fraction of cases that are appeals from courts lower in the hierarchy and the fraction of cases that are dismissed without completing full trial.[23] Since all these measures, except duration, are highly correlated with disposal rate as shown in Appendix Table A.30, I use disposal rate as my preferred measure of court performance. I also construct an index using all these measures and check for robustness of the results using the index in place of disposal rate.

**Litigating Firm Specific Court Performance** For litigating firms, I calculate a performance index that takes into account corresponding firm specific cases resolved and subsequent new cases filed in a given calendar year in each of the district court.[24] For each district, this is defined over time-period when the firm has at least one active case in the court, including the year first case is filed and the year last case is resolved.

**Constructing Judge Occupancy** The case data also contains information on which judge post (i.e. court hall within the district court) the case has been assigned to. The within-district

[22]Either pending from before 2010, or filed between 2010 and 2018.

[23]These plausibly indicate the quality or "fairness" of the district courts but it is hard to assign a normative value. For example, appeals are not only made if the objective quality of a judgement was low but are also for strategic reasons such as not having to pay the damages. Therefore, I use disposal rate as my preferred measure of court performance in all the specifications because it doesn't suffer from selection and is also strongly correlated with all other measures of court performance, including the measures on quality.

[24]Note that firms can have cases in more than one district based on the nature of the dispute.

universal nature of the dataset allows me to identify whether or not a particular judge post is occupied in a given year based on whether I observe cases being assigned to or resolved in that post. Under full occupancy, cases are assigned to and resolved by each judge post every year within the district court. From this, I calculate a measure of judge occupancy defined as the percentage of all available judge posts within the district court that are filled in a given year. One concern with this construction is if a particular post is just dormant but in reality, has a judge available. Given the workflow and annual performance incentives for judges,[25] this is not the case. Any dormancy is likely short-lived (less than a year), which is then counted as occupied if any activity is recorded in rest of the year. While I do not have the personnel records of judges for each court, I verify the calculated vacancies (complement of occupancy) and compare it with media reports. I find that the computed vacancies are of the same order of magnitude as in media reports. Additionally, I scrape the personnel records for the Principal District Judge (PDJ)[26] to verify the construction of the occupancy measure.

**Summary Stats:** Table 1 presents the summary statistics for the court variables. On an 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 the district courts are only clearing 14 percent of their yearly workload. On an average, 3312 new cases are filed and 3341 cases are resolved in a district court in a year. Cases take 617 days to be resolved on an average, with a standard deviation of 497 days. The distribution of case duration have long right tails. Cases in the tail are those that take long for resolution and add to pendency. Given the regular inflow and outflow of cases, the average speed is 76. However, this measure is widely distributed with a standard deviation of 102. The contrast between speed and disposal rate is the extent of pending cases that continue to grow year on year, which is accounted in the latter. About 22 percent of the resolved cases are dismissed without completing full trial. Dismissal of cases on either procedural or substantive grounds likely explains higher average speed relative to disposal rate. Lastly, around 19 percent of cases are appeals against lower court judgements.

## 2.2 Prowess Data

On the firms' side, I use Prowess dx academic dataset covering 49202 firms made available by the Center for Monitoring Indian Economy (CMIE). The data are collated from annual reports, stock exchanges, and regulator reports covering the universe of all listed companies ($\approx$ 5000 listed on Bombay and National Stock Exchanges) as well as a sample of unlisted public and private

[25]Performance measures for judges are based on their output - number of cases resolved - as well as quality of judgement and other measures of collegiality. Current performance evaluation method is described here.

[26]These are head judges of the district courts for whom joining and leaving dates are available on their respective court website.

companies representing formal, registered firms [27]. 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 account for $\approx 40\%$ of sales, 60% of VAT, and 87% of exports,[28] this dataset captures a large share of the value addition in the economy. Firm specific variables include annual financials and various production outcomes. Annual financial data is available from 1986 in addition to details on firm characteristics including ownership type, NIC code, year of incorporation, registered entity type, and identifying details including the name and location of registered office. This dataset covers many sectors in addition to manufacturing, including finance, transport and logistics, construction, wholesale, mining and metal production, and business services.

## 2.3 Other Complementary Datasets

In addition to the above two main datasets, I use ancillary datasets to obtain additional variables for the analyses. These include Indian central bank data[29] on district-wise annual credit and deposit details of commercial banks from 2010 to 2019, disaggregating lending by sectors. Additionally, I use population census data, district-wise annual agricultural[30] and crime data[31] for balance checks. Lastly, I scrape personal information on the Principal District Judge from each of the district court websites to create a panel dataset on judge tenure using their joining and leaving dates. This is used for additional robustness checks in support of the identification strategy.

## 2.4 Matching E-Courts Data to Firms

**Matching firms by registered office district** Of the 49202 firms in Prowess dataset that are spread across India, 13298 firms match with the court-level panel data across 161 of 195 sample district courts. Remaining 34 districts from the e-courts dataset result in zero match with any firms in the Prowess dataset. 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 firm sample for my analysis. I test for robustness using balanced panel of firms, with reported data across all study years. Appendix Figure A.19 describes the firm sample construction process in detail.

[27] Registered with the Ministry of Corporate Affairs.

[28] As per the Economic Survey, 2018 report.

[29] These are available through the Reserve Bank of India data warehouse.

[30] Area and production statistics from the Ministry of Agriculture and Farmers Welfare available here: `https://aps.dac.gov.in`

[31] National Crime Records Bureau annual crime statistics http://ncrb.gov.in/

**Summary Stats:** Table 1 bottom panel presents the summary statistics for firms in the sample court districts. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015), made available by the Government of India. Average annual revenue from sales is INR 5452 million (≈ USD 77 million), annual profits net of taxes is INR 184 million (≈ USD 2.6 million), wage bill at INR 417 million (≈ USD 6 million). For the fraction of firms for whom employment headcount is available,[32] average number of employees is 2 but has a large range between 0 and 154. Annual value of land and capital assets (plants and machinery) average at INR 309 million (≈ USD 4.4 million) and INR 2889 million (≈ USD 41 million) respectively. On credit outcomes, annual total long term borrowing from banks average at INR 1866 million (≈ USD 26 million). Average lending by firms registered in the sample district[33] to other firms and agents (including employees) amount to about INR 420 billion (≈ USD 6 billion). Finally, the average lending by non-banking lenders called the non-banking finance companies (NBFC) is INR 8.3 billion (≈ USD 120 million).

**Matching firms with cases** Further, because I know the identity of firms, I merge them with the trial dataset[34] to obtain a litigating firm level panel dataset, disaggregated by the court of litigation. Overall, 6417 of 49202 firms (13 percent) have cases in the sample courts, with 6138 unique firms arising out of one-to-one match [35]. Of these, 4047 firms have cases that were filed within the study period (2010-2018), and hence are considered as the sample of litigating firms for subsequent analyses. Appendix Figure A.19 details the construction of this firm sample. The remaining 2000 firms have had cases prior to the study period, and given the roll-out timeline of the e-courts system, are likely to be a selected sample arising out of differing priorities on digitizing past cases.

## 2.5 A Descriptive Analysis of Litigation Behavior

Table 2 describes the characteristics of all 6138 firms with cases in the sample courts and compares them to firms without cases in these courts. Note that, because firms can have cases anywhere depending on the jurisdiction as laid down in the Code of Civil/Criminal Procedure, [36] the set of litigating firms in this sample can be registered in any district, including outside my sample districts. On an average, litigating firms are older (33 years), more likely to be a public limited company, more like to be government owned (stated owned enterprise), business group owned,

[32]Annual disclosure laws does not require firms to report employee headcount. However, most publicly listed firms report this number.

[33]A small fraction of all firms engage in inter-firm lending.

[34]I employ a nested approach to matching the case records with firms based on the recorded names, following heuristics as listed in the appendix

[35]About 300 firms appear as co-petitioners or co-respondents on these cases that I ignore at the moment.

[36]The Supreme Court of India condemns the practice of forum shopping, as detailed in the judgement of *Chetak Construction Ltd vs. Om Prakash and Ors, 1998.*

and foreign owned. Among financial institutions, banks are litigation intensive, with close to 50 percent of all banks in the firm sample matched with the case dataset.

Panels in Figure 4 show that banks litigate intensively. I define litigation intensity as the fraction of firms in a specific sector that have one or more cases in the trial dataset. In the banking sector, close to 50 percent of the banks have at least one case in the sample district courts. For firms in non-financial sector, this fraction is close to 13 percent (top left panel in the figure). Furthermore, in over 80 percent of the litigation, banks are the petitioners ("plaintiff"), i.e. originators of the suit. NBFCs, also lenders, are also more likely to initiate litigation (over 60 percent) conditional on litigation choice. The bottom panel in Figure 4 shows the broad nature of disputes under litigation. Specifically, banks and NBFCs are more likely to be engaged in contract arbitration, special civil petition pertaining to monetary instruments, [37] and importantly in execution petitions. Execution petition is filed when the petitioner has judgement in their favor but require execution orders from the court to implement the judgement. For example, when a lender wins a debt default case, they need to apply for an execution order to ensure a bailiff accompanies them in taking possession of the pledged collateral. Finally, parsing a random sample of 77 judgements involving banks reveals that 64 (over 83%) are in favor of the bank. This occurs either by undergoing full trial and the judge penning their decision in favor of the bank or by reaching a settlement with the defaulting borrower before completion of the trial, leading to its dismissal.

This analysis reveals the following stylized facts on the role of courts in shaping credit behavior:

1. Financial sector is litigation intensive and are more likely to initiate litigation.

2. They use the district court systems for all manners of civil suits, especially those involving credit defaults and other types contract breaches (dishonoring of cheques under the Negotiable Instruments Act).

3. These firms are most likely winners in the trials given the large share of execution petitions of judgements that are mostly in their favor.

Using these stylized facts, I build a simple model of credit behavior with repayment enforced through the possibility of litigation. The ensuing equilibrium is determined by stochastic shocks faced by the borrower in their production process as well as the enforcement quality by the district courts.

[37] Filed under Negotiable Instruments Act.

# 3 Conceptual Framework

The model adds to the set up in Banerjee and Duflo (2010) by considering a 2 player static game for lending decision in an environment with imperfect institutions, in a similar flavor as discussed in Besley and Coate (1995). Subsequently, I consider the effects on all firms in the local economy through an increase in borrowing from external lenders (i.e. banks).

## 3.1 A Simple Model of Credit Markets with Enforcement Costs

I consider a representative lender-borrower game where borrower needs to invest, $K(W)$, in a project with returns $F(K)$, where $K$ is the total capital expenditure and $W$ is the exogeneous funds/initial wealth that she owns. She needs an additional $K_B(W) = K - K_M(W)$ to start the project, with $K_M(W)$ that she raises from the market and $K_B(W)$ as borrowing from the lender (bank), on which the lender earns a return $R > 1$. Assume $K_B(W) = bW$, that is, borrowing linearly depends on initial wealth. 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 $\eta K$ in the process, with remaining payoff at $f(K) - \eta K$. The lender loses the entire principal, $-K_B(W)$. Repayment results in $f(K) - RK_B(W)$ as payoff to the borrower and the lender earns $RK_B(W)$. The game is depicted in Figure 5. Under non-repayment, the lender can choose to litigate, incurring a cost $C(\gamma) > 0, \frac{\partial C}{\partial \gamma} < 0$, where $\gamma$ is the quality of enforcement by the corresponding district court. Once the lender chooses to litigate, they mostly win as seen in the data (or introduce a probability of winning, $p >> 1 - p$, but for tractability, I skip this stochastic component, without affecting the exposition). This possibility of evasion and costly litigation makes the lender account for these costs in the credit contract. Specifically, litigation would be a dominant strategy for the lender if

$$RK_B(W) - C(\gamma) \geq -K_B(W) \implies R \geq \frac{C(\gamma)}{K_B(W)} - 1 \tag{1}$$

By backward induction, 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, if $f(K) - RK_B(W) > f(K) - RK_B(W) - C(\gamma)$. When the project fails, which happens with probability $1 - s$, the borrower is unable to repay and defaults. The lender files a suit in the court to take possession of the collateral if the net benefits exceed net costs. Recovering loan from monetizing collateral is a costly process with the lender earning a return $R' < R$ and incurring an additional litigation cost of $C(\gamma)$. The monetized collateral generates returns $R'$ as a function of the borrower's wealth $W$, such that $R'K_B(W) = \delta W$, where $\delta$ is the depreciation factor. On the other hand, if the lender fails to litigate, they lose the principal lent and incur a payoff of $-K_B(W)$. The condition for litigation to be dominant strategy in this situation gives the collateral requirement

and total borrowing in the credit contract set by the lender as

$$\delta W - C(\gamma) \geq -K_B(W) \implies \delta W + K_B(W) \geq C(\gamma) \tag{2}$$

Borrower's expected payoff from production is $s(f(K) - RK_B) - (1-s)(\delta W)$ and engages in production if expected payoff is greater than 0, that is:

$$f(K) \geq RK_B(W) + \frac{1-s}{s}\delta W \tag{3}$$

which implies that the value of production should be greater than the sum of repayment to bank and the value of risk involved in the production process (odds ratio times the collateral value).

Finally, the lenders participation constraint requires that their expected payoff from lending should be weakly greater than the opportunity cost of the capital, where $\phi$ is the market returns. That is,

$$sRK_B(W) + (1-s)R'K_B(W) \geq \phi K_B(W) \implies \frac{W}{K_B(W)} \geq \frac{\phi - sR}{\delta(1-s)} \tag{4}$$

Along with constraint (1), the threshold level of wealth required for lending, $W^*$, is the solution to the following equation:

$$\frac{(\phi + s)K_B(W^*)}{\delta(1-s)} - W^* = \frac{s}{\delta(1-s)}C(\gamma) \tag{5}$$

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 5.

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 credit 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, filing a complaint against the borrower for default in the court of relevant jurisdiction. If litigates, then the lender almost

certainly wins (or has a relatively high probability of winning) but incurs a cost $C(\gamma)$. The payoff in this situation is $(RK_B(W) - C(\gamma), f(K) - RK_B(W) - C(\gamma))$. If lender chooses not to litigate, the payoffs are $(-K_B(W), f(K) - \eta K_B(W))$.

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 litigates, again, the lender almost certainly wins but incurs a cost $C(\gamma)$. The payoff would be $(\delta W - C(\gamma), -\delta W - C(\gamma))$. If the lender does not litigate, the payoff would be $(-K_B(W), 0)$.

Constraints (1) and (5) define the credit contract. Additionally $R \geq \phi$ else the lender would rather invest in external markets than engaging in credit contracts. This gives the relationship between returns, $R$, borrowing, $K_B(W)$, and the threshold wealth, $W^*$ required to borrow a non-zero amount, as depicted in Figure 6.

**Proposition 1: Credit Market Response to Court Performance** As court performance, $\gamma$, increases, the credit market response varies as follows:

1. Effects on $W^*$ is negative. That is, an improvement in court performance lowers the threshold of wealth required for lending.
2. Effects 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:** Differentiating (1) and (5) with respect to $\gamma$ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as follows:

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

$$\frac{\partial W^*}{\partial \gamma} = \frac{s\frac{\partial C(\gamma)}{\partial \gamma}}{\delta(1-s)\Big(b\Big(\frac{W^* + \frac{s}{\delta(1-s)}C(\gamma)}{\underbrace{K_B(W^*)}_{=bW^*}}\Big) - 1\Big)} = \frac{W^* \overbrace{\frac{\partial C(\gamma)}{\partial \gamma}}^{\text{-ve}}}{C(\gamma)} < 0$$

## 3.2 General Equilibrium Effects

In this section, I model the production effects of credit market response to changes in court performance. Additionally, the model also accounts for alternate channels of effects of court performance, for example through transaction costs (monitoring costs, $m$, incurred by the firm). Let $F$ be 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 price taker. The firm's problem is to maximize their profits as follows:

$$\text{Max}_{X_1,X_2}\big(\Pi = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - \phi m(\gamma)\big) \tag{6}$$
$$s.t\ w_1X_1 + w_2X_2 + \phi m(\gamma) \leq W + B(\gamma)$$

where $w_1$ and $w_2$ are the unit costs of inputs $X_1$ and $X_2$. $m(\gamma)$ is the monitoring costs arising in a setting with court performance $\gamma$, as defined in the section above. $W$ is the exogenous initial level of assets or wealth. $B(\gamma, .)$ is the borrowing from credit markets at a particular return, $R(\gamma, .)$, which are determined as in the Lender-Borrower set-up above.

**Proposition 2: General Equilibrium Effects of Court Performance** As court performance, $\gamma$, increases, the firm responds as follows:

1. Optimal input use increases for credit constrained firms.
2. For credit constrained firms, increase in $\gamma$ increases production output whereas the effects on optimal profits is ambiguous. The welfare effects for such firms depends on the difference between increase in borrowing limits, reduction in monitoring costs and an increase in input costs.
3. For credit unconstrained firms, profits increase through decrease in monitoring costs.

**Proof** 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, $\gamma$, i.e. $m_\gamma < 0$. From the discussion above, borrowing increases with an increase in court performance i.e. $B_\gamma > 0$. Further, from the functional form assumptions, we have $Q_{x_1x_1}Q_{x_2x_2} - Q_{x_1x_2}Q_{x_2x_1} = 0$.

**Constrained Optimization:**

$$\begin{aligned}
\mathcal{L} &= pQ(X_1, X_2) - w_1X_1 - w_2X_2 - \phi m(\gamma) + \lambda\big(W + B(\gamma) - w_1X_1 - w_2X_2 - \phi m(\gamma)\big) \\
&\text{FOC:} \\
\frac{\partial \mathcal{L}}{\partial X_1} &= pQ_{x_1} - w_1 - w_1\lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial X_2} &= pQ_{x_2} - w_2 - w_2\lambda = 0 \\
\frac{\partial \mathcal{L}}{\partial \lambda} &= W + B(\gamma) - w_1X_1 - w_2X_2 - \phi m(\gamma) = 0
\end{aligned}$$

I solve above using Implicit Function Theorem where $X_1, X_2, \lambda$ are endogenous variables and $\gamma$ as the exogenous variable to the firm's problem. Solving requires application of Cramer's Rule with the following as main steps:

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

Finally, an application of the envelope theorem enables examining how the value function changes with the exogenous court performance, $\gamma$. Specifically, I find:

$$\begin{aligned}
\frac{dV(\gamma)}{d\gamma} &= \frac{\partial \Pi^*}{\partial \gamma} + \lambda\frac{\partial g^*(\gamma)}{\partial \gamma} \text{ where } g(.) \text{ is the constraint} \\
\frac{\partial \Pi^*}{\partial \gamma} &= \underbrace{(pQ_{x_1} - w_1)}_{\text{In competitive factor markets, this is 0}}\frac{\partial X_1^*}{\partial \gamma} + \underbrace{(pQ_{x_2} - w_2)}_{\text{In competitive factor markets, this is 0}}\frac{\partial X_2^*}{\partial \gamma} - \phi m_\gamma > 0 \\
\frac{\partial g^*}{\partial \gamma} &= \underbrace{(B_\gamma - \phi m_\gamma)}_{\text{marginal benefit}} - \Big(\underbrace{w_1\frac{\partial X_1^*}{\partial \gamma} + w_2\frac{\partial X_2^*}{\partial \gamma}}_{\text{marginal cost}}\Big)
\end{aligned}$$

$\frac{\partial g^*}{\partial \gamma} > 0$ if increase in marginal benefits from an improvement in institutional output 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.

### 3.3 Key Tests

The model leads to the following key tests to empirically examine using the data:

H1: Firm borrowing from banks increases with an increase in court output.

H2: Borrowings increase for firms with smaller ex-ante asset size (wealth threshold for borrowing decreases).

H3: Sales and input use increase with an increase in court output, in particular among firms with smaller ex-ante asset size.

H4: Profits increase with an increase in court output for firms with larger ex-ante asset size.

## 4 Identification Strategy

I study two fundamental questions concerning the role of courts, as a key judicial institution, in promoting firm growth. First, I address how the litigation process itself affects firm and market behavior. Second, I answer how court performance impacts production and profits of all incumbent[38] firms, irrespective of their litigation status, and examine whether enforcement of credit contracts plays a role through credit market adjustments. In all my analyses, the unit of observation is firm-district-year. For litigating firms, the court performance measures vary by firm-district-year whereas for all firms, the court performance measure varies at the district-year level. The empirical specification for estimating the relationship between court performance and firm outcome is as follows:

$$Y_{fdt} = \phi_d + \phi_{st} + \theta Court\ Performance_{dt} + \mathbf{X'}_f\Delta + \epsilon_{fdt} \tag{7}$$

where $f$ indicates the firm in the district court $d$, in state $s$ at year $t$. $Y_{fdt}$ is the firm outcome of interest in year $t$ and $Court\ Performance_{dt}$ is the court performance measure of the district court in year $t$. $\mathbf{X}_f$ is a vector of firm specific controls and $\epsilon_{fdt}$ is the idiosyncratic error. I account for all time-varying unobserved factors at the state level by including state-year fixed effects, $\delta_{st}$, and time-invariant district unobserved characteristics by including district fixed effects, $\phi_d$. However, the court performance measure, $Court\ Performance_{dt}$, is likely to be endogenous with firm outcomes if district courts are more efficient due to differential trends in infrastructure growth within the district or are less efficient due to increasing population from migration or

[38]By incumbent firms, I mean those incorporated before the study period, i.e. before 2010. I focus on incumbent firms to ensure that the estimates are not confounded by endogenous firm entry.

increased crime that add to the caseload, slowing down court performance. Alternately, districts with greater concentration of high growth firms may mechanically have slower courts if productive firms are more likely to litigate, potentially leading to causality running the other way. Therefore, I instrument $Court\ Performance_{dt}$ with judge occupancy, $Occup_{dt}$, which is the percentage of judge positions that are occupied (and correspondingly, not vacanct) in the district $d$ in year $t$ using 2SLS estimation strategy. The first stage estimating equation is as follows:

**Using Judge Occupancy Shock as an Instrument:**

$$Court\ Performance_{dt} = \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X'}_f \Pi + \nu_{fdt} \tag{8}$$

In all the empirical specifications, I cluster the standard error by district-year. This is because the choice of my instrument generates quasi-random variation at the district-year level, and so I cluster the standard errors at the level of treatment assignment (Cameron and Miller (2015), Bertrand et al. (2004)). 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 between years within a district, respectively.

**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 endogenous explanatory variable - disposal rate - $D_i$ and $Z_i$, the continuous judge occupancy rate instrument. For this approach to yield a causal estimate, the following assumptions need to be satisfied:

1. **Independence and Exclusion Restriction:** I argue that the variation induced in the occupancy rate due to a combination of the judge rotation system and existing vacancies is likely orthogonal to firm and court performance potential outcomes. I provide two pieces of evidence in support of this claim. One pertains to the institutional feature of the Indian judiciary involving assignment of judges to district courts and the second features empirical evidence by testing for correlations between time varying district characteristics and pre-period firm outcomes respectively with judge occupancy. Specifically, I run the following specifications and test whether $\rho = 0$ and $\Omega = 0$.

$$District\ Char_{dt-s} = \nu_d + \nu_{st} + \rho Occup_{dt} + \eta_{dt};\ s > 0 \tag{9}$$

$$Y_{fdt-s} = \kappa_d + \kappa_{st} + \Omega Occup_{dt} + \mathbf{X'}_f \Gamma + \epsilon_{fdt};\ s > 0 \tag{10}$$

The first piece of evidence arises from the process of assigning judges to district courts. District judges are recruited by the respective state high courts and only serve within the

state unless promoted to higher judiciary. Additionally, they serve a short term between 1-2 years in each seat and are subsequently transferred to a different district within the same state where they haven't worked in the past ("non-repeat" constraint). Given the problem of vacancy of judges in district courts across India, which is nearly 25% [39] of all current positions, this system of rotation shifts the "vacancy" exogenously to different district courts every year. The rotation system is decided by the corresponding state High Court administrative committee. Specifically, the assignment process is as follows:

(a) 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.

(b) 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. They cannot include any district they have already served in the past.

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

(d) 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[40] 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.

Common preferences for districts, such as preference for home district, are likely to be static over time. Some of these are accounted under district fixed effects, specifically if preferences are correlated with time invariant district characteristics, such as presence of urban agglomerations or coastal location. On the other hand, it is plausible that the ranking is endogenous to district specific time varying characteristics. However, given the frequent rotation, it is unlikely that the judges always get their preferred location. For example, if the same rank is also given by a more senior judge, then the tie is broken based on seniority. Therefore, this process can only violate the exogeneity assumption if judge preferences also simultaneously evolve along with outcomes of interest and if all judges always get their preferred location.

The second piece of evidence arises from testing the empirical specifications (3) and (4). I find that the judge occupancy is uncorrelated with prior period court performance as well

[39] https://www.livemint.com/news/india/india-s-next-generation-reforms-must-begin-in-courts-1560838699823.html

[40] For example, the average tenure of the head judge, for whom I was able to get tenure data, is about 18 months whereas the average trial duration is close to 21 months.

as district level time varying characteristics such as agricultural sown areas (fraction of total area), and per capita crime variables (Table 3). Further, I also find that judge occupancy is uncorrelated with prior period firm outcomes (Table 4). The joint test of significance fails to reject the null hypothesis of no correlation between these measures and judge occupancy.

Each year, judge occupancy increases with respect to preceding year for a fraction of the districts, stays the same for some, and declines for the remaining. The fraction of districts where occupancy declines increases over the study period, which highlights the overall trend and increasing problem of undersupply of judges. Simulating the rotation process over the study period for each state through random permutations of judge occupancy generates district specific distribution of occupancy that is statistically indistinguishable from the observed distribution.[41]

Finally, I use tenure and district assignment data of Principal District Judges (PDJs) - the head judge of district courts, [42] I show that the average tenure is about 1.5 years (Figure A.20, top panel) and that the system of rotation leads to "gap days" before the successor judge takes charge (Figure A.20, bottom panel). This effect of rotation on vacancy is likely an underestimate since the courts do not remain without a head judge for long, but provides suggestive evidence on the relationship between the rotation system and creation of vacancy as a result. Further, I find that the tenure of PDJs is uncorrelated with district level time varying characteristics and annual firm outcomes, suggesting that the rotation system likely yields exogenous variation in judge tenure and consequently also occupancy. [43]

2. **First Stage and Monotonicity:** Figure 7 and Table 5 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. This is substantial given the mean baseline disposal rate is only 14 percent. Expressing this in terms of standard deviation (SD) in judge occupancy, 1 SD increase leads to 21 percent, or a 0.25 SD increase in disposal rate. The estimate is similar using the index instead of disposal rate as the measure of court performance. The remaining columns in Table 5 present other ways of measuring the same treatment, and with the exception of case duration and share dismissed, have significant positive coefficients on judge occupancy. Since all these measures are highly correlated with each other (Table A.30), I use log disposal rate as the preferred measure of court performance in all subsequent specifications. To enable the interpretation of the IV estimate as some form of weighted average of causal response/weighted LATE (Angrist and Imbens (1995)), the instrument needs to satisfy an additional assumption of monotonicity. Monotonicity assumption

[41] Kolmogorov-Smirnov test fails to reject the equality of distributions.
[42] For whom I was able to get data on tenure and district assignments from the district specific court websites
[43] Tables A.31 and A.32 in the appendix show this result.

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 (Table 6). These patterns suggest that the monotonicity assumption likely holds. The interpretation of the 2SLS estimates as LATE implies that the estimated effects are applicable only for the "treatment compliers" in the sample. That is, judge occupancy has an effect on courts as an institution and subsequently on firm growth in district-years where court performance responds to a marginal change in judge occupancy. On the other hand, some district courts may already be working effectively irrespective of marginal changes in judge occupancy ("always-taker"), whereas for a few others, any marginal change in judge occupancy may have no effect on their disposal rate ("never-takers"). Therefore, the estimates presented here will refer to the causal effects on the sub-sample where disposal rate responds to changes in judge occupancy. Table 6 indicates that compliers are concentrated in the first two terciles of district courts by court size (total judge posts) as well as corresponding district population densities.

Finally, I argue that judge occupancy affects firm outcomes only through court performance. Exclusion restriction may be violated, for example, if judge occupancy directly affects firm outcomes through input markets or crime. However, these are downstream effects of court performance. I show in the section below that judge occupancy affects credit market through improved court performance that benefits many lenders that are engaged in litigation. I also discuss that judge occupancy does not have direct effects on crime behavior but through court performance (i.e. faster or slower sentencing) that is presented in the appendix.

In the next two sections, I present the results of the impact of court performance on firm outcomes, and test the propositions to establish that the functioning of the local credit markets is an important channel for the observed effect.

# 5 Effects of Court Performance on Litigating Firms

In this section, I examine the direct effects of court performance on firms that are involved in litigation. I separate the analysis by examining the effects on banks and the subset of non-financial firms that appear as a respondent.

The ideal experiment to estimate the causal effects of litigation delays in a specific district court would involve the trials being randomly assigned across years where in some years courts are faster (or slower) than counterfactual years in resolving the same trial. While this is not the case and that there may be a selection effect on litigants in the trial dataset, I use judge occupancy as an instrument to induce quasi-random variation in court performance as before, but during the period

when the firm has at least one case active in the court. Therefore, this analysis examines what happens to the outcomes of the already litigating firms when the court experiences judge supply shocks (i.e. variation in judge occupancy).

## 5.1 Effect of Court Performance on Banks

For banks, I use district wise annual credit summary data to obtain the left hand side variables. These include total loan accounts and total outstanding loan amount in a given district-year. Further, the credit data allows me to examine the heterogeneity by public sector ownership of banks as well as by sectoral allocation of loans.

**Estimating specifications**

$$O_{dt} = \delta_d + \delta_{st} + \delta_c + \beta Court\ Performance_{dt} + \upsilon_{dt} \tag{11}$$

$$Court\ Performance_{dt} = \alpha_d + \alpha_{st} + \alpha_c + \lambda Occup_{dt} + \xi_{dt} \tag{12}$$

where $O_{dt}$ is either total loan accounts or total outstanding debt pooled across all banks in a district $d$, with trials of type $c$ in the corresponding court in state $s$ and year $t$. $Court\ Performancedt$ and $Occupancy_{dt}$ are as defined in Section 4. The specification accounts for district fixed effects, and state-year fixed effects as elaborated in Section 4, in addition to case-type fixed effects to account for differences in litigation issues.[44]

Table 7 presents results from estimating above specification across all loan accounts in a district. Column 4 presents the first stage, which implies that a one percentage point increase in judge occupancy increases disposal rate by 0.78 percent. Columns 1-3 presents OLS, IV, and reduced form estimates respectively. The OLS estimate is attenuated towards 0, indicating plausible omitted variables that are negative correlated with the court performance measure. For example, an influx of population over time is likely negatively associated with court performance but likely positively correlated with total loan accounts in the district. The IV estimate accounts for omitted variables subject to the instrument conditions satisfied by judge occupancy as discussed in the section above. The IV estimate implies an elasticity of 0.11, that is, the total number of loan accounts increase by 0.11 percent for 1 percent increase in disposal rate. The reduced form estimate implies an increase in total loan accounts by 0.085 percent for 1 percentage point increase in judge occupancy. Given the average number of loan accounts in a district in a year is about 340,000, the estimate implies an increase by $\approx$ 6800 new loan accounts for 1 standard deviation increase in judge occupancy.

[44]This accounts for procedural differences in processing litigation relating to debt default vs. other contractual breaches, which may have separate laws governing them.

Examining total outstanding loan amount pooled across all banks in a district-year in Table 8 reveals no significant effect on the aggregate repayment behavior. On the other hand, the number of loan accounts and total outstanding loan amount for public sector banks respond favorably to improved court performance. Tables 9 and 10 show the results on loan account and outstanding loan for public sector banks by district-year. The IV estimates indicate that the loan accounts increase by 0.23 percent and outstanding loan decreases by 0.31 percent for 1 percent increase in disposal rate.

Finally, I find that loan accounts increase significantly for manufacturing and consumption purposes (for example: housing loan, vehicle purchase loan, etc.) relative to agriculture. Tables 11, 12, and 13 show that loan accounts increase by 0.27, 0.14, and 0.045 percent for 1 percent increase in disposal rate, although the estimate is not significant for agriculture.

## 5.2 Effects on Respondent Firms

A trial that concludes in a timely fashion likely halts the production process for respondent firms if the judgement is against them. As seen above, this is generally true in the case of debt-defaults where judgements mainly favor the lender. This, for example, could put a halt to the production process if inventory stock, machinery, or building was pledged as a secured collateral. In the case of industrial-labor dispute with the firm as the respondent, the court may order the firm to pay damages to the labor or may require a laid off employee to be reinstated. In such instances, timely adjudication may have a negative effect on respondent firms. In this section, I examine the effects on non-financial respondent firms using a similar specification as described above. Since I do not have establishment level data for non financial firms, I add firm fixed effects to the specification 11,12, to account for time invariant unobserved characteristics of the respondent firm. The identifying variation remains the same as before - shocks to judge occupancy during the period when the firm has at least one active case in a given district court. Column 4 of Table 14 presents the first stage for this sample, which is of similar sign and relative magnitude.

Columns 1-3 of Table 14 presents the OLS, IV, and the reduced form estimates for the sample of non-financial firms that appear as respondents. These indicate a weak negative impact on profits and suggestive negative impact on sales revenue and wage bill. On the other hand, the effect on employee headcount is weakly positive. Getting sued in a court is potentially damaging for non-financial firms and can be used by banks as strategic choice to improve their repayment behavior, especially when courts function in a timely fashion.

The pattern of effects on banks at the district level reveals that improved court performance support banks in their lending operations by expanding the number of borrowers they would lend

to. The increased lending is directed towards production activities directly as well as towards demand generation through consumption loans. In the next section, I present the results on production outcomes on all firms excluding banks in the court jurisdiction.

# 6 Effects of Court Performance on All Firms in the Local Economy

In this section, I present the results from testing the hypotheses arising out of the credit market model. Correspondingly, I examine firm's (excluding banks) borrowing and lending outcomes as well as production outcomes including sales revenue, profits net of taxes, input use - wage bill, number of employees where reported, plant and machinery, and land. I transform all outcome variables and the explanatory variables - disposal rate - into their logarithmic equivalent so that we can interpret the outcome in terms of elasticity. Where logarithmic transformation is not feasible - i.e. when the values are 0 or negative such as in the case of profits, I use inverse hyperbolic sine transformation without changing the interpretation of the coefficients. All baseline raw outcome measures are reported in INR million, adjusted to inflation.

Mapping back to the four key hypotheses presented earlier, I discuss the effects of courts on incumbent firm outcomes, starting with borrowing and lending behavior and subsequently discussing the effects on input use and firm production - sales and profits net of taxes. Further, I show the effects by ex-ante asset size distribution of the firms to test the hypotheses on credit constrained firms using below median asset size as a proxy for credit constraint. For these estimations, I show the results both in tabular as well as in a graphical form by plotting the reduced form and IV coefficients from regressing both leads and lags of the outcome of interest on judge occupancy and disposal rate, respectively.

**Borrowing from Banks:** Figure 9 and Column 1 of Table 15 show the OLS, IV, and reduced form estimates of court performance on long term (repayment over period $>$ 1 year) borrowing from banks by all firms within the jurisdiction. Higher disposal rate in district courts effected through improved judge occupancy increases the extent of firms' long term borrowing from banks. The elasticity with respect to disposal rate is 0.39, which is statistically and economically significant. The reduced form estimates imply that the total borrowing from banks increases by 0.5 percent for every 1 percentage point increase in judge occupancy or by 11 percent for 1 SD increase in judge occupancy. The coefficient estimate remains positive and of similar magnitude using a balanced panel of firms (Column 1 Table 16) as well as after weighting the regression by the number of incumbent firms per district (Column 1 Table 17).

**Inter-Firm Lending** I examine the lending behavior of the firms within the jurisdiction which is in the form of inter-firm lending, including trade credit and loans to subsidiaries, as well as loans to employees in Column 2 of Table 15 and Figure 11. While only a small number of firms engage in lending functions, the extent of lending is impacted by the quality of contract enforcement through the corresponding district courts. This behavior is highly elastic, with the coefficient estimated close to 1, that remains stable using balanced panel of firms, with or without weighting by the number of incumbent firms per district (Column 2 of Table 16 and 17). The reduced form estimates imply a 2-5 percent increase in lending for every 1 percentage point increase in judge occupancy. This again reflects the highly elastic nature of this aspect of firm operation, again with a caveat that very few firms engage in lending behavior.

The comparative statics following the credit market implications of improvement in court performance showed that borrowing increases particularly for credit constrained firms, thereby expanding production by increasing input use to optimal levels. However, due to both increase in production and an increase in expenditure on inputs, the effects on profits on such firms are a-priori unclear. On the other hand, credit unconstrained firms are likely to experience an increase in profits from reduced transaction costs.

**Firm Input Use:** In this paragraph, I turn to input use that include annual wage bill and employee headcount [45]. Figure 12 and Columns 3-6 Table 18 show reduced form and IV estimates of judicial capacity and court performance on firms' input use. I note positive effects on labor use - wage bill and weakly on headcount (although effects on headcount is imprecisely estimated and are sensitive to specifications). Specifically, the elasticity of wage bill with respect to court performance is $\approx 0.2$, which remains stable across different specifications - using a balanced panel of firms, with and without weights (Columns 3-4 Table 19 and 20). Reduced form estimates imply that the wage bill increases around 0.4 percent for every 1 percentage point increase in judge occupancy. This suggests that firms plausibly engage in labor intensive production when the courts are effective.

While the estimates on capital inputs - plants, machinery, and land (both freehold and leasehold), are weak without weighting by number of firms in the district, accounting for the weights in Columns 5-6 of Table 20 reveals a positive and significant coefficient on the value of plant and machinery as well as weakly on land.

**Firm Sales Revenue and Profits:** The reduced form estimates of judge occupancy on firm sales revenue as shown in the left panel of Figure 13 is positive but imprecise. However, the IV estimates in the right panel imply a positive and statistically significant effect of court performance. Column 1 of Table 18 presents OLS, IV, and the reduced form estimates for sales revenue using

[45] where available; firms are not mandated to disclose number of workers but all publicly listed firms do

lagged court variables. The elasticity suggests that the sales increases by 0.1 percent for 1 percent increase in disposal rate. This remains stable across specifications using balanced panel of firms with and without weights (Column 1 Table 19 and 20) but is imprecisely estimated.

The panels in Figure 14 depicts the estimates for profits. The reduced form and IV estimates indicate a 0.5 percent and 0.26 percent increase in profits for 1 percentage point increase in judge occupancy and 1 percent increase in disposal rate, respectively (Column 2 of Table 18). The estimates are consistent and statistically significant using a balanced panel of firms, with and without weights as show in Column 2 of Table 19 and Table 20.

**Heterogeneity by Ex-Ante Wealth** In order to show heterogeneity by ex-ante asset size (i.e. a proxy for credit constraint) of firms as per the model proposition, I categorize firms into those below median of ex-ante asset size and those above the median. Figure 10 shows that the borrowings increase for firms with lower ex-ante wealth but displays no effect on those above median. This supports the proposition that improved judge occupancy and court performance lowers the wealth threshold for borrowing. I also find suggestive positive effects on sales revenue for firms with smaller ex-ante asset size as indicated in Figure 15, supporting the proposition that credit constrained firms experience an expansion in production. Whereas profits increase among ex-ante wealthier firms as seen in Figure 16, indicating the absence of opposing effects of increased input expenditure for such firms.

**Firm Fixed Effects** In all specifications above, the estimates are computed as the local average treatment effect of court performance across non-banking firms in the court jurisdiction. This could mask distributional effects where loans may be targeted to firms that were earlier likely credit constrained. To study within firm response to court performance over time, I add firm fixed effects to the main specification. Table 21 presents the results on borrowing-lending outcomes and Table 22 shows results on production outcomes. Overall, I note weak effects on borrowing-lending that are not statistically significant. On the other hand, the effects on profits and annual wage bill are similar in magnitude but imprecisely estimated whereas employee headcount and value of land holdings exhibit a statistically significant negative response. This could be explained by the credit market response that creates new borrowers expanding production in such firms. In markets with inelastic supply of inputs, this could potentially lead to relocation of factors of production, showing a declining use of inputs for an average firm.

## 6.1 Discussion of the results

The results indicate that the shocks to judge occupancy result in credit market response over the next 1-2 years by increasing credit access to otherwise credit constrained firms, both directly

through borrowings as well as indirectly through generating demand via consumption loans. This leads to an expansion in production through increased use of inputs, and increases profits on an average. While there could be many channels through which courts can influence firms such as improved property rights, the context and the dataset enables testing the importance of credit markets under effective contract enforcement hypotheses.

Comparing the estimated elasticities on borrowing from banks with those reported in Ponticelli and Alencar (2016) in the Brazilian context reveals substantial similarity, where the authors present the estimated elasticity of borrowing with respect to court congestion[46] as 0.178.[47] In the context of this study, this estimate is slightly higher at 0.385. The effect on sales (or firm output) is similar; they estimate the elasticity of firm output at 0.083 whereas I estimate it for revenue from sales at 0.098. Though the estimates are comparable, this paper underlines the importance of district court performance on ordinary credit market behavior and its consequences on lending and recovery of loans by banks in contexts 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 credit defaults, including ordinary debt recovery and contractual dispute trials in courts of first instance. In the sections below, I examine the interaction of court performance with introduction of laws, including changes in India's bankruptcy law, to identify the complementarity between legal and judicial institutions.

# 7 Interaction Between Courts and Legal Reforms

This section of the paper connects back to the big question on institutions and development. Courts are but one component of legal institutions, which includes laws and regulations framed by the legislature and policies by the executive. Glaeser and Shleifer (2003) make an efficiency based comparative analysis of litigation vs. regulation based institutional regimes to identify which of the two, or a combination of the two emerge as the optimal choice in a given context. India is a regulatory state, where the courts function to administer justice as per the laws and are expected to play a complementary role in achieving the objectives enshrined in the laws. In this context, courts with low judicial capacity may diminish the effectiveness of any progressive reform. For example, Besley and Burgess (2004) discuss the effects of labor-industrial dispute regulation in India on manufacturing sector, showing that regulation favoring labor rights reduced manufacturing profits, employment, and increased urban poverty. What happens when courts are effective under such a system? On the one hand, any litigation under pro-labor legal environment

[46]Measured as log backlog per judge.

[47]The authors' measure of congestion has backlog in the numerator whereas in my definition it is in the denominator. Therefore, I compare the absolute value of these elasticities with respect to court congestion measures that are qualitatively similar.

could likely favor the labor side in a dispute, so higher judicial capacity could magnify the results as in Besley and Burgess (2004). On the other hand, because disputes are resolved quickly with better courts, an improved trust in market based contracts could increase firm profits if firms subvert formal employment and hire temporary workers in response to pro-labor reforms as in Chaurey (2015). I examine this empirically by testing whether judge occupancy affects firm outcomes in the context of a pro-labor industrial environment.

I also study the interaction between judge occupancy and bankruptcy reform on firm outcomes using the 2016 overhaul of bankruptcy procedure under the newly legislated Insolvency and Bankruptcy Code. This is closely related to Ponticelli and Alencar (2016) where they show lower court capacity diminishes the effects of bankruptcy reforms because the enforcement of creditor rights are weak in such a context. Both these contexts, i.e. industrial dispute resolution and bankruptcy laws, provide a change in the legal environment arising out of the respective legal reforms. This provides an opportunity to study the complementarities between the effectiveness of courts and overall strengthening or weakening of rights under different legal regimes.

## 7.1 Does Judicial Incapacity limit Industrial-Labor Reform?

I use Besley and Burgess (2004) classification of Indian states as pro-industry, pro-labor, and neutral with respect to their industrial-labor dispute regulations. In their study, the authors show that states that regulate laws in favor of labor rights experience lower manufacturing profits and employment, and a consequent increase in urban poverty. I expand their findings by studying the interaction of the regulatory environment with judicial capacity on all formal sector firms, including those in the manufacturing. The empirical specification is as follows:

$$Y_{fdt} = \delta_d + \delta_{st} + \gamma_1 Judge\ Occp_{dt} \text{ x } Pro\ Industry_s + \gamma_2 Judge\ Occp_{dt} \text{ x } Pro\ Labor_s + \gamma_3 Judge\ Occp_{dt} + \mathbf{X}_f \Delta + \epsilon_{fdt} \quad (13)$$

where $Y_{fdt}$ is outcome of incumbent firm's $f$, with registered office location in district $d$ under the ambit of industrial-labor laws of state $s$. $Judge\ Occp_{dt}$ is the measure of judicial capacity in district $d$, year $t$. $Pro\ Industry_s$ and $Pro\ Labor_s$ are dummy variables indicating whether a state has regulations in favor of business-owner rights or in favor of labor-rights. The leave-out group are states with neutral legislations, i.e. favoring neither business owners or labor rights. To account for all time invariant district level and time varying state level unobserved characteristics, I include district and state-year fixed effects. Finally, I account for firm specific characteristics including age, and sectoral dummies.

**Effects across all sectors** Pooling firms across all sectors, as shown in table 23, I find positive and significant effects of improved judge occupancy on profits net of taxes in both pro-industry and pro-labor states while a negative but insignificant effects in neutral states. However, I cannot reject the null that improved judge occupancy differentially affects pro-industry relative to pro-labor states. Specifically, a one percentage point increase in judge occupancy increases profits by 2.6 percent in pro-industry states and by 1.8 percent in pro-labor states. On the other hand, improved judge occupancy has negative effects on wage bill in pro-industry (significant at 10%) and pro-labor states (imprecise) whereas a positive effect in neutral states. The estimates imply that a one percentage point improvement in judge occupancy lowers wage bill by 0.6 percent, 0.3 percent and increases by 0.75 percent in pro-industry, pro-labor, and neutral states respectively. For a sample of firms that disclose employee headcount, I find positive effects of improved judge occupancy on employment in pro-industry showing an increase of 2.5 percent for every percentage point increase in judge occupancy. Employment also increases by 2.2 percent in pro-labor states whereas decreases by 1.9 percent in neutral states.

**Effects on manufacturing sector** Focusing on firms in the manufacturing sector alone as in table 24, I find similar direction and magnitude of results, with profits increasing with an improvement in judge occupancy in both pro-industry and pro-labor states whereas decreasing profits in neutral-states. The effects are similar on wage bill, whereas the I find no significant effects on employment (in terms of headcount).

These results suggest that higher judge occupancy leads to improved firm profits but lower wage bill when the laws strengthen the rights of either business-owners or labor in a state. On the other hand, improved judge occupancy has the opposite effect when laws are enacted in a neutral manner. In the next section, I examine the complementarity in the context of bankruptcy reforms.

## 7.2 Does Judicial Incapacity Limit Bankruptcy Reform?

India enacted an overarching reform addressing the process of bankruptcy in 2016 by introducing Insolvency and Bankruptcy Code to strengthen creditor's rights. The policy focus of this reform was to enable business environment and aid creditor's recovery of bad loans by easing the process of liquidation and/or reinvestment in defaulting companies. Therefore, this reform should likely have a positive effect on the overall credit markets, improve the outcomes for banks, which may then get passed on to borrowers. However, any positive effects may be mitigated by low judge occupancy, especially if the precursors to bankruptcy proceedings involve civil suits pertaining to debt contracts. In order to study this complementary between judge occupancy and the bankruptcy reform, I employ a difference in difference identification strategy by comparing the differences in firm outcomes in ex-ante high judge occupancy (i.e. measured before the passing of the reform)

districts with those with lower occupancy across the reform period. I define ex-ante high judge occupancy as those districts that are in the top 25th percentile of the pre-reform judge occupancy levels.

$$Y_{fdt} = \alpha_{st} + \beta_1 High\ Judge\ Occp_d \text{ x } Post_t \text{ x } Year_t + \beta_2 High\ Judge\ Occp_d \text{ x } Post_t + \beta_3 High\ Judge\ Occp_d \text{ x } Year_t + \beta_4 High\ Judge\ Occp_d + \mathbf{X}_f\Gamma + \nu_{fdt} \quad (14)$$

where $Y_{fdt}$ is outcome of incumbent firm's $f$, with registered office location in district $d$. $High\ Judge\ Occp_d$ is the dummy indicating whether district $d$ is in the top quartile of judge occupancy in the pre-reform period. $Post_t$ is the dummy indicating whether year $t$ is post reform; $Post_t = 1$, for $t > 2016$ and 0 otherwise. $Year_t$ indicates the difference between year $t$ and 2010. The leave-out group includes districts not in the top quartile of pre-reform judge occupancy. To account for all time varying state level unobserved characteristics, I include state-year fixed effects. Finally, I account for firm specific characteristics including age, and sectoral dummies. Since the "treatment" group varies at the district level only, I cluster the standard errors by district. I also estimate a variant of the above specification but in levels, interacted with bank dummy $Bank_{fd}$, i.e. whether a given firm $f$ in district $d$ is a bank or not.

$$Y_{fdt} = \alpha^0_{st} + \beta^0_1 High\ Judge\ Occp_d \text{ x } Post_t \text{ x } Bank_{fd} + \beta^0_2 High\ Judge\ Occp_d \text{ x } Post_t + \beta^0_3 Bank_{fd} \text{ x } Post_t + \beta^0_4 High\ Judge\ Occp_d \text{ x } Bank_{fd} + \beta^0_5 High\ Judge\ Occp_d + \beta^0_6 Bank_{fd} + \mathbf{X}_f\Gamma^0 + \nu^0_{fdt} \quad (15)$$

**Effects across all firms** I find no pre-trends in the high judicial capacity districts, enabling causal inference from the above estimation strategy. Examining the estimates in the first specification with the pooled sample of firms in Table 25, I find that sales revenue is 1.4 log points higher in better judge occupancy districts post reform but this advantage dissipates over time. Other than sales revenue, I find no significant effects on wage bill, employment, capital or land use, and profits.

**Effects on banks** Results for banks in Table 26 show that they experience an improvement in profits by 4.2 log points post reforms in high judge occupancy districts relative to banks in low occupancy districts. However, they make lower income from financial services, have lower wage bill and likely hire less relative to banks in low capacity districts. A plausible explanation for this result is that the banks are able to recover bad loans, which would have otherwise had to be written off

as a loss in their profit-loss statement. Under higher judge occupancy post reforms, it is likely that these debts are recovered, posting a profit. On the other hand, the lower income could indicate less lending to potentially bad borrowers. Finally, since employees in banks are mainly engaged in financial services, including monitoring loans, lower wage bill could likely indicate a potential reduction in monitoring costs. This is suggestive that judicial capacity is likely an important complement to legislative or policy reforms.

In both examples above, I find that courts play a complementary role to legal reforms aimed at strengthening the rights of certain groups. Therefore, one must also take into account existing judicial capacities when implementing legal reforms focused on strengthening the rights or the contracting environment.

# 8 Conclusion

This paper estimates the causal effects of court performance measured as the rate at which trials are resolved on formal sector firm growth. Judge occupancy is an important factor determining the effectiveness of courts as an institution for the enforcement of contracts. Higher judge occupancy increases local lending by banks and other lending organizations. Using the universe of case level micro-data filed at 195 district courts between 2010 and 2018, I show that the current state of disposal rate is abysmally low and around 25 percent of judge posts are vacant on an average. Increasing judge occupancy by 1 percentage point increases the court output by 1 percent. In terms of judge headcount, adding an extra judge increases court output by 6 percent.

Courts as an institution are important for firm growth and I provide evidence in favor of credit market channel as one of the important channels. This is because banks litigate more intensively compared to any other type of firm, and are also more likely to initiate litigation as petitioners. The types of petitions they bring also clearly indicate that the lenders win the trials. In such a context, improved litigation experience increases the extent of loans made by banks, targeting manufacturing and consumption. On the other hand, timely resolution of litigation has a negative effect on respondent non-financial firms, suggesting that the lenders could exercise their choice to litigate to induce repayment in the local credit markets.

Indeed, as hypothesized, I note that all firms with registered office in the court district borrow more from banks, particularly those with smaller ex-ante asset size indicating that the wealth threshold for borrowing drops. Banks' lending is also supplemented by increased lending from other financial institutions such as the NBFCs as well as inter-firm lending. A flush of credit relaxes credit constraints firms face, leading to an expansion in production. Profits also increase,

specifically for credit unconstrained firms, for whom improved institutional environment likely lowers transaction costs.

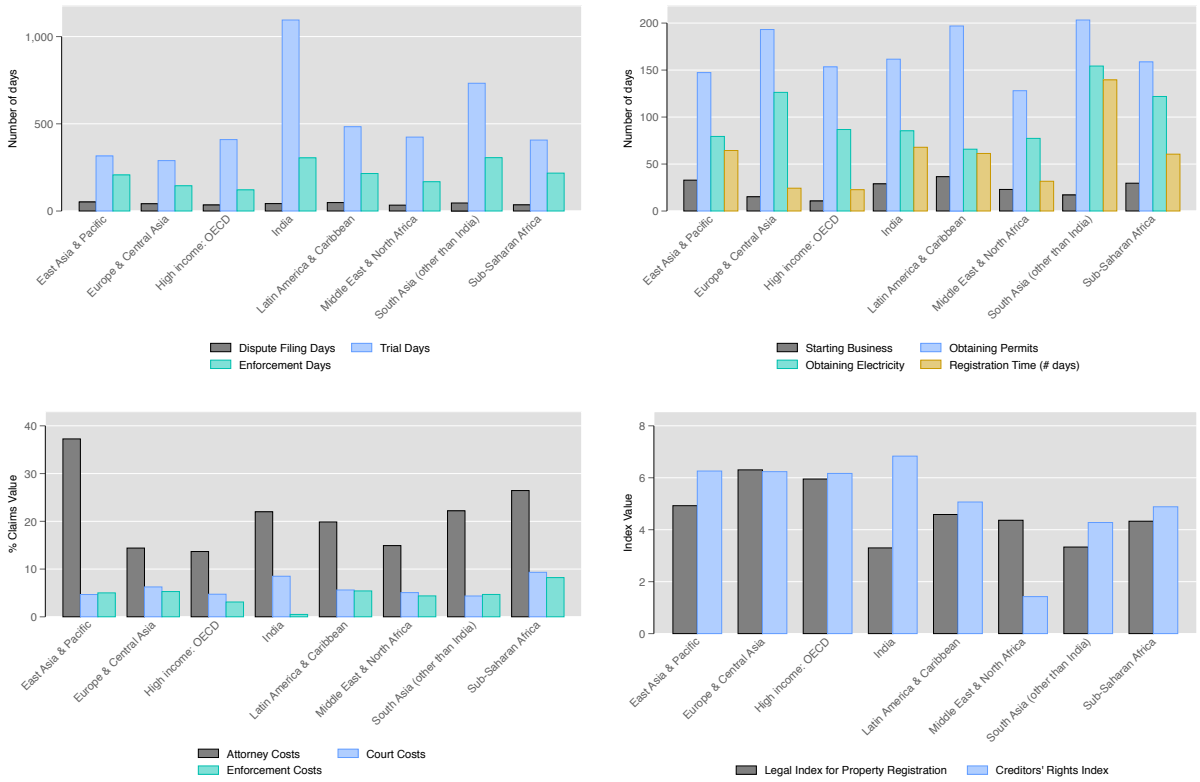
This indicates that the problem of vacancy in district courts has serious economic repercussions. This is consistent with the current demand by legal experts for addressing the issue of vacancy as well as expanding recruitment to strengthen the district judiciary. Given the benefits in the form of firm growth, the state will be able to recover the costs of hiring additional human resource from the increase in tax collection from improved firm profits. This paper makes a strong policy case for increasing the budgetary allocation to the judicial sector from the current allocation of 0.01 percent of national expenditure.

Finally, the functioning of courts are complementary to legal reforms. Using two specific examples, namely bankruptcy resolution and industrial-labor policies, this paper shows that low judicial capacity hinders the effects of the reforms that intend to strengthen the rights of certain groups - creditors, business owners, or labor as examined. Therefore, strengthening judicial institutions requires not just having a strong legal framework in terms of laws and policies, but also timely implementation of justice in the form of well functioning courts.

The scope of this paper is limited to the outcomes of firms in registered, 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 administration institutions for production processes. More research is required to examine the interplay between formal and informal justice administration institutions and selection into formal sector for production.

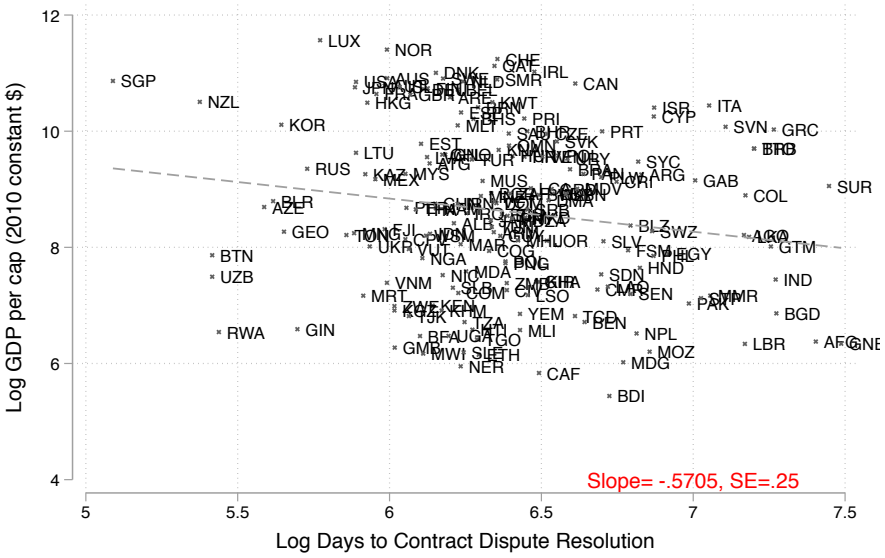
# 9 Figures

Figure 1: World Bank Doing Business Survey Database



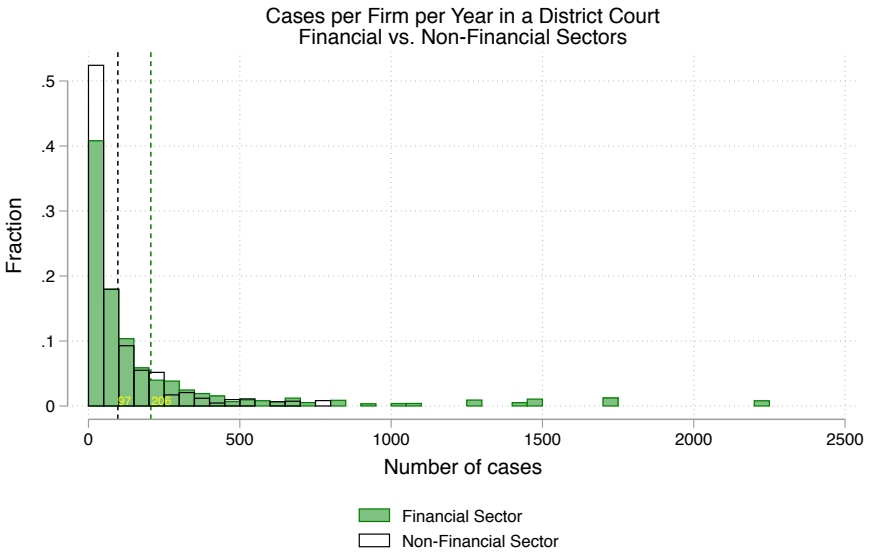

Notes: Data source: Doing Business database, World Bank. All contract enforcement variables are calculated from the perspective of the court of first instance.

Figure 2: GDP per capita and Contract Enforcement



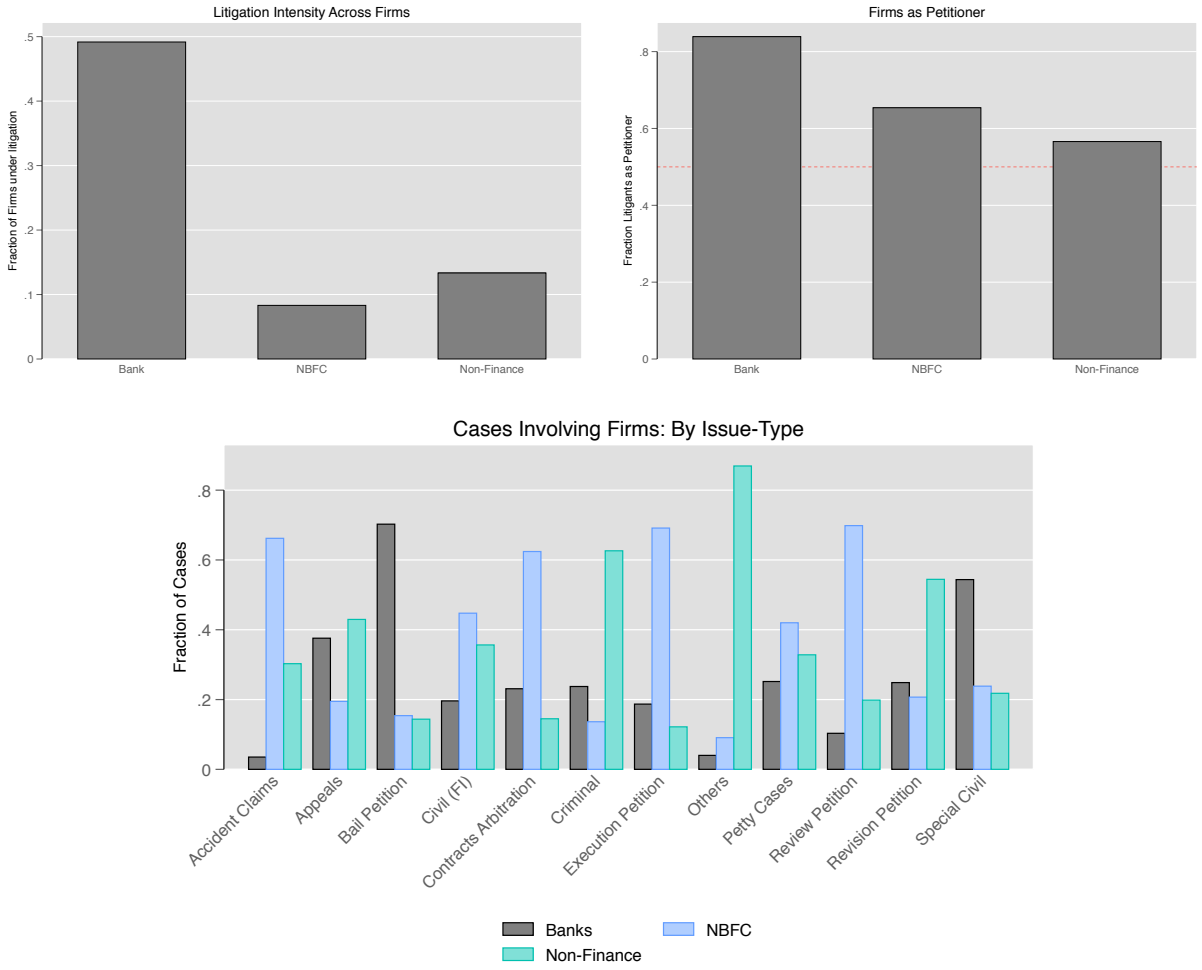

Notes: Data source: Doing Business and WDI databases, World Bank. All contract enforcement variables are calculated from the perspective of the court of first instance.

Figure 3: Distribution of Cases per Litigating Firm




Notes: Above graphs show the distribution of number of cases per litigating firm across district courts during the sample period. Some firms, such as banking and insurance firms, have a large number of cases across different courts in the sample.

Figure 4: Litigation Intensity by Firm Type




Notes: Top-Left panel shows that match rate between the firm sample in the universe of cases in sample courts. Top-Right panel shows the distribution of the matched firm by whether they are the petitioner or respondent to the litigation(s). Bottom left panel shows the distribution of the issue-types of cases involving the firms. Financial firms (i.e. banks and NBFCs) are more likely to be engaged in civil and contractual litigation whereas non-financial firms are likely engaged in other types of cases (likely fraud under criminal investigation). Bottom right shows the distribution of petitioner-respondent-issue type within firm specific cases.

Figure 5: Model: Lender-Borrower Game

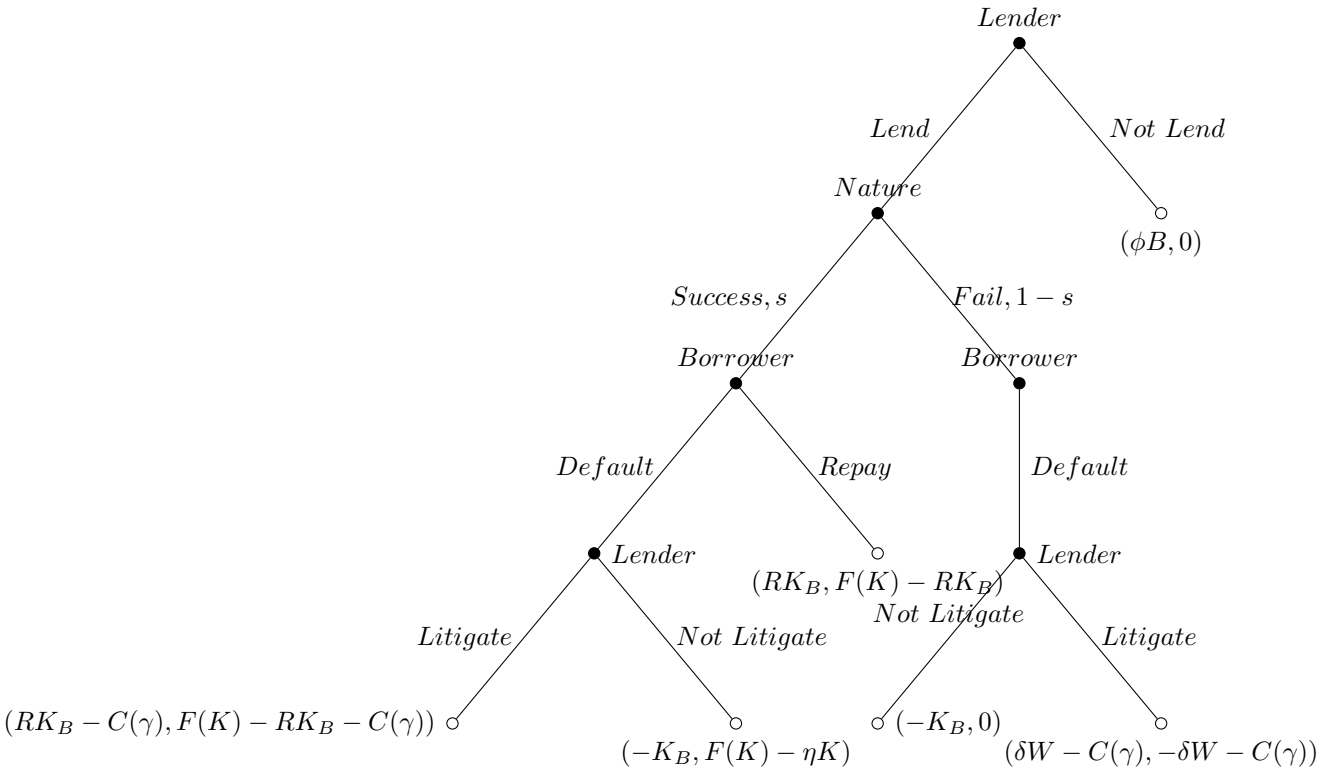



Figure 6: Model: Credit Contract

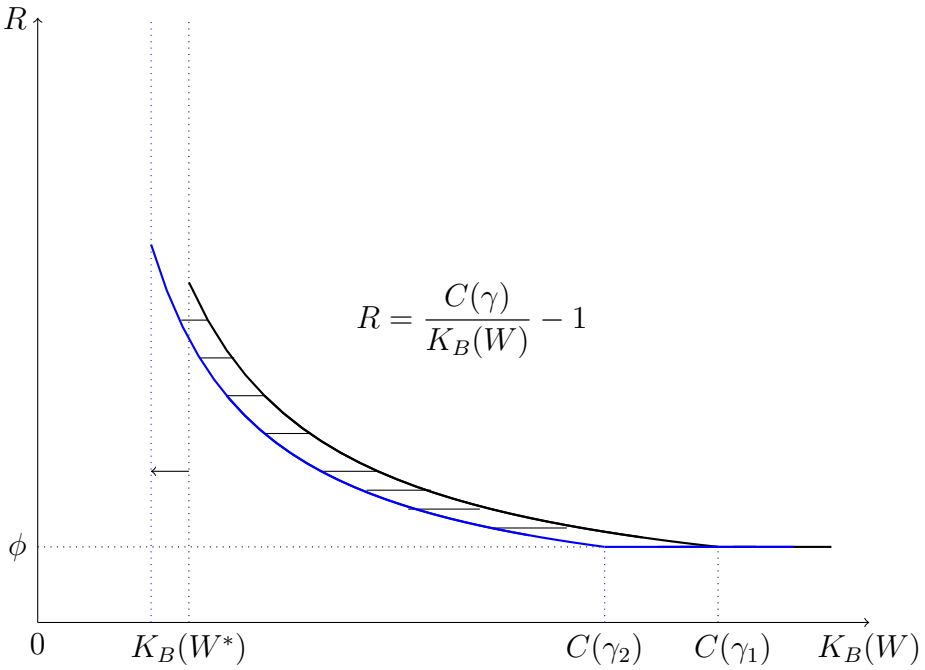
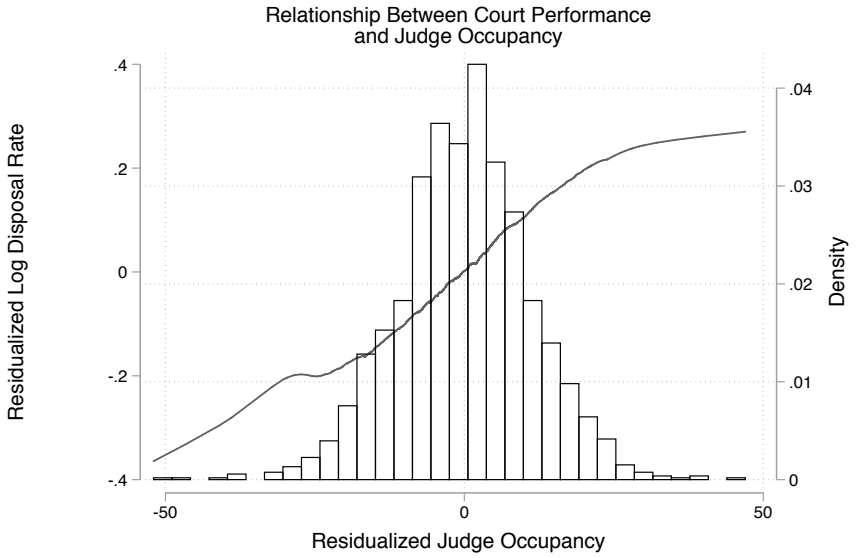
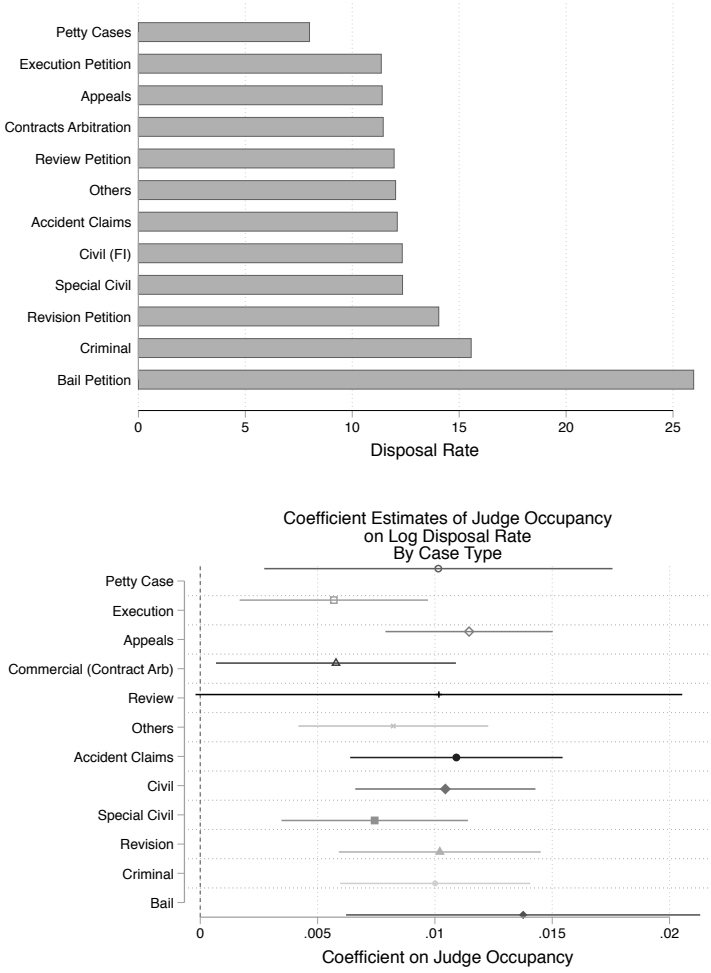


Figure 7: Court Performance and Judge Occupancy: First Stage



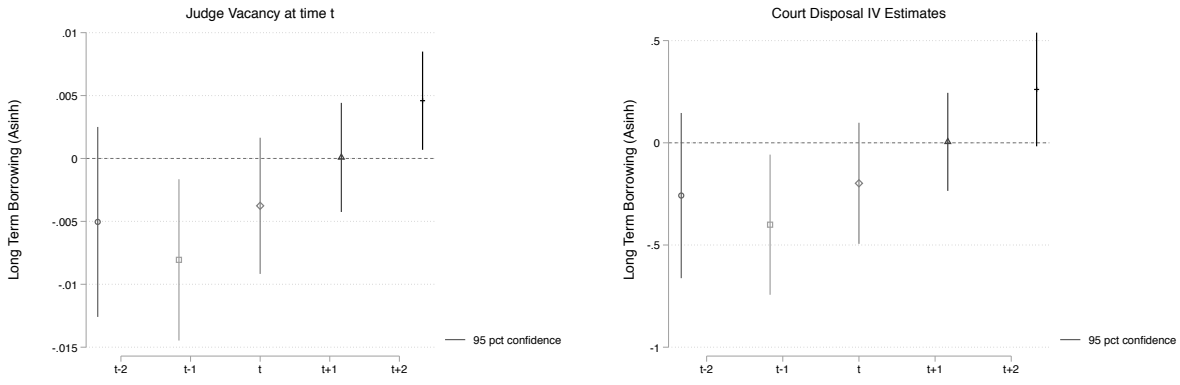

Notes: Above graph shows log-linear relationship between disposal rate and judge occupancy, after controlling for district, year, and state year fixed effects.

Figure 8: Court Performance and Judge Occupancy: Estimates Across Case-Types



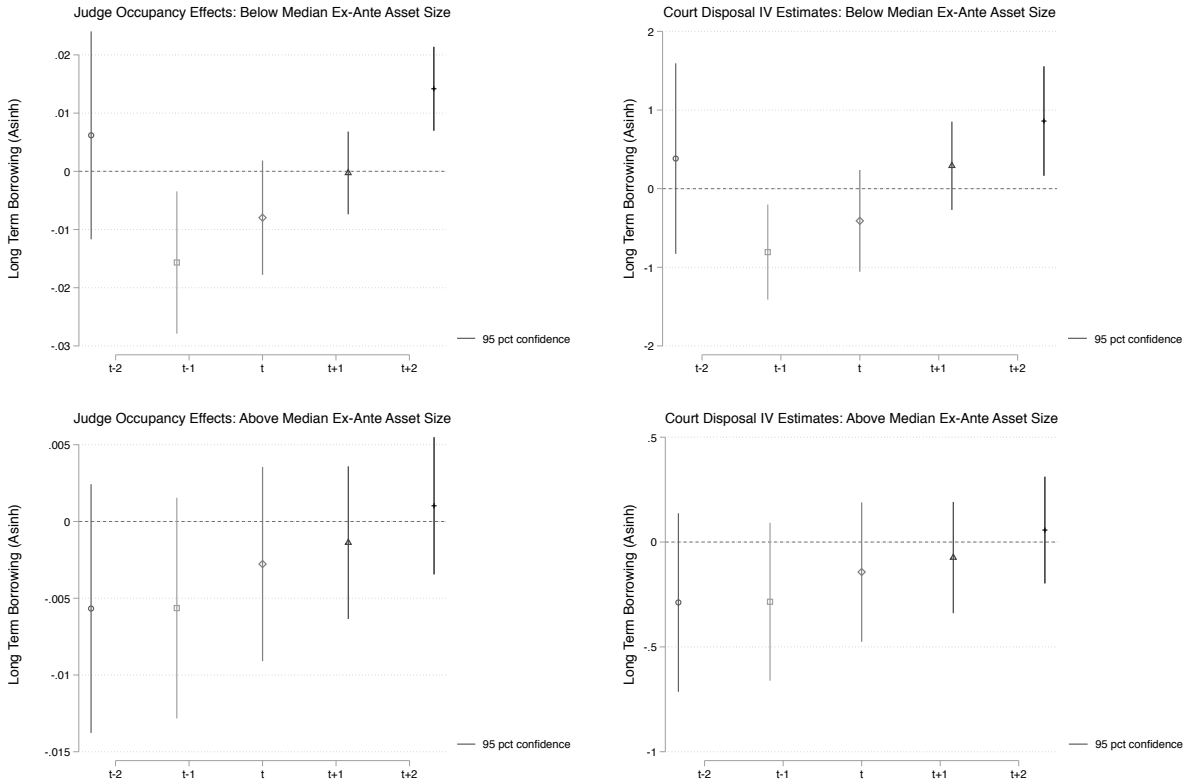

Notes: All standard errors are clustered by district-year.

Figure 9: Effects on Firm's Borrowing from Banks



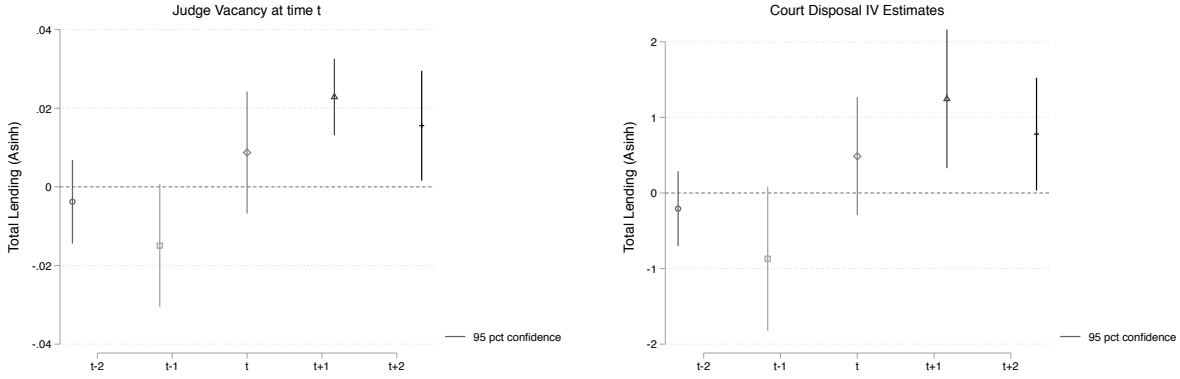

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year.

Figure 10: Heterogeneous Effects of Court Output by Asset Size: Borrowings



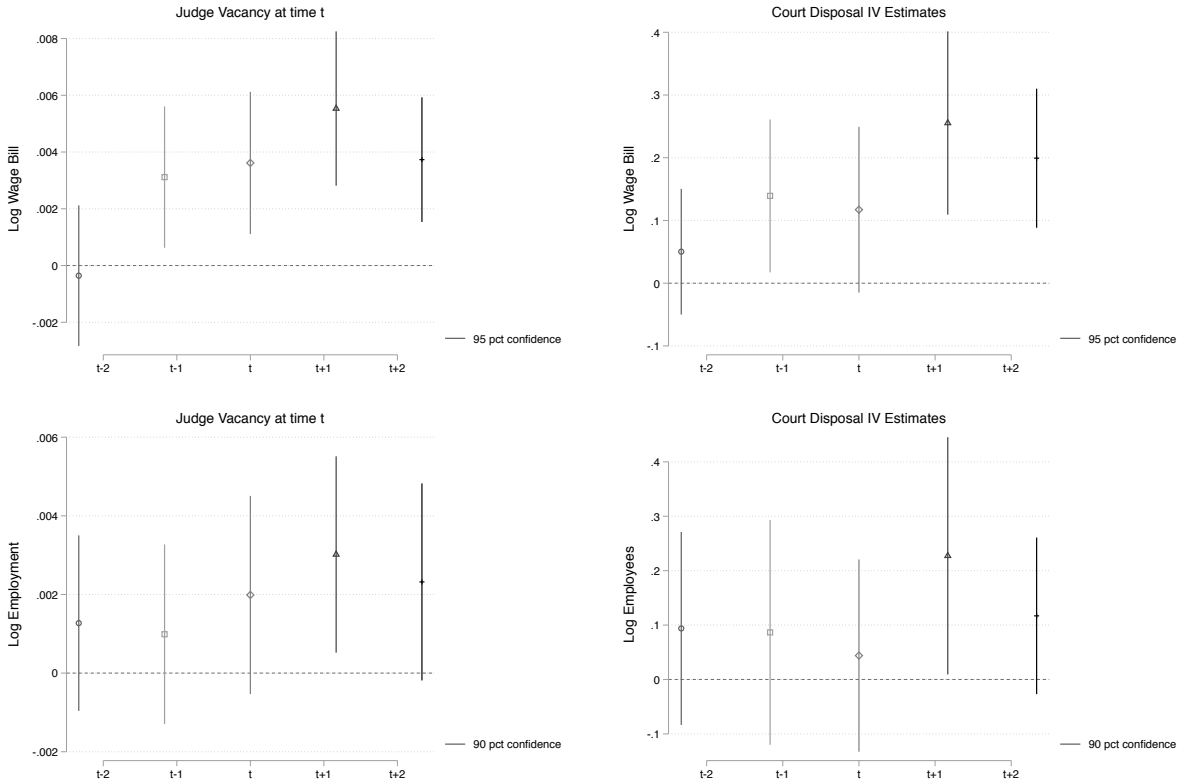

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year.

Figure 11: Lending by Firms Located in Court Jurisdiction



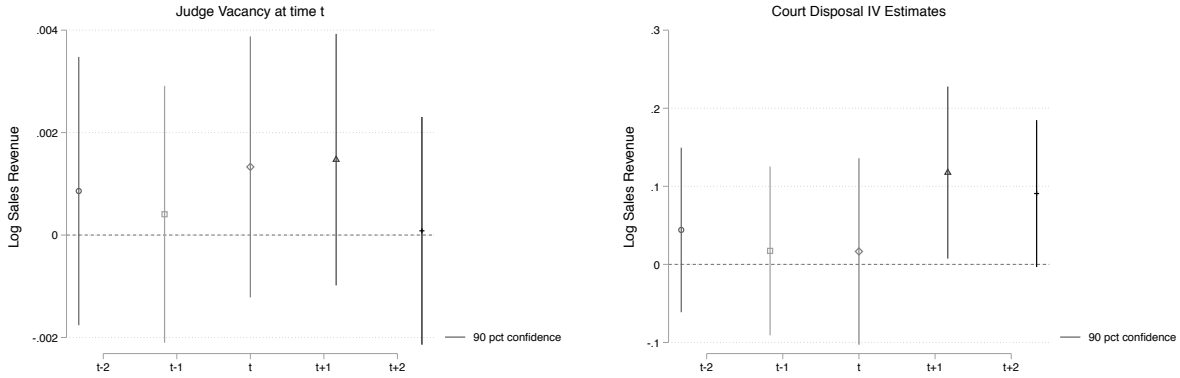

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year. The sample includes NBFCs (top) and lending firms (bottom) whose registered offices are co-located in the same district as the corresponding court.

Figure 12: Effects on Labor-Use



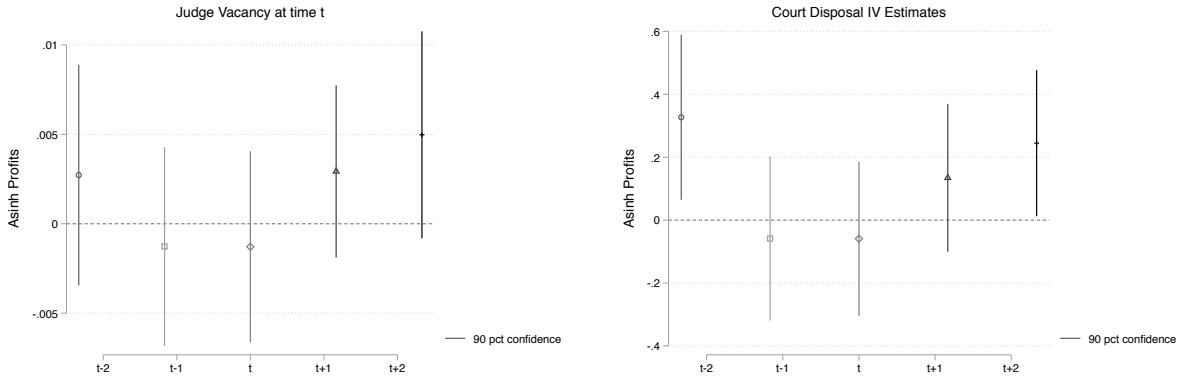

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year. The sample includes all firms whose registered offices are co-located in the same district as the corresponding court.

Figure 13: Effects on Sales



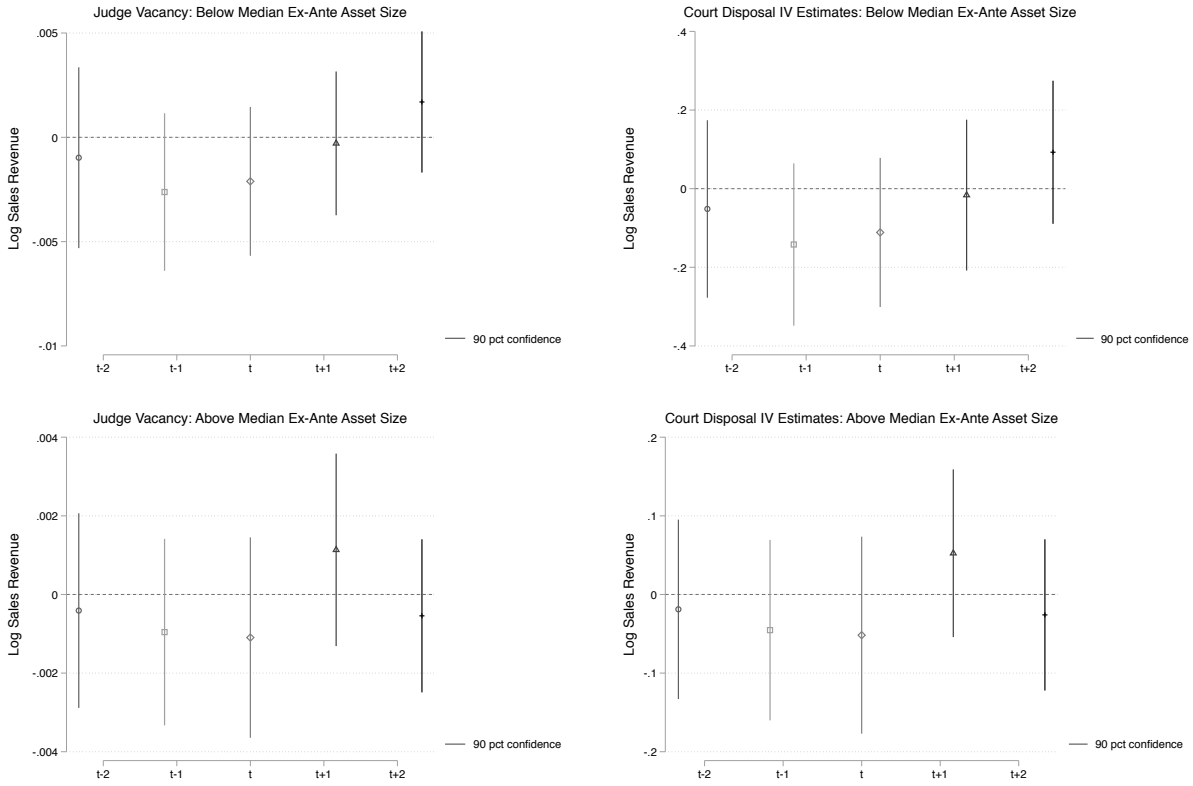

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year. The sample includes all firms whose registered offices are co-located in the same district as the corresponding court.

Figure 14: Effects on Profits



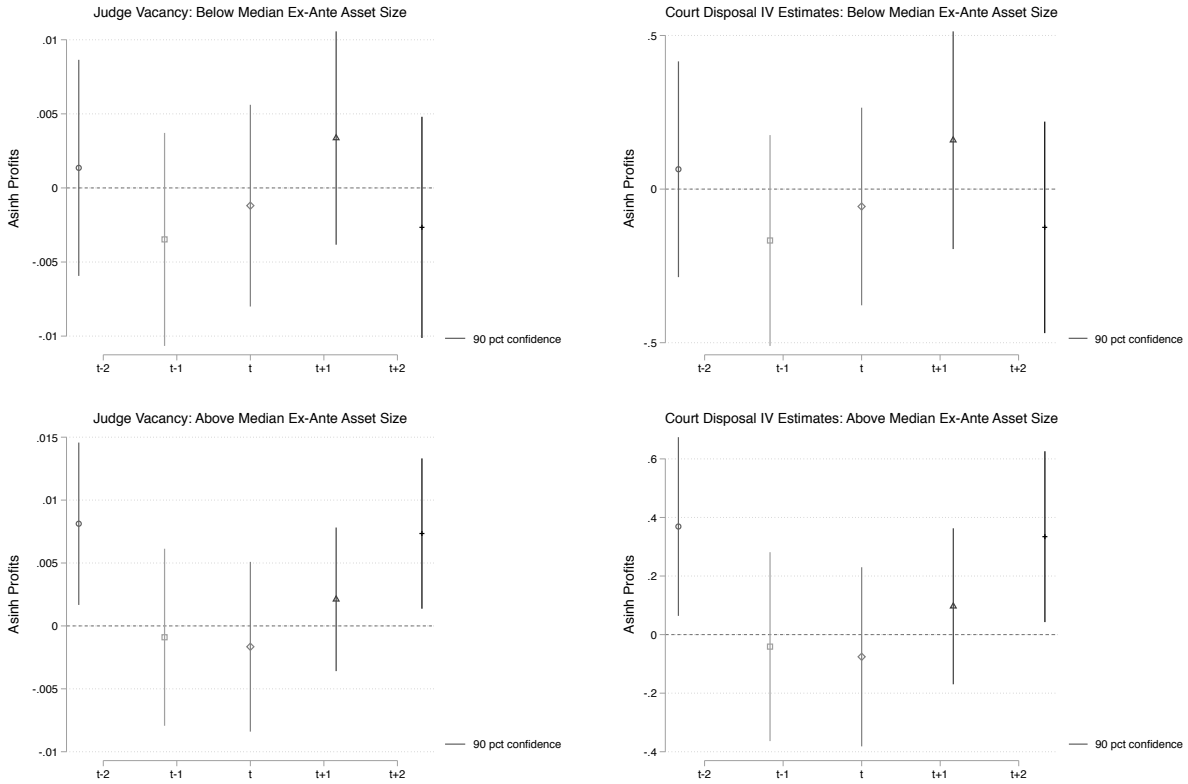

Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year. The sample includes all firms whose registered offices are co-located in the same district as the corresponding court.

Figure 15: Heterogeneous Effects of Court Output by Asset Size: Sales




Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year.

Figure 16: Heterogeneous Effects of Court Output by Asset Size: Profit




Notes: The graphs above plot the reduced form and IV coefficients from regressing lags and leads of the outcome variable on judge occupancy and disposal rate, respectively. All standard errors are clustered by district-year.

# 10 Tables

Table 1: Summary Statistics

| | (1) | | | | |
|---|---|---|---|---|---|
| | Observations | Mean | Std Dev | Min | Max |
| Court Variables | | | | | |
| Total Judge Posts | 1755 | 18 | 19 | 1 | 108 |
| Percent Judge Occupancy | 1723 | 77 | 21 | 10 | 100 |
| Disposal Rate | 1755 | 14 | 12 | 0 | 86 |
| Speed | 1723 | 76 | 102 | 0 | 2580 |
| No. Filed | 1723 | 3312 | 3712 | 1 | 34427 |
| No. Resolved | 1504 | 3341 | 3693 | 1 | 37994 |
| Percent Lower Court Judgement Appealed | 1723 | 19 | 16 | 0 | 100 |
| Percent Cases Dismissed | 1504 | 22 | 17 | 0 | 100 |
| Case Duration | 1498 | 617 | 497 | 0 | 5135 |
| Firm Variables | | | | | |
| Revenue from Sales (real terms, million INR) | 20029 | 5452 | 23513 | 0 | 796688 |
| Profits (in real terms, million INR) | 24010 | 184 | 4003 | -144347 | 158634 |
| Wage Bill (in real terms, million INR) | 21847 | 417 | 2104 | -0 | 70354 |
| No. of Workers | 4075 | 2 | 7 | 0 | 154 |
| Land value (real terms, million INR) | 16243 | 309 | 1713 | 0 | 50578 |
| Plant value (real terms, million INR) | 18124 | 2889 | 16736 | 0 | 878342 |
| Long Term Borrowing (real terms, million INR) | 9313 | 1866 | 9284 | 0 | 251188 |
| Inter-firm Lending (real terms, million INR) | 297 | 419962 | 733941 | 9 | 4595152 |
| NBFC Lending (real terms, million INR) | 631 | 8298 | 26556 | 0 | 306740 |

Notes:

Table 2: Description of Firms with Cases in Sample Court Districts

| | (1) | | | | |
|---|---|---|---|---|---|
| | Not in Court (Mean) | Not in Court (SD) | In Court (Mean) | In Court (SD) | P-Value |
| 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 |
| Not in Court | 43064 | | | | |
| Firms in Court | 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.

## 10.1 Balance Tables

Table 3: Balance on district time-varying characteristics

| | (1) Percent Judge Occupancy | (2) Percent Judge Occupancy |
|---|---|---|
| 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) | |
| Pct Sown Area (t-1) | | 0.000216 |
| | | (0.000206) |
| Pct Sown Area (t-2) | | 0.000443** |
| | | (0.000201) |
| Per cap Crime (t-1) | | 0.000469 |
| | | (0.000364) |
| Per cap Crime (t-2) | | 0.000405 |
| | | (0.000380) |
| P-value(joint test) | 0.580 | 0.790 |

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

Notes: All standard errors are clustered at the district-year level.

Table 4: Balance on firm outcomes

| | (1) Percent Judge Occupancy | (2) Percent Judge Occupancy |
|---|---|---|
| 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) | 0.66 | 0.46 |

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

Notes: All standard errors are clustered at the district-year level.

## 10.2 Tables: First Stage Effects of Judge Occupancy on Court Performance

Table 5: First Stage: Judge Occupancy and Overall Court Output

| | (1) Log Disposal Rate | (2) Log Speed (Outflow/Inflow) | (3) Log New Filing | (4) Log New Disposed | (5) Log Case Duration at Disposal | (6) Log Share Dismissal | (7) Log Appeal | (8) Index |
|---|---|---|---|---|---|---|---|---|
| Percent Judge Occupancy | 0.00978*** | 0.00682*** | 0.0169*** | 0.00964*** | 0.000726 | -0.000679 | 0.00172 | 0.00745*** |
| | (0.00182) | (0.00217) | (0.00165) | (0.00228) | (0.00148) | (0.00183) | (0.00153) | (0.00231) |
| Observations | 1714 | 1714 | 1714 | 1485 | 1478 | 1485 | 1714 | 1478 |
| District Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State x Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dependent Variable (Raw) | 14.33 | 76.22 | 3312.2 | 3340.6 | 616.8 | 21.76 | 19.09 | 0 |
| F-Stat | 28.81 | 9.880 | 104.8 | 17.86 | 0.240 | 0.140 | 1.270 | 10.43 |
| R-Squared | 0.750 | 0.830 | 0.910 | 0.850 | 0.660 | 0.670 | 0.690 | 0.790 |

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

Notes: All standard errors are clustered at the district-year level.

Table 6: 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 |
| District Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State x Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 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:

## 10.3 Tables: Litigating Firms

Table 7: Litigating Banks' Outcomes: Total Loan Accounts

| | (1) Log Total Accounts (OLS) | (2) Log Total Accounts (2SLS) | (3) Log Total Accounts (RF) | (4) Log Disp (First Stage) |
|---|---|---|---|---|
| Log Disposal Rate (lagged) | 0.00754 | 0.109** | | |
| | (0.00752) | (0.0476) | | |
| Judge Occupancy (lagged) | | | 0.000848** | 0.00780*** |
| | | | (0.000329) | (0.00166) |
| Observations | 4279 | 4279 | 4279 | 4757 |
| District Fixed Effects | Yes | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 377178.3 | 377178.3 | 377178.3 | 3.330 |
| F-Stat | 1.010 | 5.270 | 6.640 | 22 |
| Adj R-Squared | 0.980 | -0.250 | 0.980 | 0.590 |

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

Notes: All standard errors are clustered at the district-year level. Above specification focuses only on Scheduled Commercial Banks, for which the data is provided by the Reserve Bank of India.

Table 8: Litigating Banks' Outcomes: Outstanding Loan Amount

| | (1) Log Loan Outstanding (OLS) | (2) Log Loan Outstanding (2SLS) | (3) Log Loan Outstanding (RF) | (4) Log Disp (First Stage) |
|---|---|---|---|---|
| Log Disposal Rate (lagged) | 0.0178* | -0.0383 | | |
| | (0.00927) | (0.0569) | | |
| Judge Occupancy (lagged) | | | -0.000297 | 0.00780*** |
| | | | (0.000435) | (0.00166) |
| Observations | 4279 | 4279 | 4279 | 4757 |
| District Fixed Effects | Yes | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 14024.7 | 14024.7 | 14024.7 | 3.330 |
| F-Stat | 3.700 | 0.450 | 0.470 | 22 |
| Adj R-Squared | 0.980 | -0.120 | 0.980 | 0.590 |

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

Notes: All standard errors are clustered at the district-year level. Above specification focuses only on 27 Scheduled Commercial Banks. The data used here is provided by the Reserve Bank of India.

Table 9: Litigating Banks' Outcomes: Public Sector Bank Total Loan Accounts

| | (1) OLS | (2) IV | (3) Reduced Form |
|---|---|---|---|
| Log Disposal (lagged) | -0.00589 | 0.225** | |
| | (0.0168) | (0.109) | |
| Judge Occupancy (lagged) | | | 0.00176** |
| | | | (0.000771) |
| Observations | 4158 | 4158 | 4158 |
| District Fixed Effects | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 6930.2 | 6930.2 | 6930.2 |
| F-Stat | 0.120 | 4.240 | 5.200 |
| Adj R-Squared | 0.940 | -0.350 | 0.940 |

Standard errors in parentheses

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

Notes: All standard errors are clustered at the district-year level. Above specification focuses only on Scheduled Commercial Banks, for which the data is provided by the Reserve Bank of India.

Table 10: Litigating Banks' Outcomes: Public Sector Bank Outstanding Loan Amount

| | (1) OLS | (2) IV | (3) Reduced Form |
|---|---|---|---|
| Log Disposal (lagged) | -0.00907 | -0.305** | |
| | (0.0238) | (0.141) | |
| Judge Occupancy (lagged) | | | -0.00239** |
| | | | (0.00101) |
| Observations | 4158 | 4158 | 4158 |
| District Fixed Effects | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 3556.2 | 3556.2 | 3556.2 |
| F-Stat | 0.150 | 4.660 | 5.610 |
| Adj R-Squared | 0.960 | -0.340 | 0.960 |

Standard errors in parentheses

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

Notes: All standard errors are clustered at the district-year level. Above specification focuses only on 27 Scheduled Commercial Banks. The data used here is provided by the Reserve Bank of India.

Table 11: Litigating Banks' Outcomes:: Loans to Manufacturing Sector

| | (1) OLS | (2) IV | (3) Reduced Form |
|---|---|---|---|
| Log Disposal (lagged) | -0.0222 | 0.269* | |
| | (0.0185) | (0.137) | |
| Judge Occupancy (lagged) | | | 0.00211** |
| | | | (0.000948) |
| Observations | 4158 | 4158 | 4158 |
| District Fixed Effects | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 12794.0 | 12794.0 | 12794.0 |
| F-Stat | 1.450 | 3.820 | 4.930 |
| Adj R-Squared | 0.930 | -0.350 | 0.930 |

Standard errors in parentheses

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

Notes: All standard errors are clustered at the district-year level. The data used here is provided by the Reserve Bank of India.

Table 12: Litigating Banks' Outcomes: Consumption Loans

| | (1) OLS | (2) IV | (3) Reduced Form |
|---|---|---|---|
| Log Disposal (lagged) | 0.0208* | 0.141** | |
| | (0.0106) | (0.0604) | |
| Judge Occupancy (lagged) | | | 0.00110** |
| | | | (0.000431) |
| Observations | 4158 | 4158 | 4158 |
| District Fixed Effects | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 133731.0 | 133731.0 | 133731.0 |
| F-Stat | 3.810 | 5.420 | 6.520 |
| Adj R-Squared | 0.970 | -0.180 | 0.970 |

Standard errors in parentheses

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

Notes: All standard errors are clustered at the district-year level. The data used here is provided by the Reserve Bank of India.

Table 13: Litigating Banks' Outcomes: Agricultural Loans

| | (1) OLS | (2) IV | (3) Reduced Form |
|---|---|---|---|
| Log Disposal (lagged) | 0.00173 | 0.0447 | |
| | (0.00858) | (0.0503) | |
| Judge Occupancy (lagged) | | | 0.000350 |
| | | | (0.000391) |
| Observations | 4158 | 4158 | 4158 |
| District Fixed Effects | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 181327.5 | 181327.5 | 181327.5 |
| F-Stat | 0.0400 | 0.790 | 0.800 |
| Adj R-Squared | 0.980 | -0.100 | 0.980 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < .05$, $^{***}$ $p < 0.01$

Notes: All standard errors are clustered at the district-year level. The data used here is provided by the Reserve Bank of India.

Table 14: Respondent Non-Financial Litigating Firm Outcomes

| | (1) Log Revenue from Sales | (2) Asinh Profits | (3) Log Wage Bill | (4) Log Workers | (5) Log Plant Value | (6) Log Land Value | (7) First Stage |
|---|---|---|---|---|---|---|---|
| | | | OLS | | | | |
| Log Disposal Rate (t-2) | 0.0135 | -0.109* | 0.00140 | 0.0204*** | 0.00158 | 0.0148* | |
| | (0.0237) | (0.0640) | (0.00289) | (0.00739) | (0.00542) | (0.00762) | |
| | | | OLS | | | | |
| Log Disposal Rate (t-2) | -0.0254 | -0.758* | -0.000122 | 0.0493* | 0.0110 | 0.0396 | |
| | (0.132) | (0.401) | (0.0181) | (0.0297) | (0.0255) | (0.0549) | |
| | | | Reduced Form | | | | |
| Judge Occupancy (t-2) | -0.000385 | -0.0109** | -0.00000174 | 0.000771* | 0.000171 | 0.000581 | 0.0134*** |
| | (0.00200) | (0.00522) | (0.000257) | (0.000450) | (0.000395) | (0.000792) | (0.00255) |
| Observations | 10255 | 10636 | 10488 | 5748 | 9484 | 8659 | |
| Firm Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | |
| Case Type Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | |
| Other fixed effects | District, Year, State-Year | District, Year, State-Year | District, Year, State-Year | District, Year, State-Year | District, Year, State-Year | District, Year, State-Year | |
| Mean Dependent Variable | 318296.8 | 8877.7 | 14914.7 | 32.65 | 106324 | 16683.3 | |
| F-Stat | 0.320 | 2.920 | 0.230 | 7.650 | 0.0800 | 3.740 | |
| Adj R-Squared | 0.130 | 0.680 | 0.990 | 0.980 | 0.990 | 0.950 | |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < .05$, $^{***}$ $p < 0.01$

Notes: Standard errors clustered by district-year. The sample of firms above are the litigating respondent firms found in the court sample that are other than NBFCs or banks (i.e. financial firms).

## 10.4 Tables: All Firms

Table 15: Court Performance and All Firm Intermediate Outcomes

| | (1) Asinh Long Term Borrowing | (2) Total Lending | (3) NBFC Lending |
|---|---|---|---|
| | | OLS | |
| Log Disposal Rate (t-2) | 0.0257 | 0.212*** | 0.0819 |
| | (0.0350) | (0.0738) | (0.136) |
| | | IV | |
| Log Disposal Rate (t-2) | 0.385* | 0.979** | 1.163* |
| | (0.208) | (0.428) | (0.602) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | 0.00502** | 0.0238*** | 0.0127** |
| | (0.00227) | (0.00557) | (0.00548) |
| Observations | 9297 | 227 | 611 |
| District Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 1865.7 | 423505.8 | 8485.5 |
| Adj R-Squared | 0.140 | 0.400 | 0.270 |

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 lagged disposal rate (by 1-2 years) from OLS and 2SLS estimations respectively, and column 4 provides the reduced form coefficients on lagged judge occupancy (by 1-2 years). All standard errors are clustered at the district-year level.

Table 16: Court Performance and All Firm Intermediate Outcomes: Balanced Panel

| | (1) Asinh Long Term Borrowing | (2) Total Lending | (3) NBFC Lending |
|---|---|---|---|
| | | OLS | |
| Log Disposal Rate (t-2) | 0.0399 | 0.141 | 0.148 |
| | (0.0386) | (0.150) | (0.122) |
| | | IV | |
| Log Disposal Rate (t-2) | 0.692** | 0.712 | -0.600 |
| | (0.305) | (0.622) | (3.091) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | 0.00747*** | 0.0203 | -0.00157 |
| | (0.00261) | (0.0203) | (0.00724) |
| Observations | 6347 | 126 | 488 |
| District Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | State, Year, State-Year | State, Year, State-Year | State, Year, State-Year |
| Mean Dependent Variable | 2548.3 | 60051.8 | 9532.2 |
| Adj R-Squared | 0.110 | 0.580 | 0.390 |

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 lagged disposal rate (by 1-2 years) from OLS and 2SLS estimations respectively, and column 4 provides the reduced form coefficients on lagged judge occupancy (by 1-2 years). All standard errors are clustered at the district-year level.

Table 17: Court Performance and All Firm Intermediate Outcomes: Balanced Panel (Weights)

| | (1) Asinh Long Term Borrowing | (2) Total Lending | (3) NBFC Lending |
|---|---|---|---|
| | | OLS | |
| Log Disposal Rate (t-2) | 0.0430 | 0.186 | 0.155 |
| | (0.0423) | (0.149) | (0.312) |
| | | IV | |
| Log Disposal Rate (t-2) | 0.460 | 0.810** | -4.114 |
| | (0.338) | (0.406) | (11.30) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | 0.00752* | 0.0482*** | -0.0128 |
| | (0.00392) | (0.0166) | (0.0142) |
| Observations | 6347 | 126 | 488 |
| District Fixed Effects | Yes | Yes | Yes |
| Other fixed effects | State, Year, State-Year | State, Year, State-Year | State, Year, State-Year |
| Mean Dependent Variable | 2548.3 | 60051.8 | 9532.2 |
| Adj R-Squared | 0.0600 | 0.300 | 0.180 |

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 lagged disposal rate (by 1-2 years) from OLS and 2SLS estimations respectively, and column 4 provides the reduced form coefficients on lagged judge occupancy (by 1-2 years). All standard errors are clustered at the district-year level.

Table 18: Court Performance and All Firm Outcomes

| | (1) Log Revenue from Sales | (2) Asinh Profit | (3) Log Wage Bill | (4) Log Employees | (5) Log Plant Value | (6) Log Land Value |
|---|---|---|---|---|---|---|
| | | | OLS | | | |
| Log Disposal Rate (t-2) | -0.0321 | 0.00895 | 0.0179 | -0.00723 | -0.0268 | -0.0182 |
| | (0.0249) | (0.0488) | (0.0160) | (0.0394) | (0.0167) | (0.0138) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | 0.0980* | 0.257* | 0.205*** | 0.120 | -0.0317 | 0.0248 |
| | (0.0570) | (0.142) | (0.0571) | (0.156) | (0.0643) | (0.0571) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | 0.000285 | 0.00524 | 0.00381*** | 0.00221 | -0.00207* | 0.000470 |
| | (0.00135) | (0.00358) | (0.00115) | (0.00313) | (0.00112) | (0.00108) |
| Observations | 20015 | 23863 | 21700 | 3944 | 18112 | 16230 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |
| Mean Dependant Var (Raw) | 5,455.83 | 148.224 | 353.6 | 353.6 | 2,890.07 | 308.75 |
| F-Stat | 340.73 | 70.93 | 436.24 | 104.89 | 348.54 | . |
| Adj R-Squared | .24 | .05 | .27 | .34 | .23 | .13 |

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

Notes: The data includes incumbent firms (incorporated before 2010) with at least 2 years data. Firms excludes banks with registered in these districts. All standard errors are clustered at the district-year level.

Table 19: Court Performance and All Firm Outcomes: Balanced Panel

| | (1) Log Revenue from Sales | (2) Asinh Profit | (3) Log Wage Bill | (4) Log Employees | (5) Log Plant Value | (6) Log Land Value |
|---|---|---|---|---|---|---|
| | | | OLS | | | |
| Log Disposal Rate (t-2) | 0.00585 | 0.0310 | 0.00781 | -0.00530 | -0.0165 | -0.0280** |
| | (0.0201) | (0.0461) | (0.0119) | (0.0299) | (0.0169) | (0.0131) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | 0.0719 | 0.418* | 0.107** | -0.00722 | -0.0287 | -0.0113 |
| | (0.0637) | (0.215) | (0.0508) | (0.139) | (0.0709) | (0.0674) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | 0.00141 | 0.00877** | 0.00219** | -0.000128 | -0.000551 | -0.000210 |
| | (0.00127) | (0.00390) | (0.000981) | (0.00251) | (0.00134) | (0.00127) |
| Observations | 13103 | 15342 | 14476 | 3933 | 11743 | 10995 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |
| Mean Dependant Var (Raw) | 7,064.22 | 284.336 | 529.079 | 2.341 | 4,053.76 | 415.661 |
| Adj R-Squared | .27 | .06 | .29 | .31 | .23 | .13 |

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

Notes: The data here is balanced panel of firms. Firms excludes banks with registered in these districts. All standard errors are clustered at the district-year level.

Table 20: Court Performance and All Firm Outcomes: Balanced Panel (Weights)

| | (1) Log Revenue from Sales | (2) Asinh Profit | (3) Log Wage Bill | (4) Log Employees | (5) Log Plant Value | (6) Log Land Value |
|---|---|---|---|---|---|---|
| | | | OLS | | | |
| Log Disposal Rate (t-2) | 0.0323** | 0.0513 | 0.0277** | -0.0334 | 0.0345** | 0.00343 |
| | (0.0135) | (0.0432) | (0.0136) | (0.0395) | (0.0148) | (0.0149) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | 0.0611 | 0.173* | 0.113*** | 0.0717 | 0.103** | 0.135* |
| | (0.0389) | (0.0909) | (0.0391) | (0.161) | (0.0479) | (0.0751) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | 0.00248 | 0.00744** | 0.00478*** | 0.00246 | 0.00403** | 0.00510** |
| | (0.00162) | (0.00364) | (0.00142) | (0.00531) | (0.00188) | (0.00211) |
| Observations | 13103 | 15342 | 14476 | 3933 | 11743 | 10995 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |
| Mean Dependant Var (Raw) | 7,064.22 | 284.336 | 529.079 | 2.341 | 4,053.76 | 415.661 |
| Adj R-Squared | .29 | .03 | .33 | .36 | .22 | .1 |

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

Notes: The data here is balanced panel of firms. Firms excludes banks with registered in these districts. Regressions are weighted by the number of firms in the district. All standard errors are clustered at the district-year level.

## 10.5 Tables: Firm Fixed Effects

Table 21: Court Performance and All Firm Intermediate Outcomes: Firm Fixed Effects

| | (1) Asinh Long Term Borrowing | (2) Total Lending | (3) NBFC Lending |
|---|---|---|---|
| | | OLS | |
| Log Disposal Rate (t-2) | -0.0471 | -0.139 | -0.0390 |
| | (0.0300) | (0.283) | (0.102) |
| | | IV | |
| Log Disposal Rate (t-2) | -0.108 | 0.0540 | 3.027 |
| | (0.176) | (0.927) | (3.484) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | -0.00133 | 0.00105 | 0.0145*** |
| | (0.00212) | (0.0173) | (0.00440) |
| Observations | 6149 | 94 | 470 |
| Year Fixed Effects | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 2,548.28 | 60,051.8 | 9,532.19 |
| Adj R-Squared | .88 | .96 | .93 |

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

Notes: All specifications use firm fixed effects on a balanced panel of firms. Firms excludes banks with registered in these districts. All standard errors are clustered at the district-year level.

Table 22: Court Performance and All Firm Outcomes: Firm Fixed Effects

| | (1) Log Revenue from Sales | (2) Asinh Profit | (3) Log Wage Bill | (4) Log Employees | (5) Log Plant Value | (6) Log Land Value |
|---|---|---|---|---|---|---|
| | | | OLS | | | |
| Log Disposal Rate (t-2) | -0.0481*** | -0.0248 | -0.00688 | -0.0278 | -0.0177 | -0.0271* |
| | (0.0166) | (0.0855) | (0.00890) | (0.0219) | (0.0145) | (0.0158) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | -0.0995 | 0.620 | 0.0613 | -0.283** | -0.0918 | -0.165** |
| | (0.0761) | (0.401) | (0.0456) | (0.140) | (0.0665) | (0.0794) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | -0.00143 | 0.00933* | 0.000879 | -0.00446** | -0.00138 | -0.00246** |
| | (0.00105) | (0.00523) | (0.000582) | (0.00192) | (0.000888) | (0.00106) |
| Observations | 13030 | 15311 | 14432 | 3812 | 11703 | 10970 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 7,064.22 | 284.336 | 529.079 | 2.341 | 4,053.76 | 415.661 |
| Adj R-Squared | .93 | .47 | .96 | .95 | .94 | .9 |

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

Notes: All specifications use firm fixed effects on a balanced panel of firms. Firms excludes banks with registered in these districts. All standard errors are clustered at the district-year level.

## 10.6 Tables: Interaction b/w Courts and Legal Reforms

Table 23: Judicial Capacity and State Industrial-Labor Policy: All Sectors

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Log Revenue from Sales | Log Wage Bill | Log Employees | Asinh Profits | Log Land Value | Log Plant Value |
| Pro-Industry State x Judge Occupancy | -0.000927 | -0.00627** | 0.0249*** | 0.0261*** | -0.00478* | -0.0000304 |
| | (0.00408) | (0.00307) | (0.00929) | (0.00985) | (0.00271) | (0.00350) |
| Pro-Labor State x Judge Occupancy | 0.000761 | -0.00307 | 0.0217** | 0.0184* | -0.0000172 | 0.000329 |
| | (0.00427) | (0.00315) | (0.00864) | (0.00957) | (0.00292) | (0.00369) |
| Percent Judge Occupancy (t-2) | 0.000338 | 0.00755*** | -0.0194** | -0.0126 | 0.00170 | -0.00218 |
| | (0.00366) | (0.00259) | (0.00785) | (0.00793) | (0.00206) | (0.00319) |
| Observations | 20028 | 21846 | 4067 | 24009 | 16238 | 18122 |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 5,452.3 | 417.184 | 2.374 | 184.404 | 309.087 | 2,888.56 |
| F-Stat | 296.82 | 430.33 | 60.51 | 61.25 | 66.65 | 299.46 |
| Adj R-Squared | .24 | .26 | .3 | .05 | .12 | .23 |
| Control | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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

Notes: The time-frame considered here is between 2010 and 2018 since the start of the e-courts program. The court measures are lagged by 2 years. All dependent (financial) variables are in million INR. All standard errors are clustered at the district-year level. The dummies categorization states as pro-labor, pro-industry, or neutral is from Besley and Burgess, 2004. Of the 15 states in my sample, 4 states are pro-labor, 6 are pro-industry, and 4 neutral.

Table 24: Judicial Capacity and State Industrial-Labor Policy: Manufacturing

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Log Revenue from Sales | Log Wage Bill | Log Employees | Asinh Profits | Log Land Value | Log Plant Value |
| Pro-Industry State x Judge Occupancy | -0.00504 | -0.0101*** | 0.00130 | 0.0314** | -0.00933*** | -0.00732** |
| | (0.00406) | (0.00360) | (0.00795) | (0.0145) | (0.00360) | (0.00297) |
| Pro-Labor State x Judge Occupancy | -0.00690* | -0.00595* | -0.0000713 | 0.0164 | -0.00343 | -0.00605* |
| | (0.00412) | (0.00349) | (0.00761) | (0.0126) | (0.00358) | (0.00319) |
| Percent Judge Occupancy (t-2) | 0.00506 | 0.00959*** | 0.00313 | -0.0195* | 0.00278 | 0.00410* |
| | (0.00345) | (0.00291) | (0.00592) | (0.0106) | (0.00297) | (0.00233) |
| Observations | 10794 | 10897 | 2278 | 11622 | 10062 | 10987 |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 6,559.27 | 350.512 | 1.757 | 139.738 | 275.386 | 3,585.61 |
| F-Stat | 49.12 | 116.32 | 35.91 | 20.48 | 56.42 | 59.75 |
| Adj R-Squared | .1 | .17 | .19 | .05 | .13 | .14 |
| Control | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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

Notes: The time-frame considered here is between 2010 and 2018 since the start of the e-courts program. The court measures are lagged by 2 years. All dependent (financial) variables are in million INR. All standard errors are clustered at the district-year level. The dummies categorization states as pro-labor, pro-industry, or neutral is from Besley and Burgess, 2004. Of the 15 states in my sample, 4 states are pro-labor, 6 are pro-industry, and 4 neutral.

Table 25: Judicial Capacity and Bankruptcy Reform: All Firms Excluding Banks

| | (1) Log Revenue from Sales | (2) Log Wage Bill | (3) Log Employees | (4) Asinh Profits | (5) Log Land Value | (6) Log Plant Value |
|---|---|---|---|---|---|---|
| High Judge Occp x Trend x Post | -0.259** | -0.0703 | 0.00452 | 0.139 | -0.0152 | -0.130 |
| | (0.112) | (0.0600) | (0.177) | (0.401) | (0.130) | (0.101) |
| High Judge Occp x Post | 1.377*** | 0.357 | -0.339 | -0.591 | 0.189 | 0.698 |
| | (0.523) | (0.301) | (0.989) | (2.026) | (0.663) | (0.524) |
| High Judge Occp Trend | 0.0213 | -0.0295 | 0.0550 | -0.0962 | -0.00561 | -0.0000776 |
| | (0.0545) | (0.0333) | (0.136) | (0.0890) | (0.0219) | (0.0297) |
| High Judge Occupancy | -0.272 | -0.298* | -0.317 | -0.205 | -0.450** | -0.161 |
| | (0.198) | (0.174) | (0.595) | (0.352) | (0.203) | (0.159) |
| Observations | 19572 | 21218 | 3641 | 23372 | 15847 | 17719 |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Court State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 5,307.01 | 341.951 | 1.983 | 131.198 | 298.629 | 2,786.36 |
| F-Stat | 146.97 | 184.93 | 93.32 | 294.9 | 20.68 | 58.42 |
| Adj R-Squared | .2 | .23 | .29 | .02 | .05 | .19 |
| Control | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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

Notes: The time-frame considered here is between 2010 and 2018 since the start of the e-courts program. Raw dependent (financial) variables are in million INR. All standard errors are clustered at the district level. Districts are categorized as ex-ante high judge occupancy based on judge occupancy prior to the reform.

Table 26: Judicial Capacity and Bankruptcy Reform: Banks

| | (1) Log Inc Fin. Srvcs | (2) Log Wage Bill | (3) Log Employees | (4) Asinh Profits |
|---|---|---|---|---|
| Banks x High Judge Occp x Post | -1.001*** | -0.980** | -1.207 | 4.225* |
| | (0.273) | (0.386) | (0.913) | (2.201) |
| Banks x Post | 0.130 | 0.0370 | 0.824*** | -5.446** |
| | (0.141) | (0.113) | (0.128) | (2.129) |
| High Judge Occp x Post | -0.0919 | -0.106 | -0.175 | -0.129 |
| | (0.0781) | (0.0912) | (0.278) | (0.220) |
| Bank Dummy x High Judge Occp | -0.107 | -0.225 | -0.987 | -5.295*** |
| | (0.723) | (0.608) | (0.896) | (1.672) |
| High Judge Occupancy | -0.206 | -0.377*** | -0.161 | -0.455** |
| | (0.153) | (0.138) | (0.304) | (0.216) |
| Banking Co | 7.384*** | 5.748*** | 4.883*** | 6.738*** |
| | (0.611) | (0.530) | (0.510) | (0.482) |
| Observations | 19477 | 21347 | 3752 | 23501 |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Court State FE | Yes | Yes | Yes | Yes |
| Mean Dependant Var (Raw) | 104,062 | 9,915.96 | 14.045 | 7,873.62 |
| F-Stat | 151.46 | 233.47 | 69.56 | 347.21 |
| Adj R-Squared | .14 | .25 | .33 | .03 |
| Control | Firm Level Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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

Notes: The time-frame considered here is between 2010 and 2018 since the start of the e-courts program. Raw dependent (financial) variables are in million INR. All standard errors are clustered at the district level. Districts are categorized as ex-ante high judge occupancy based on judge occupancy prior to the reform.

# A Appendix

## A.1 Describing Outcome Variables

**Intermediate outcomes: Borrowing/Lending** These variables depict the intermediate steps linking court output 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. **Bank Deposits:** Details on saving and term deposits also from RBI data on district wise number of deposit accounts (in thousands) and total deposited amount (in INR Million) annually aggregated across the national level banks.

3. **Total Lending and Advances by NBFC:** Total loans and advances (in INR million) made by NBFCs with registered office in the court district as available in Prowess data.

4. **Inter-Firm Lending:** Total loans and advances (in INR million) made by non-financial firms to other firms that are either subsidiaries or in supply-chain or as investment as available in Prowess data.

5. **Total Bank Borrowings:** Long term (over 12 months) borrowings (in INR million) from banks by non-financial firms reported in Prowess data.

6. **Total Borrowing by Securitization:** Above long term borrowings variables separated into secured (collateralized) and unsecured borrowing.

**Impact variables:** Following variables represent inputs, production, and profits mapping onto firm's profit maximization.

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. **Revenue from financial services (for lenders):** This variable is the revenue earned from financial services, i.e. lending services, which can be the main service provided by the firm as in the case of banks, NBFCs, or as ancillary service in the form of trade or subsidiary credit. This is not captured under the sales variable above.

3. **Profits net of taxes:** I generate this variable by subtracting total income and total expenditure inclusive of tax to obtain profits net of taxes.

4. **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.

5. **Total employed labor:** This variable is not directly available in the Prowess dataset. I generate it by dividing total wage bill and total wage bill per employee. This variable is only available for large companies that disclosure their employment details. Firms that do disclosure this, do so for all years. Together with wage bill, this variable represents the quanta of labor use in the production process.

6. **Net value of plants and machinery:** This incorporates reported value of plants and machinery used in production net of depreciation/wear and tear.

7. **Net value of land assets:** The variable reports the value of the firm's real estate holdings net of depreciation. Some firms require physical real estate footprint for carrying out production processes, for example, as in manufacturing. However, the dataset does not include details on space in order to separate changes in valuations from that arising from changes in price vs. changes in actual space acquired/sold.

## A.2 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".

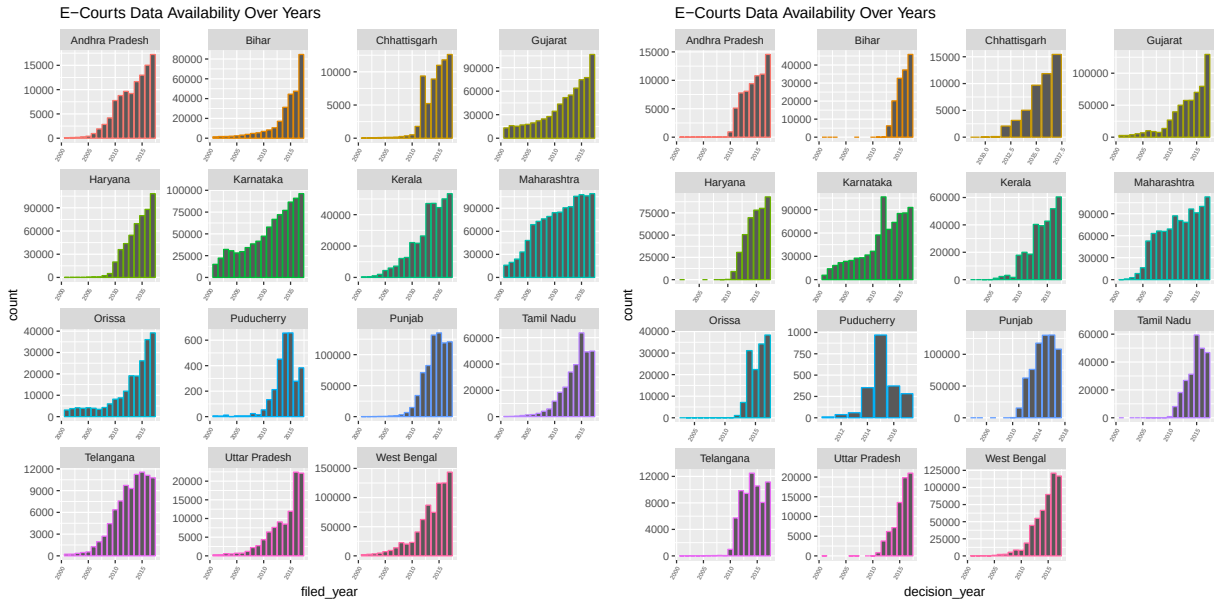
4. Ensure not to categorize cases as belonging to firms when firm names are used as landmark in the addresses of individual litigants. To do this, I detect words such as "opposite to" "above", "below", "near", and "behind". These adverbs are often used in describing landmarks. I excludes were firm names 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.

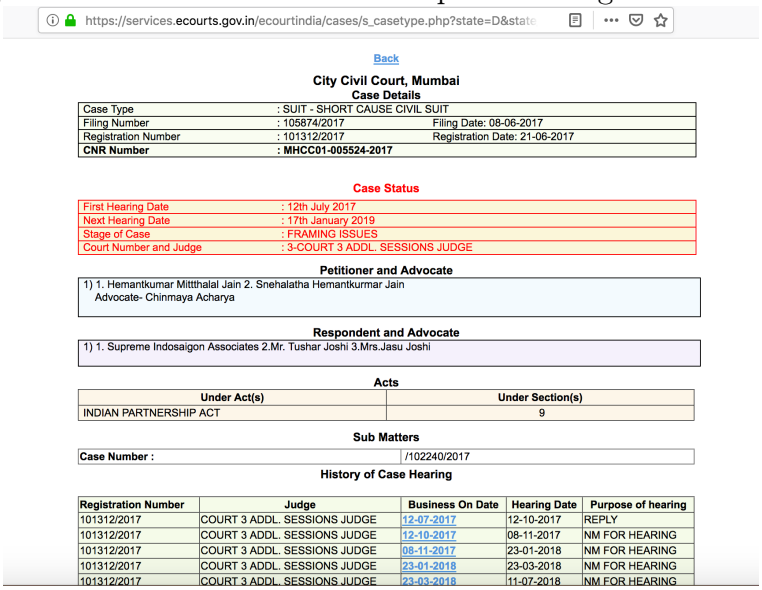
## A.3 Appendix: Figures

Figure A.17: Data Availability




Notes: Above graphs show the histograms of cases by year of filing and year of disposal in this study's e-courts sample database. From these, we infer the correct period for analysis is between 2010 and 2018, when the universe of data from court functioning is available.

Figure A.18: Court Variables: Sample Case Page on E-Courts



https://services.ecourts.gov.in/ecourtindia/cases/s_casetype.php?state=D&state

Back

**City Civil Court, Mumbai**

**Case Details**

| | | |
|---|---|---|
| Case Type | : SUIT - SHORT CAUSE CIVIL SUIT | |
| Filing Number | : 105874/2017 | Filing Date: 08-06-2017 |
| Registration Number | : 101312/2017 | Registration Date: 21-06-2017 |
| **CNR Number** | **: MHCC01-005524-2017** | |

**Case Status**

| | |
|---|---|
| First Hearing Date | : 12th July 2017 |
| Next Hearing Date | : 17th January 2019 |
| Stage of Case | : FRAMING ISSUES |
| Court Number and Judge | : 3-COURT 3 ADDL. SESSIONS JUDGE |

**Petitioner and Advocate**

1) 1. Hemantkumar Mittthalal Jain 2. Snehalatha Hemantkurmar Jain
Advocate- Chinmaya Acharya

**Respondent and Advocate**

1) 1. Supreme Indosaigon Associates 2.Mr. Tushar Joshi 3.Mrs.Jasu Joshi

**Acts**

| Under Act(s) | Under Section(s) |
|---|---|
| INDIAN PARTNERSHIP ACT | 9 |

**Sub Matters**

| | |
|---|---|
| **Case Number :** | /102240/2017 |

**History of Case Hearing**

| Registration Number | Judge | Business On Date | Hearing Date | Purpose of hearing |
|---|---|---|---|---|
| 101312/2017 | COURT 3 ADDL. SESSIONS JUDGE | 12-07-2017 | 12-10-2017 | REPLY |
| 101312/2017 | COURT 3 ADDL. SESSIONS JUDGE | 12-10-2017 | 08-11-2017 | NM FOR HEARING |
| 101312/2017 | COURT 3 ADDL. SESSIONS JUDGE | 08-11-2017 | 23-01-2018 | NM FOR HEARING |
| 101312/2017 | COURT 3 ADDL. SESSIONS JUDGE | 23-01-2018 | 23-03-2018 | NM FOR HEARING |
| 101312/2017 | COURT 3 ADDL. SESSIONS JUDGE | 23-03-2018 | 11-07-2018 | NM FOR HEARING |

Notes: Note that these fields represent meta data of the case. Detailed description of cases are only available for a subset of resolved cases as they are made available by the respective courts. So, my dataset contains rich details on case attributes but no details on judgement.

Figure A.19: Construction of Firm Sample

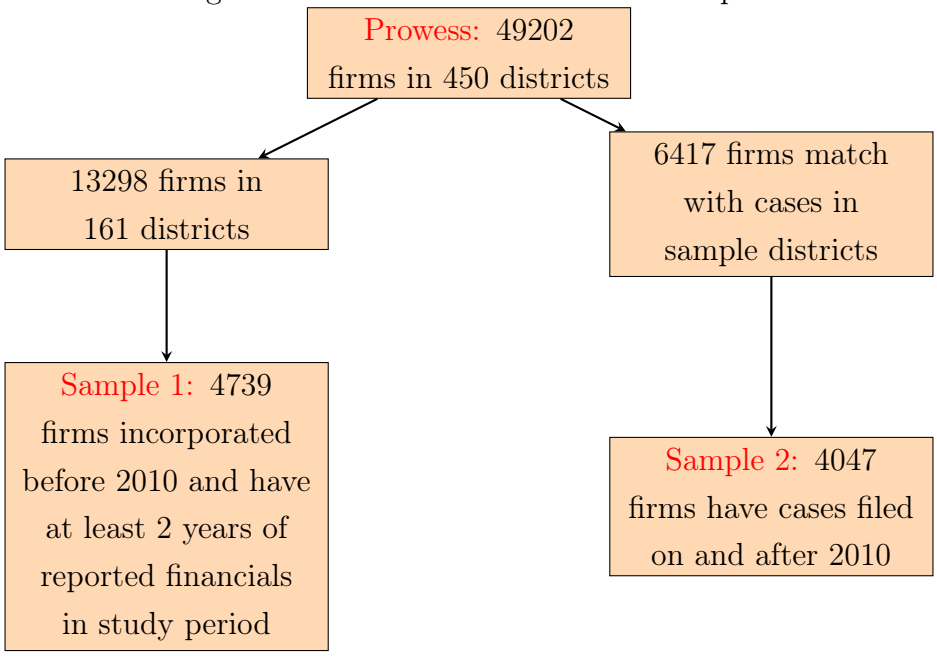
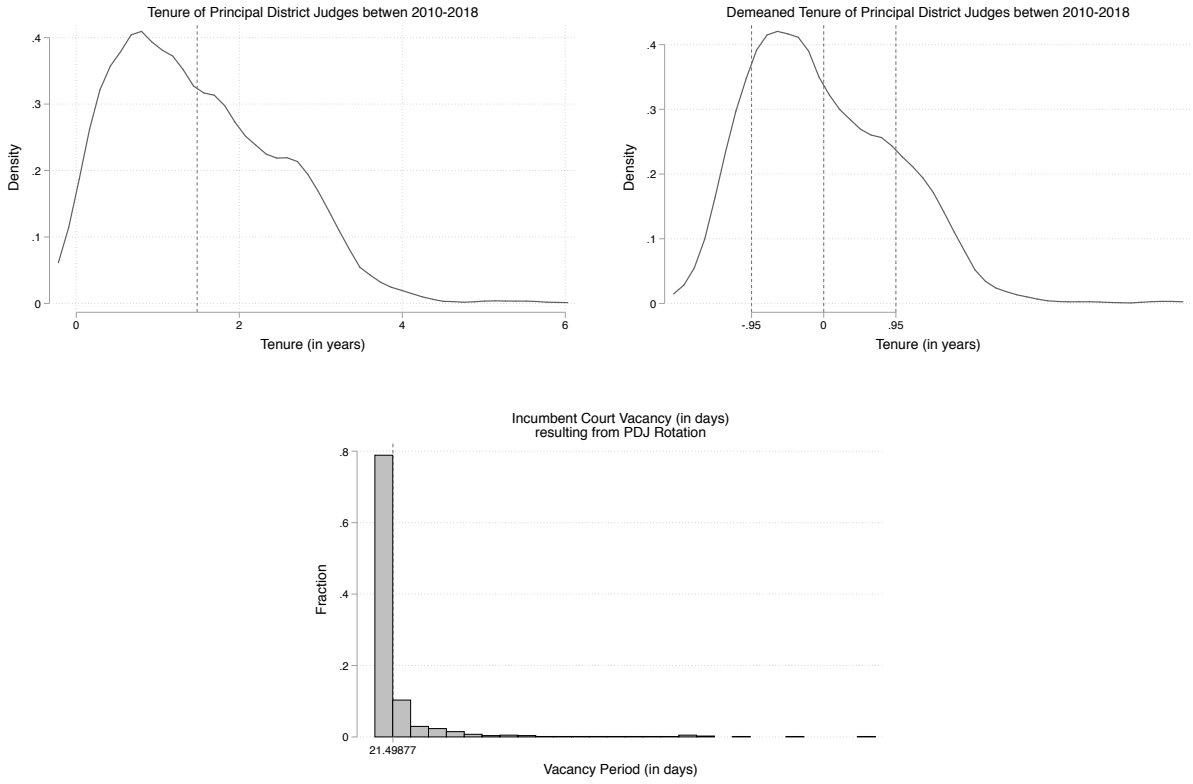


Figure A.20: Judge Tenure: An Example of Principal District Judge




Notes: Above graphs show the distribution of turn-around and tenure of the highest position in the District and Session Court - the Principal District Judge.

## A.4 Appendix: Tables

Table A.27: Study E-Courts Sample District Coverage

| State | Districts in Sample | Total Districts in State | Fraction (Districts) |
|---|---|---|---|
| Andhra Pradesh | 6 | 13 | 0.46 |
| Bihar | 17 | 39 | 0.44 |
| Chhattisgarh | 6 | 19 | 0.32 |
| Gujarat | 21 | 26 | 0.81 |
| Haryana | 16 | 21 | 0.76 |
| Karnataka | 22 | 30 | 0.73 |
| Kerala | 11 | 14 | 0.79 |
| Maharashtra | 16 | 35 | 0.46 |
| Orissa | 17 | 30 | 0.57 |
| Punjab | 17 | 20 | 0.85 |
| Tamil Nadu | 27 | 32 | 0.84 |
| Telangana | 3 | 10 | 0.3 |
| Uttar Pradesh | 4 | 71 | 0.06 |
| West Bengal | 13 | 19 | 0.68 |

Notes: Total districts from 2011 Census. The number of districts has changed since but the number of District and Sessions Courts in our sample and their jurisdictions haven't changed since 2011. Note that the sample takes into account formation of new state of Telangana from Andhra Pradesh in 2014, as reflected in the overall E-Courts database. However, the number of districts remain unchanged, with 10 districts of undivided Andhra Pradesh coming under Telangana.

Table A.28: Description of Firms Registered in Sample Court Districts

| | (1) | | | | |
|---|---|---|---|---|---|
| | Sample Mean | 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 |
| Companies in Study Sample | 13298 | | | | |
| Companies Not in Study Sample | 15042 | | | | |
| Districts without Companies in Prowess | 34 | | | | |

Notes: "Not in Sample" excludes Delhi and Mumbai, which are the two largest cities in India also appearing among top global cities. 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 A.29: Description of Firms by Litigant Type

| | (1) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Petitioner Only | SD | Respondents Only | SD | Both | SD | Petitioner vs. Both | Respondent vs. Both | Only Pet. vs. Only Resp. |
| Firm Age (yrs) | 33.124 | 19.972 | 30.120 | 18.342 | 38.069 | 24.158 | 0.0000 | 0.0000 | 0.0000 |
| **Entity Type:** | | | | | | | | | |
| Private Ltd | 0.288 | 0.453 | 0.317 | 0.466 | 0.215 | 0.411 | 0.0000 | 0.0000 | 0.0000 |
| Public Ltd | 0.702 | 0.458 | 0.667 | 0.471 | 0.757 | 0.429 | 0.0002 | 0.0000 | 0.0000 |
| Govt Enterprise | 0.000 | 0.000 | 0.001 | 0.034 | 0.001 | 0.024 | 0.3228 | 0.5045 | 0.8439 |
| Foreign Enterprise | 0.000 | 0.000 | 0.003 | 0.052 | 0.004 | 0.062 | 0.0088 | 0.5149 | 0.0920 |
| Other Entity | 0.010 | 0.100 | 0.011 | 0.106 | 0.024 | 0.152 | 0.0017 | 0.0015 | 0.0001 |
| **Ownership Type:** | | | | | | | | | |
| Privately Owned Indian Co | 0.701 | 0.458 | 0.677 | 0.468 | 0.501 | 0.500 | 0.0000 | 0.0000 | 0.0000 |
| Privately Owned Foreign Co | 0.040 | 0.195 | 0.045 | 0.206 | 0.045 | 0.208 | 0.3933 | 0.9077 | 0.6245 |
| State Govt Owned Co | 0.019 | 0.137 | 0.019 | 0.137 | 0.066 | 0.249 | 0.0000 | 0.0000 | 0.0000 |
| Central Govt Owned Co | 0.015 | 0.120 | 0.020 | 0.141 | 0.054 | 0.225 | 0.0000 | 0.0000 | 0.0000 |
| Business Group Owned Co | 0.226 | 0.418 | 0.239 | 0.427 | 0.334 | 0.472 | 0.0000 | 0.0000 | 0.0000 |
| **Finance vs. Non-Finance:** | | | | | | | | | |
| Non Finance Co | 0.842 | 0.364 | 0.879 | 0.326 | 0.796 | 0.403 | 0.0003 | 0.0000 | 0.0000 |
| Non Banking Finance Co | 0.150 | 0.357 | 0.113 | 0.317 | 0.156 | 0.363 | 0.6467 | 0.0000 | 0.0044 |
| Banking Co | 0.007 | 0.082 | 0.007 | 0.086 | 0.048 | 0.214 | 0.0000 | 0.0000 | 0.0000 |
| **Broad Industry:** | | | | | | | | | |
| Trade, Transport, and Logistics | 0.155 | 0.362 | 0.181 | 0.385 | 0.153 | 0.360 | 0.8781 | 0.0166 | 0.1008 |
| Construction Industry | 0.085 | 0.279 | 0.097 | 0.296 | 0.119 | 0.324 | 0.0008 | 0.0235 | 0.0016 |
| Business Services | 0.233 | 0.423 | 0.199 | 0.399 | 0.256 | 0.436 | 0.1110 | 0.0000 | 0.0002 |
| Commercial Agriculture | 0.028 | 0.166 | 0.023 | 0.149 | 0.024 | 0.152 | 0.3969 | 0.8146 | 0.7816 |
| Mining | 0.029 | 0.169 | 0.036 | 0.185 | 0.040 | 0.195 | 0.0895 | 0.4703 | 0.1910 |
| Manufacturing | 0.469 | 0.499 | 0.465 | 0.499 | 0.409 | 0.492 | 0.0003 | 0.0002 | 0.0000 |
| Petitioner Only | 1770 | | | | | | | | |
| Respondents Only | 2558 | | | | | | | | |
| Both | 1810 | | | | | | | | |

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. A firm is coded as petitioner only if the firm appears only as a petitioner in the sample court data. Similarly for respondent only. Firms that appear as petitioner as well as respondent are coded as "Both".

Table A.30: Correlations Between the Measures of Overall Court Output

| | (1) | | | | | | |
|---|---|---|---|---|---|---|---|
| | Log Disposal Rate | Log Speed Firm | Log Number Filed | Log Number Disposed | Log Case Duration | Log Share Dismissed | Log Appeal |
| Log Disposal Rate | 1.00 | | | | | | |
| Log Speed Firm | 0.92*** | 1.00 | | | | | |
| Log Number Filed | 0.65*** | 0.67*** | 1.00 | | | | |
| Log Number Disposed | 0.69*** | 0.84*** | 0.75*** | 1.00 | | | |
| Log Case Duration | -0.07** | 0.14*** | -0.08** | 0.03 | 1.00 | | |
| Log Share Dismissed | 0.25*** | 0.22*** | 0.11*** | 0.21*** | -0.06* | 1.00 | |
| Log Appeal | 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 except duration are highly correlated with the disposal rate measure.

# A.5 Appendix: Tables Testing Tenure Independence

Table A.31: District Time-Varying Outcomes and Judge Tenure

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Log Pop Density | Log % Sown Area (t-1) | Log % Sown>1(t-1) | Log Crime per cap (t-1) | Log Bailable Crime per cap (t-1) |
| PDJ Tenure | -0.0271 | -0.00436 | -0.0171 | 0.0331 | 0.116 |
| | (0.0277) | (0.00582) | (0.0407) | (0.0383) | (0.105) |
| Observations | 319 | 224 | 224 | 103 | 103 |
| District Fixed Effects | No | Yes | Yes | Yes | Yes |
| Other Fixed Effects | State, State-Year FE | State, State-Year FE | State, State-Year FE | State, State-Year FE | State, State-Year FE |
| F-Stat | 0.950 | 0.560 | 0.180 | 0.750 | 1.210 |
| Adj R-Squared | 0.600 | 0.980 | 0.950 | 0.950 | 0.820 |
| Mean Dep Var | 534.6 | 54.22 | 25.95 | 0.00214 | 0.000362 |
| SD Dep Var | 327.3 | 19.61 | 27.21 | 0.00135 | 0.000273 |

Standard errors in parentheses

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

Note: All standard errors are clustered at the district-year level.

Table A.32: Independence: Past Firm Outcomes and Judge Tenure

| | (1) Log Sales (t-1) | (2) Asinh Profit (t-1) | (3) Log Wage Bill (t-1) | (4) Log Plant Value (t-1) | (5) Log Land Value (t-1) |
|---|---|---|---|---|---|
| Log Judge Tenure (PDJ) | -0.119 | -0.300 | 0.0520 | -0.0981 | 0.0319 |
| | (0.107) | (0.202) | (0.0704) | (0.0917) | (0.0961) |
| Observations | 1856 | 2278 | 2021 | 1874 | 1852 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes | Yes | Yes |
| F-Stat | 51.3 | 57.65 | 116.24 | 17.62 | 15.55 |
| Adj R-Squared | .27 | .07 | .28 | .2 | .1 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < .05$, $^{***}$ $p < 0.01$

Note: All standard errors are clustered at the district-year level.

Table A.33: Robustness Check Firm Borrowing: Clustering by State-Year

| | (1) Observations | (2) OLS | (3) 2SLS | (4) Reduced Form |
|---|---|---|---|---|
| Borrowing from Bank | 9297 | 0.0257 | 0.385 | 0.00502** |
| | | (0.0366) | (0.237) | (0.00240) |
| Total Lending | 227 | 0.212** | 0.979* | 0.0238*** |
| | | (0.0863) | (0.514) | (0.00638) |
| NBFC Lending | 611 | 0.0819 | 1.163 | 0.0127* |
| | | (0.170) | (0.738) | (0.00685) |
| Year Fixed Effects | | Yes | Yes | Yes |
| Court-State Time Fixed Effects | | Yes | Yes | Yes |
| Court District FE | | Yes | Yes | Yes |
| Firm Controls | | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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 A.34: Robustness Check Firm Borrowing: Clustering by District

| | (1) Observations | (2) OLS | (3) 2SLS | (4) Reduced Form |
|---|---|---|---|---|
| Borrowing from Bank | 9297 | 0.0257 | 0.385 | 0.00502* |
| | | (0.0435) | (0.251) | (0.00296) |
| Total Lending | 227 | 0.212* | 0.979** | 0.0238*** |
| | | (0.120) | (0.349) | (0.00791) |
| NBFC Lending | 611 | 0.0819 | 1.163 | 0.0127* |
| | | (0.139) | (0.774) | (0.00641) |
| Year Fixed Effects | | Yes | Yes | Yes |
| Court-State Time Fixed Effects | | Yes | Yes | Yes |
| Court District FE | | Yes | Yes | Yes |
| Firm Controls | | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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 district level.

Table A.35: Robustness Check Firm Outcomes: Clustering by State-Year

| | (2) OLS | (3) 2SLS | (4) Reduced Form |
|---|---|---|---|
| Log Revenue from Sales | -0.0323 | 0.0976* | 0.000264 |
| | (0.0338) | (0.0585) | (0.00157) |
| Asinh Profit | 0.00309 | 0.256* | 0.00528 |
| | (0.0497) | (0.139) | (0.00380) |
| Log Wage Bill | 0.0245 | 0.202*** | 0.00381*** |
| | (0.0183) | (0.0540) | (0.00132) |
| Log Employees | -0.0158 | 0.0441 | 0.000756 |
| | (0.0392) | (0.137) | (0.00248) |
| Log Land Value | -0.0181 | 0.0249 | 0.000473 |
| | (0.0160) | (0.0532) | (0.00131) |
| Log Plant Value | -0.0266 | -0.0318 | -0.00207* |
| | (0.0222) | (0.0714) | (0.00115) |
| Year Fixed Effects | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes |
| Firm Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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 A.36: Robustness Check Firm Outcomes: Clustering by District

| | (2) OLS | (3) 2SLS | (4) Reduced Form |
|---|---|---|---|
| Log Revenue from Sales | -0.0323 | 0.0976 | 0.000264 |
| | (0.0390) | (0.0700) | (0.00172) |
| Asinh Profit | 0.00309 | 0.256 | 0.00528 |
| | (0.0539) | (0.175) | (0.00456) |
| Log Wage Bill | 0.0245 | 0.202*** | 0.00381*** |
| | (0.0211) | (0.0690) | (0.00145) |
| Log Employees | -0.0158 | 0.0441 | 0.000756 |
| | (0.0417) | (0.194) | (0.00358) |
| Log Land Value | -0.0181 | 0.0249 | 0.000473 |
| | (0.0161) | (0.0818) | (0.00166) |
| Log Plant Value | -0.0266 | -0.0318 | -0.00207 |
| | (0.0210) | (0.0796) | (0.00136) |
| Year Fixed Effects | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes |
| Court District FE | Yes | Yes | Yes |
| Firm Controls | Firm Level Controls | Firm Level Controls | Firm Level Controls |

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 district level.

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