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

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**Abstract**

Courts are considered important in the functioning of markets, and yet, there is limited causal evidence showing this. This paper estimates the causal effects of courts' effectiveness on formal sector firm outcomes, illustrating ex-post contract enforcement in local credit markets as an important channel. To show this, I construct a novel panel dataset on court-level variables from 6 million trial-level data across 195 district courts in India and exploit quasi-random variation in judge vacancy for causal identification. There are three key implications of this paper. First, reducing marginal judge vacancy reduces court backlog by 6%. Second, this stimulates bank lending in local credit markets through improved liquidity from debt recoveries. Third, this affects credit availability, production, and profitability of firms located within the court's jurisdiction. The results imply an 8:1 benefit to cost ratio of reducing marginal judge vacancy.

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# 1 Introduction

Enforcement of contracts and property rights have strong implications for the development of formal financial sector, investment, and growth (Coase 1960, Glaeser et al. 2001, Johnson et al. 2002, Acemoglu and Johnson 2005, Field 2005, Nunn 2007). Courts play the important role of a third party enforcer when self-enforcement mechanisms or social norms fail to resolve conflicts (North 1986, Kornhauser and MacLeod 2010, Anderson 2018). However, long lags in dispute resolution through courts can increase uncertainty and transaction costs, preventing effective contracting and weakening *de facto* rights (Djankov et al. 2003), specifically for financial sector firms whose transactions are contractual in nature. Timely resolution of debt related disputes and enforcement of creditor's rights strengthens the financial sector by improving repayment behavior, so that credit may be efficiently allocated (La Porta et al. 1997, La Porta et al. 1998, Vig 2013). Exploiting a novel dataset on trial proceedings and quasi-random variation in the supply of judges (i.e. judge vacancy), this paper studies the effects of court congestion or backlog on bank lending and subsequently, firm growth, along the entire causal chain.

As of July 2019, district courts in India had over 11 million cases (including 3 million civil cases) pending for more than 3 years, while the state high courts had close to 1.6 million cases pending (NJDG Dashboard). In contrast, the United States had only about 60,000 civil cases pending as of March 2019 (FCMS, 2019). This implies that there are 10 times more pending civil cases per capita in India relative to the United States. These delays imply potentially large losses for litigators, in addition to any overall market and economy-wide effects. The World Bank's Doing Business indicators rank India below most countries, including neighboring South Asian nations, in the area of contract enforcement.[1]

In this paper, I estimate the causal effects of congestion in district courts on the growth of formal sector firms in India, showing the role of credit markets as an important channel linking the two. The district courts are typically the court of first instance for commercial and civil disputes above a certain monetary value, and for criminal trials of serious offenses, including white collar crimes. I construct a panel of annual court level variables using a unique dataset that I assembled from 6 million public records of trial proceedings active between 2010 and 2018 across 195 district courts in India. These records present the universe of all ongoing trials in the sample courts during the nine year period. Specifically, I compute an annual measure of inverse court congestion called

[1] 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. This implies that the ratio of pending cases is larger even accounting for the differences in population, indicating plausible institutional constraints. 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 84,000 towards litigation expenses in a suit between a foreign company and an Indian firm. Figure 1 and Figure 2 show the problem of lengthy trial duration in India and the negative association between per capita GDP and trial duration.

disposal rate, measured as the percentage of annual workload, including the backlog of unresolved cases from prior years, that is resolved in a calendar year. I then match this with a formal sector firm-level panel dataset called Prowess, restricting to firms incorporated before the study period, by the district of their registered office location. This enables analysis using these firms as units of observation over the nine year study period. Matching firms by their registered office location presents the relevant legal jurisdiction for the firm, as also followed in von Lilienfeld-Toal et al. (2012).[2] Prowess, collated by the Centre for Monitoring the Indian Economy (CMIE), contains annual financial balance sheet data, as well as other important variables including registered office location, ownership, industrial sector, and production details. This matching 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, court congestion is likely endogenous to credit market and firm outcomes if unobserved, district-specific, time-varying factors, such as population trends, crime trends, etc., affect congestion, credit demand, and firm growth. Therefore, I instrument congestion with a measure of judge supply and estimate the causal effects using an instrumental variables (IV) estimation strategy. I compute this measure of judge supply, which I call "judge occupancy", as the share of total judge posts in a district court that are filled in a given year.

Since judges are a key input of the court production function, variation in judge occupancy strongly determines court congestion, satisfying the first stage IV criterion.[3] Additionally, this variation arises from a combination of existing undersupply of judges and a judge rotation policy that is administratively determined and implemented by an authority higher than the district court. This creates a within-district variation in judge occupancy that is likely orthogonal to credit and firm growth in the corresponding area, serving as a plausibly exogenous shock to court congestion. The district court judges typically have a short tenure of under 2 years, and are transferred to districts where they have not worked in the past either as a judge or as a lawyer. This assignment policy is uniform across India, with minor variations determined by the respective state high courts. As a result, existing vacancies in any given district court get shifted to a different one with annual rotations. This creates potentially exogenous variation in judge occupancy within a district court over time, making it a promising instrument for court congestion. The exclusion restriction may still be violated if the state high court ensures that judge occupancy is increased to relax backlog based on district level dynamics. However, recruitment of judges requires coordination between the state high court, part of the unitary judicial system, and the national executive in a federal polity. These coordination frictions further add to the plausible exogeneity of judge occupancy by

[2] Registered office location is also the corporate headquarters in many instances, and is the relevant jurisdiction where potential litigations, when the firm is on the offense, are filed. The relevant court for a given dispute type is determined by the Code of Civil Procedure, 1908.

[3] Judge occupancy strongly determines the timeliness of adjudication both from a statistical sense in terms of first stage coefficient and $R^2$ as well as practically, as understood from discussions with former members of the judicial and legal experts.

reducing the likelihood of strategic manipulation by any entity in the judiciary or the executive. Consistent with this, I find no evidence of pre-trends in court variables, lending by banks, and firm outcomes with respect to judge occupancy in a district court in any given year. The first stage relationship between judge occupancy and disposal rate is strong, both statistically and economically. Specifically, I find that a one percentage point increase in judge occupancy increases disposal rate by 1 percent. In other words, one additional judge post that is filled increases judge occupancy by about 6 percent, which translates into nearly 1 percentage point or 6 percent improvement in disposal rate over a baseline of 14 percent.

In order to shed light on the entire causal chain linking court congestion to firm growth, I also match firms in Prowess to individual trials in my sample courts, wherever the firm appears as either the plaintiff (petitioner) or the defendant (respondent). This allows me to estimate the direct effects on such firms, again using judge occupancy as an instrument for court congestion during the period of litigation involving the specific firm. I find that banks are heavy users of district courts relative to any other type of firms. Specifically, close to 50 percent of banks in the Prowess dataset are also present in my trial dataset. In contrast, only 13 percent of non-financial firms in the Prowess dataset are present in the trial dataset. Further, banks initiate litigation (filing plaints) in 80 percent of the trials involving them. A positive judge supply shock - a one percentage point increase in judge occupancy - occurring once a case is filed, increases the disposal rate by 0.78 percent, within the subset of the study period (i.e. 2010-2018) when litigation involving banks are ongoing. Using a district-level summary of bank lending by the Reserve Bank of India, I show that the reduced form effect of a 1 standard deviation increase in judge occupancy increases the number of loans in the corresponding district by nearly 2 percent after 1 year, mainly directed towards manufacturing and consumption purposes. This represents a large number of additional loans: on average, banks have about 350,000 loan accounts within any given district. The IV estimate, which can be interpreted in terms of an elasticity with respect to a reduction in court congestion, indicates that a 1 percent improvement in disposal rate increases the number of loan accounts by 0.11 percent.

An increase in lending by banks in local credit markets likely relaxes credit constraints faced by local firms. This motivates me to examine the subsequent effects of court congestion on all matched firms in the corresponding district within a window of 0-2 years, on three sets of outcomes. First, I show that firms' borrowing from banks increases with disposal rate. There is also an increase in inter-firm lending by firms that typically engage in lending in the form of trade credit, subsidiary support, and other debt investments. The results indicate an elasticity of 0.39 and 0.98 with respect to disposal rate for borrowing from banks and inter-firm lending, respectively. Second, I show that labor use in firms' production processes, measured as total labor expenditure and number of employees, increases with disposal rate with elasticities 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 lower court congestion with disposal rate elasticities of 0.1 and 0.26 respectively. To illustrate the credit channel, I employ causal mediation analysis to isolate the channel of borrowing from other post-intervention channels (Imai et al. 2011). Additionally, I present heterogeneous effects based on ex-ante wealth (asset size prior to 2010) as a proximate measure of credit constraints faced by firms in borrowing from the formal financial sector. This analysis provides suggestive evidence in support of a theory of credit contracts, where banks lend more to borrowers with larger assets when institutions are weak. An improvement in the contract enforcement environment, i.e. disposal rate, increases borrowing among firms with ex-ante assets below the median and has no effect on borrowing among firms above the median. This suggests that lower congestion in district courts increases bank lending to smaller firms, relaxing credit constraints.

The estimated elasticities enable me to conduct a back of the envelope cost-benefit analysis of adding a judge in a court with vacancies. Applying my elasticities to the baseline median values of firm production implies an increase in profits and sales revenue by INR 8,840 (USD 124) and INR 0.86 million (USD 12,000), respectively, when the disposal rate improves by one percent. Adding one more judge in a district court increases judge occupancy by about 6 percentage points, which translates to approximately 6 percent increase in disposal rate. Therefore, one additional judge in a court increases profits by about INR 53,000 (USD 750) per firm, or by 1.6 percent over a baseline median profit of INR 3.3 million (USD 46,000). With approximately 800 formal sector firms per district and a value added tax rate of 18 percent on basic manufacturing and services, the state could potentially earn close to INR 7.6 million (USD 107,000) in taxes 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 (USD 14,000) per annum, including all non-pecuniary benefits. This implies that reducing vacancy by adding one more judge generates a benefit-cost ratio of approximately 8:1. Given that the annual budgetary outlay for the law and justice sector is less than a tenth of a percent of total 2019 expenditures, there is a justifiable reason for increasing the judiciary's share to address the problem of judge vacancy.[4]

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 size and district population density, the complier share (the ratio between the first stage estimates within the sub-sample to the entire sample) is relatively lower in the top tercile of both groupings. This

[4]The calculation presented is an approximation to illustrate the magnitude of effects. The VAT system in India has provisions for input tax credit that may alter these numbers. Details about the Indian budget are available online as well as through media reports.

implies that in large courts and districts with high population densities, adding one more judge may not induce a large reduction in court congestion relative to medium sized and small courts or in districts with modest population densities. Therefore, reducing congestion in large courts may require complementary policy interventions in addition to improving judge occupancy, warranting further research.

This paper makes contributions to three strands of the literature. First, I assemble a detailed micro-level dataset on all trials in the sample district courts between 2010 and 2018 by scraping the public facing E-Courts website of the Indian judiciary. I match this with a formal sector firm panel to create two separate samples of firms - one containing all firms within the sample court jurisdictions irrespective of their direct use of the courts, and another containing all litigating firms with trials in the sample courts. As detailed in the review paper by Dal Bo and Finan (2016), research examining the judiciary, including sub-national courts, is relatively scant. For example, not much is known about how the functioning of the judiciary shapes specific markets such as property or credit markets. Understanding the role of courts in influencing credit markets is important given a large literature (Rajan and Zingales 1998, Banerjee 2003, Burgess and Pande 2005, Banerjee and Duflo 2014, Nguyen 2019) has established that access to external finance through borrowing from formal/institutional lenders is important for firm growth. In this paper, I use a first of its kind dataset and institutional features of the Indian judiciary to estimate the causal effects of court congestion on credit markets and subsequently, on the growth of firms, expanding a relatively understudied literature.

Second, this paper examines the role of judge occupancy as one of the primary levers of handling court congestion, exploiting an institutional feature that creates plausibly exogenous variation in the fraction of judge posts that remain vacant within a district over time. A burgeoning literature examines various inputs, including procedural formalism (Djankov et al. 2003), co-existence of traditional and formal statutory courts (Anderson 2018), an increase in demand for court services (Dimitrova-Grajzl et al. 2012), and judge vacancy on prosecutor behavior (Yang 2016). This paper is the first to examine the effect of judge occupancy, as a resource constraint, on court congestion affecting a range of trial types in a large economy.[5]

Finally, this paper is one of the first attempts to study a large part of the causal chain linking court congestion with bank lending and firm growth. Using causal mediation analysis, I show

[5] 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.

that credit expansion from lower congestion encourages production using more labor, 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 to data limitations, these papers are only able to study the effects of one-time cross-sectional differences in judicial capacity on the outcomes mentioned. However, the functioning of institutions is a dynamic process where time-specific variations in either supply or demand may determine the outcomes differently than they would in a static setting. Using panel data on court, credit, and firm variables, I am able to account for a large number of unobserved endogenous variables. Additionally, using an IV strategy, I show that there are substantial short run effects of lowering court congestion on bank lending and firm growth.

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 out a theoretical framework linking court congestion 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. Sections 5-7 present results from estimating the reduced form and IV specifications on banks, litigating non-financial firms, and all firms, respectively. Section 8 examines the interplay between court congestion and legal reforms. Section 9 concludes.

## 2 Measuring Court Variables and Matching Outcomes

The judiciary in India is a three tier unitary system, with Supreme Court at the apex followed by High Courts at the state level and finally the district court system that form courts of first instance for civil and criminal trials. The research question I examine in this paper concerns with the top court of the district courts system called the District and Sessions Court (hereinafter called district court), which is typically the first point of contact for disputes involving firms. Filing of trials is determined by monetary value and territorial jurisdiction of the concerned dispute. In addition, the court also oversees the functioning of all other courts within the district and is the court of appeal for judgements pronounced in the latter. 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. The High Courts and the Supreme Court of India serve mostly appellate functions whereas their original jurisdiction pertains to constitutional matters or conflicts involving the organs of state. The district courts system is the main institution responsible for administering justice and enforcing rule of law for day-to-day economic and social matters and therefore, forms the population of interest for this paper.

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 jumped from 142 in 2014 to 77 in 2018, the ranking under contract enforcement continued 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. Each record details case level meta data as well as proceedings from each hearing.[6] These districts were selected to ensure an overlap with registered formal sector firms in predominantly non-metropolitan districts to ensure a clean mapping of district courts and their territorial jurisdiction. Appendix Table A1 illustrates the sample states and the fraction of districts from each of these states covered in the dataset. While firms in the sample districts are three years older than the average firm in the excluded districts, publicly listed as well as privately held limited liability firms are similarly represented in the sample districts. Additionally, firms in banking and manufacturing sector are also similarly represented. Since the focus is non-metropolitan districts, firms common in metro areas such as those owned by government and business groups are less represented. Table A2 in the appendix provides the details on the distribution of firm types across sample and excluded districts. Appendix Figure A2 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 between these years - either pending from before 2010, or filed between 2010 and 2018.[7]

**Constructing Court Variables** From individual trial records, I construct court-level annual workflow panel data. I define the main measure of inverse court congestion, which I call the

[6] 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. 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.

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

"disposal rate", as the ratio between trials resolved and total workload in a given year, calculated as a percentage. The denominator is the sum of cases that are newly filed and those that are pending for decision as of a given calendar year. This definition has been used by Ponticelli and Alencar (2016) and Amirapu (2017) with minor variations based on their data. I also calculate other ways of measuring timeliness of the adjudication process. These include what I call "speed" or clearance rate, 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 filed as appeals against judgements passed in courts lower in the hierarchy and the fraction of cases that were dismissed without completing full trial.[8] Since all these measures, except duration, are highly correlated with disposal rate as shown in Appendix Table A4, I use disposal rate as my preferred measure of court congestion. I also construct an index using all these measures and check for robustness using the index in place of disposal rate.

**For Litigating Firms** I limit the sample to the courts with trials involving the litigating firm and event window to include the time-period once the firm has the first case filed and until the last of its case is resolved. The disposal rate calculated over this sample and period includes all cases involving the firm either in the numerator, if any such cases are resolved, or in the denominator if pending for decision. Since a judge multitasks across many different cases at various stages in the trial process, I adhere to the aggregate measure of congestion rather than compute disposal rate at the firm level. This accounts for any correlations between trials within the same court.

**Constructing Judge Occupancy** The trial record also contains information on which judge post (i.e. court hall within the district court) the case has been assigned to. The within-district 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. When there is no vacancy, cases are assigned to and resolved in all judge posts within the district court. From this, I calculate a measure of judge occupancy defined as the percentage of all 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 that accounts for the number of judgements

[8]These plausibly indicate 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 could also be made for strategic reasons such as not having to pay the damages. Therefore, I use disposal rate as my preferred measure of court congestion in all the specifications because it doesn't suffer from selection and is also strongly correlated with all other measures of court workflow, including the measures on quality.

pronounced in a year, 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 in my sample courts, I verify that the calculated vacancies (complement of occupancy) compares with media reports. Additionally, I scrape the personnel records for the Principal District Judge (PDJ) to verify the exogeneity of the occupancy measure.[9]

**Summary Stats:** Panel A of 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 has a long right tail. 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

I use Prowess academic dataset covering 49202 firms made available by the Center for Monitoring Indian Economy (CMIE) to measure firm level outcomes. 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 companies representing formal, registered firms, registered with the Ministry of Corporate Affairs, Government of India. The data represents "*over 60 percent of the economic activity in the organized sector in India, which although a small subset of all industrial activity, accounts for about 75 percent of corporate taxes and 95 percent of excise duty collected by the Government of India*" (Goldberg et al. 2010). Since the organized sector accounts for $\approx$ 40% of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), this dataset captures a large share of 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 the details on firm characteristics

[9]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. For PDJ, who are the head judge of the district courts, I gather their joining and leaving dates from their respective court website to calculate vacancy in the post as well as to check for correlations between their tenure, district, and firm specific pre-period outcomes to support the identification assumptions.

including ownership type, NIC code, year of incorporation, registered entity type, and identifying details including the name and location of the 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, that are not included in other datasets (e.g. Annual Survey of Industries).

## 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 on district-wise number of bank branches, 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 and crime data for balance checks, and consumer price indices to convert the financial variables in real terms. 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.[10]

## 2.4 Matching E-Courts Data to Firms

**Matching firms by registered office district** Of the 49202 firms in the 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 a balanced panel of firms. Appendix Figure A4 describes the firm sample construction process in detail.

**Summary Stats:** Table 1 Panel B 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). The average number of employees is 2000, for the fraction of firms for whom employment headcount is available, but has a large range between a few hundreds and 154000. 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

[10] All data used here, with the exception of Prowess, are publicly available. District wise credit data are available through the Reserve Bank of India data warehouse.Area and production statistics from the Ministry of Agriculture and Farmers Welfare available here: https://aps.dac.gov.in. National Crime Records Bureau annual crime statistics available on their website.

credit outcomes, annual total long term (repayment $>$ 1 year) borrowing from banks average at INR 1866 million ($\approx$ USD 26 million). Average lending by firms registered in the sample district to other firms and agents (including employees) amount to about INR 420 billion ($\approx$ USD 6 billion). Finally, the average lending by non-banking lenders called the non-banking finance companies (NBFC) is INR 8.3 billion ($\approx$ USD 120 million).[11]

**Matching firms with cases** Further, because I know the identity of firms, I merge them with the trial dataset 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. 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 A4 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.[12]

## 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, 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 likely to be government owned (a stated owned enterprise), business group owned, or foreign owned. Among financial institutions, banks are litigation intensive, with close to 50 percent of all banks in the firm sample having matched with the case dataset.

Panels in Figure 3 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 the 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

[11] Since the dataset is collated from annual financial reports required to be disclosed under compulsory disclosure laws, only mandated variables are reported by all firms. These laws do not require firms to report employee head-count. However, many publicly listed firms report this number and therefore included in the analysis. Additionally, not all firms engage in inter-firm lending. So, the inter-firm lending variables only pertain to the fraction of firms that engage in such activity and report so.

[12] I employ a nested approach to matching the case records with firms based on the recorded names, following heuristics as listed in the appendix. In this analysis, I only retain one-to-one matches. About 300 firms appear as co-petitioners or co-respondents on these cases that I ignore at the moment.

suit. NBFCs, also lenders, are also more likely to initiate litigation (over 60 percent) conditional on litigation choice. The bottom panel in Figure 3 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 (filed under Negotiable Instruments Act) 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 judgements involving banks reveals that about two-thirds of dispute pertain to credit default, about a fifth pertain to inheritance/property related disputes and about 5% involve the bank as one of the parties in contractual dispute in predominantly government issued contracts. Over 83% of the credit related disputes have outcomes in favor of the bank. This occurs either by undergoing full trial and obtaining a judgement in their favor or by reaching a settlement with the defaulting borrower before completion of the trial, leading to its dismissal.

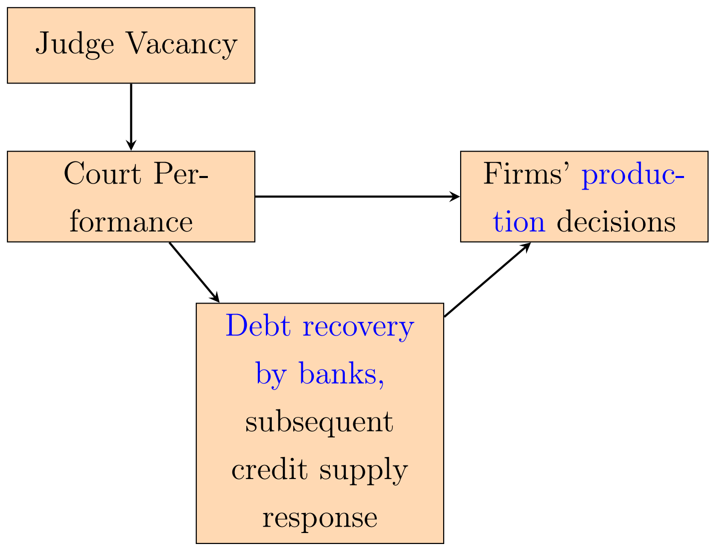
This analysis reveals the following stylized facts on the role of courts in shaping credit behavior:

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. Even when the case is dismissed without completing full trial, the outcome is generally in favor of the bank in the form of settlement reached with the defaulter.

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.

# 3 Conceptual Framework

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




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

I consider a representative lender-borrower game where borrower needs to invest, $K$, in a project with returns $f(K)$, where $K$ is the total capital expenditure. Her exogenous wealth endowment is $W$. She needs an additional $K_B = K - K_M$ to start the project, where $K_M$ is the amount she raises from the market whereas $K_B$ is met in the form of borrowing from the lender (bank) on the basis of her wealth, $W$, as collateral. The lender earns a return $R > 1$. The project meets with success with probability $s$, upon which the borrower decides to repay or evade. Evasion is costly, where the borrower needs to pay an evasion cost $\eta K$ in the process, with remaining payoff at $f(K) - \eta K$. The lender loses the entire principal, $-K_B$. Repayment results in $f(K) - RK_B$ as payoff to the borrower and the lender earns $RK_B$. On the other hand, the borrower automatically defaults under failure, in which case the lender chooses to litigate or not to monetize borrower's assets to recover their loan. The game is depicted in Figure 5. Under default, the lender can choose to litigate, incurring a cost $C_L(\gamma) > 0$, $\frac{\partial C_L}{\partial \gamma} < 0$, where $\gamma$ is inverse congestion in the corresponding district court. The borrower can either choose to accept the trial or settle out of court. Once the lender chooses to litigate and borrower accepts, lender mostly win as seen in the data. [13]

[13] Introducing a probability of winning, $p >> 1 - p$ does not add much to the exposition and for tractability, I skip this stochastic component.

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

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

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

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

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

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

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

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

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

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

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

Finally, lender's participation constraint is given by

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

The timing of the game where the lender and borrower decide on their strategies are as follows, which is depicted as an extensive form game in Figure 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 capital market while the borrower cannot start their project.

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

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

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

T1b If the project fails, the borrower automatically defaults.

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

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

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

**Proposition 1: Litigation Response of Borrowers** As the inverse court congestion, $\gamma$, increases, the wealth threshold for litigation decreases. That is, $\frac{\partial \tilde{W}}{\partial \gamma} < 0$.
**Proof:** See Appendix.

Constraints (2) and (5) define the credit contract. Additionally $R \geq \phi$ else the lender would rather invest in external markets than engaging in lending. This gives the relationship between returns, $R$, borrowing, $K_B$, and the threshold wealth, $W^*$ required to borrow, as depicted in Figure 6.

**Proposition 2: Credit Market Response to Court Congestion** As the inverse court congestion, $\gamma$, increases, the credit market response varies as follows:

1. Effect on $W^*$ is negative. That is, a reduction in court congestion lowers the threshold of wealth required for lending.

2. Effect on $R$ is negative for each level of borrowing. That is, the interest curve shifts inward.

3. Borrowing becomes cheaper, which expands total borrowing, particularly at lower levels of wealth $W$.

**Proof:** See Appendix.

## 3.2 Firm Production

In this section, I model the production effects of credit market response to changes in court congestion. Additionally, the model also accounts for alternate channels of effects of court congestion, for example through transaction costs (monitoring costs, $m$, incurred by the firm). Consider a representative firm with production function $Q = Q(X_1, X_2)$ where $Q(.)$ is twice differentiable, quasi-concave, and cross partials $Q_{X_1X_2} = Q_{X_2X_1} \geq 0$. Further assume that the firm is a price taker. The firm's problem is to maximize their profits as follows:

$$\text{Max}_{X_1,X_2}\big(\Pi = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - \phi m_i(\gamma)\big) \tag{7}$$
$$s.t\ w_1X_1 + w_2X_2 + \phi m(\gamma) \leq K_i(\gamma)\ i \in \{S, L\}$$

where $w_1$ and $w_2$ are the unit costs of inputs $X_1$ and $X_2$. $m_i(\gamma)$ is the monitoring costs arising in the production process, which is a function of inverse court congestion $\gamma$, with $\frac{\partial m_i}{\partial \gamma} \leq 0$. $i$ represents whether the firm is a small firm based on ex-ante asset size, denoted by $S$, or a large firm $L$. Further, I assume that fixed costs form a large share of monitoring costs for small firms such that $\frac{\partial m_S}{\partial \gamma} \approx 0$ whereas for large firms, $\frac{\partial m_L}{\partial \gamma} < 0$ reflecting a lowering of the variable cost. $W$ is the exogenous initial level of assets or wealth. Firm that can borrow from banks have $K_i = K_M + K_B$, which is the total borrowing from market as well as banks. This only depends on project size and hence considered exogenous to the firm's decision problem. Firms of type $S$ with assets just below the initial lending threshold $W^*$, rely mainly on market capital as banks are unwilling to lend. As court quality, $\gamma$, improves, the banks lower the threshold wealth for lending so that these firms experience an increase in borrowing. The interest rate on bank lending, $R(\gamma, .)$, is determined as in the Lender-Borrower set-up above. Finally, I assume that firms are credit constrained as shown in Banerjee and Duflo (2014).

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

1. Lending from banks becomes available for firms of type $S$, i.e. those with less assets.
2. Optimal input use $X_1, X_2$ increases on an average.
3. Increase in $\gamma$ increases production output and profits on an average.
4. Heterogeneity in effects are as follows:
   (a) For large firms, $L$, optimal inputs and profits increase if decrease in monitoring costs more than offsets the increase in input expenditure.
   (b) For marginal small firms, $S$, optimal inputs and profits increase if the increase in borrowings is sufficiently large to offset the increase in input expenditure.
   (c) For inframarginal small firms, $S$, optimal inputs and profits remain unchanged because borrowing and monitoring costs for these firms remain unchanged.
5. For credit unconstrained firms, if any, profits increase through a decrease in monitoring costs.

**Proof:** See Appendix.

### 3.3 Key Tests

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

H1: Wealthier borrowers (firms) are more likely to accept litigation as respondents. As court congestion reduces, the wealth threshold for litigation decreases.

H2: Interest rate weakly decreases for all levels of borrowing.

H3: Borrowings increase for firms with smaller ex-ante asset size (wealth threshold for borrowing decreases).

H4: Sales and input use increase with a decrease in court congestion, in particular among firms with larger ex-ante asset size.

H5: Profits increase with a decrease in court congestion, particularly 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 congestion impacts production and profits of all incumbent firms, irrespective of their litigation status, and examine whether enforcement of credit contracts plays a role through credit market adjustments. I focus on incumbent firms to ensure that the estimates are not confounded by endogenous firm entry. In all my analyses, the unit of observation is firm-district-year. The court variables vary by district-year. The empirical specification for estimating the relationship between inverse court congestion (disposal rate) and firm outcome is as follows:

$$Y_{fdt+k} = \phi_d + \phi_{st} + \theta D_{dt} + \mathbf{X'}_f\Delta + \epsilon_{fdt+k} \text{ ;} k \geq 0 \tag{8}$$

where $f$ indicates the firm in the district court $d$, in state $s$ at years $t+k$, accounting for lagged effects. $Y_{fdt+k}$ is the firm outcome of interest in years $t+k$ and $D_{dt}$ is the inverse court congestion measure (disposal rate) of the district court in year $t$. $\mathbf{X}_f$ is a vector of firm specific controls and $\epsilon_{fdt+k}$ is the idiosyncratic error. I account for all time-varying unobserved factors at the state level by including state-year fixed effects, $\phi_{st}$, and time-invariant district unobserved characteristics by including district fixed effects, $\phi_d$. However, court congestion is likely to be endogenous with firm outcomes if district courts process cases faster due to differential trends in infrastructure growth within the district or are slower due to increasing population from migration or increased crime that add to the caseload, worsening congestion. 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 $D_{dt}$ with judge occupancy, $Occup_{dt}$, which is the percentage of judge positions that are occupied (and correspondingly, not vacant) in district $d$, year $t$ using 2SLS estimation strategy. The first stage estimating equation is as follows:

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

$$D_{dt} = \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X'}_f \Pi + \nu_{fdt+k} \tag{9}$$

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 variation (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 within a district due to a combination of the judge rotation system and existing vacancies is likely orthogonal to firm and court congestion potential outcomes. I provide two pieces of evidence in support of this claim. One pertains to the institutional feature of the Indian judiciary involving differences in powers over finances and personnel management 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 $\Omega = 0$.

$$\begin{aligned} District\ Char_{dt-k} &= \nu_d + \nu_{st} + \rho Occup_{dt} + \eta_{dt-k};\ k > 0 \quad (10) \\ Y_{fdt-k} &= \kappa_d + \kappa_{st} + \Omega Occup_{dt} + \mathbf{X'}_f \Gamma + \epsilon_{fdt-k};\ k > 0 \quad (11) \end{aligned}$$

The first piece of evidence arises from the process of frequent rotation of judges to different district courts that shifts existing vacancies across these courts. District judges are recruited by the respective state high courts and only serve within the state unless promoted to the 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% of all current positions as reported in the media, this system of rotation shifts the vacancies exogenously to different district courts every year. The procedure for rotation is decided and implemented by the corresponding state High Court administrative committee. Specifically, the assignment process is based on serial dictatorship mechanism by seniority that is uniform across the country, detailed as follows:

(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.

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

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

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

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. To test for this, I run the following specifications regressing judge occupancy and changes in judge occupancy in a given year $t$ on past period disposal rate and change in disposal rate, respectively. This would test if the judge assignment process is affected by existing levels or changes in court congestion in the district courts.

$$\begin{aligned} Occup_{dt} &= \nu'_d + \nu'_{st} + \rho' D_{dt-k} + \eta'_{dt};\ k > 0 \qquad (12) \\ \Delta Occup_{dt} &= \kappa'_d + \kappa'_{st} + \Omega' \Delta D_{dt-k} + \epsilon'_{dt};\ k > 0 \qquad (13) \end{aligned}$$

Another institutional feature that lends to the plausible exogeneity of the instrument is that the judiciary follows a unitary structure in contrast to the rest of the polity that is federal. The unitary structure implies that the funds for any expenditure, either for court infrastructure or recruiting judges and administrative court staff, requires approval from the central executive - the Finance Ministry of Government of India. This limits the role of the state high courts in effectively responding to backlogs on a frequent basis. This implies, for example, that the total number of judge posts in a district court is fixed in the short run, which is a function of district population measured during decadal census.

**Balance tests:** The second piece of evidence arises from testing the empirical specifications (10) and (11). I find that the judge occupancy is uncorrelated with prior period court variables as well as district level time varying characteristics such as agricultural sown areas (fraction of total area), and per capita crime variables (Table 3, Columns 1-2). Further, I also find that judge occupancy is uncorrelated with prior period firm outcomes (Table 3, Columns 3-4). The joint test of significance fails to reject the null hypothesis of no correlation between these measures and judge occupancy. Further, testing specifications (12) and (13) reported in Table 4 reveals that there is no "gaming" in the assignment of judges to district courts based on levels or changes in court congestion.

Patterns in data reveal that 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 in vacancies, highlighting the 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. That is, Kolmogorov-Smirnov test fails to reject the equality of distributions.

Finally, I test for plausible violation of the exogeneity assumption through event study specifications for each year as well as for the year when judge occupancy is hundred percent within the district court. Figure 7 the results from this test. The leave out time period is the year before full occupancy for the specification using the year of full occupancy as the "event". All figures plot the coefficients on disposal rate, residualized of all fixed effects. I find that both level and changes in disposal rate show no pre-trends, providing suggestive evidence of orthogonality of not just the number of vacancies (assumed in the numerator of judge occupancy) within a given district court but also the denominator, which is the total number of judge posts (tested using the year of full occupancy).

**Verification using judge tenure data:** Finally, I use tenure and district assignment data of Principal District Judges (PDJs) - the head judge of district courts, to show that the average tenure is about 1.5 years (Figure A6, top panel) and that the system of rotation leads to "gap days" before the successor judge takes charge (Figure A6, 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. Table A5 and Table A6 in the appendix show this result.

2. **First Stage and Monotonicity:** Figure 8 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 an index of all measures instead of disposal rate as the measure of court congestion. The remaining columns in Table 5 present other ways of measuring the same treatment, all of which positively respond to judge occupancy, with the exception of case duration and share dismissed.[14] As mentioned in Section 2, I use log disposal rate as the preferred measure of court congestion 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 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

[14] This is unsurprising, given case duration and dismissals are inversely related to timely adjudication process.

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 congestion 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 congestion. 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 congestion. I show in the section below that judge occupancy affects credit market through reduced congestion that benefits many lenders that are engaged in litigation. I also verify that judge occupancy does not have direct effects on crime behavior but through congestion (i.e. faster or slower sentencing).

In the following sections, I present the results of the impact of court congestion on firm outcomes, by first testing the propositions to establish that the functioning of the local credit markets is an important channel for the observed effect.

# 5 Effects of Court Congestion on Banks

In this section, I examine the direct effects of disposal rate on banks that use courts intensively and initiate the litigation in over 80% of the cases. As detailed in the credit market model, a reduction in court congestion is hypothesized to improve the lending outcomes for all banks.

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. However, this is not the case and that there is likely a selection on filing cases in the trial dataset. I use judge occupancy as an instrument to induce quasi-random variation in court congestion as before, but limit the event window to the period when the bank (firm) has at least one case active in the court. Therefore, this analysis examines what happens to the outcomes of an already litigating bank when the court experiences judge supply shocks (i.e. variation in judge occupancy).

I use district wise annual credit summary data to obtain the left hand side variables, that capture aggregate loan outcomes for banks within a local credit market, i.e. a district. 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**

$$Y_{dt+s} = \delta_d + \delta_{st} + \delta_c + \beta D_{dt} + \upsilon_{dt};\ s \geq 0 \tag{14}$$

$$D_{dt} = \alpha_d + \alpha_{st} + \alpha_c + \lambda Occup_{dt} + \xi_{dt} \tag{15}$$

where $Y_{dt+s}$ 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 years $t+s$, accounting for lagged effects. $D_{dt}$ and $Occup_{dt}$ 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.[15]

Panel A of 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 disposal rate. For example, an influx of population over time is likely positively associated with court congestion and 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.

Examining total outstanding loan amount pooled across all banks in a district-year in Panel B of Table 7 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 reduced court congestion. Table 8 shows the results on loan account and outstanding loan for public sector banks by district-year. The IV estimates indicate that the loan accounts

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

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. Table 9 shows 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.

# 6 Effects on Respondent Firms

## 6.1 What drives firms to accept litigation?

In this section, I turn attention to the subset of non-financial firms that appear as a respondent. These firms are alleged to be in the offense by the petitioner in breach of contracts. As hypothesized, many of the firms accused of contract breaches may settle with the petitioner out of court without completing the trial process. On the other hand, for certain firms - mainly larger firms by asset size - it may actually be a rational response to continue with litigation, if their expected payoff from litigating is higher than settling. I test for this in the data by examining the fraction of firms, by ex-ante wealth distribution, found in the trial dataset as a respondent at least once (labeled "ever respondent"). I also test this by restricting the sample to the subset of the firms that have likely defaulted on debt repayment, based on their credit ratings. These firms are tracked by credit rating agencies that provide a letter grade based on their debt repayment behavior. I classify firms receiving low ratings as those likely to default on loans. The reason for their low ratings is because they missed repayment in the past. Figure 10 shows that larger firms are more likely to appear as a respondent in comparison to smaller firms, even after accounting for likelihood of default. Columns 1-2 of Table 10 demonstrate this pattern by accounting for district and state-time fixed effects. Column 3-4 show the regression coefficients of regressing whether or not a firm appears as a respondent in a given year on the interaction between wealth distribution, i.e. whether below or above median, and annual judge occupancy. I find that as judge occupancy improves, more among firms with below median wealth engage as respondents in litigations compared to the counterfactual with low occupancy. On the other hand, larger firms are less likely to engage as occupancy improves relative to a situation with low occupancy. Columns 5-6 account for firm fixed effects in place of district fixed effects. Though I lose precision in estimation as well as magnitude, the coefficient on the interaction term remains positive. This provides suggestive evidence on the selection margin for litigation, i.e. smaller firms are less likely to engage in litigation as a respondent. However, as judge occupancy improves, smaller firms begin with engage in litigation whereas larger firms are less likely to litigate on the margin.

## 6.2 Effect of Court Congestion on Respondent Firms

Next, I examine what happens to already litigating respondent firms that experience a judge shock. A trial that concludes in a timely fashion likely halts the production process for respondent firms if the judgement is against them, as is likely in the case of debt default. 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 where the firm appears as a respondent against a worker, the court may order the firm to pay damages to the worker 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 11 presents the first stage for this sample, which is of similar sign and relative magnitude.

Columns 1-3 of Table 11 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 reduced court congestion supports 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.

# 7 Effects of Court Congestion 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 (all firms 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, 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 court congestion 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 11 and Column 1, Panel A of Table 12 show the OLS, IV, and reduced form estimates 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, Panel B Table 12) as well as after weighting the regression by the number of incumbent firms per district (Column 1, Panel C Table 12).

**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 Panel A, Column 2 of Table 12 and Figure 12. 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, Panel B and Panel C of Table 12, respectively). 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.

**Interest Incidence on Borrowing:** This variable, computed by CMIE, captures the ratio of a firm's interest costs to its average borrowings and is the closest measure of average interest rate incurred by the firm in a given year. Table 13 presents the effect of disposal rate on this measure, with a lag of two years, among all firms (Column 1), firms with ex-ante asset size below the median (Column 2), and firms with above median asset size (Column 3). Overall, I note a modest increase in interest rate on average across all firms, and in particular for firms above the median in asset size. On the other hand, firms with below median asset experience a negative effect (although imprecise) on interest incidence, as hypothesized within the conceptual framework. The patterns and magnitude remain similar using a balanced panel of firms as well as when weighted by the number of firms in the district (see Panel B and Panel C of Table 13). The IV estimates imply an elasticity of about 5% with respect to disposal rate. This translates to 0.5 percentage point reduction in interest incidence over a baseline interest incidence of 10 percent of average borrowings for this group of firms. This is substantial considering that banks charge a processing fees of 2-3% on most business loans.

The comparative statics following the credit market implications of reduction in court congestion showed that borrowing increases particularly for credit constrained firms, thereby expanding production by increasing input use to optimal levels. In addition, 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 [16]. Figure 14 and Panel A Columns 3-6 Table 14 show reduced form and IV estimates of judge occupancy and disposal rate 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 disposal rate is $\approx 0.2$, which remains stable across different specifications - using a balanced panel of firms, with and without weights (Columns 3-4, Panel B and Panel C of Table 14). 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, Panel C of Table 14 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 IV estimates on firms' sales revenue as shown in the left panel of Figure 13 is positive and significant. Panel A Column 1 of Table 14 presents OLS, IV, and the reduced form estimates for sales revenue using lagged court variables. The elasticity suggests

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

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, Panel B and Panel C of Table 14) but is imprecisely estimated.

The panel on the right in Figure 13 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 (Panel A Column 2 of Table 14). The estimates are consistent and statistically significant using a balanced panel of firms, with and without weights as show in Column 2, Panel B and Panel C of Table 14.

**Heterogeneity by Ex-Ante Wealth** In order to show heterogeneity by asset size of firms (i.e. a proxy for credit constraint) as per the model proposition, I categorize firms into those below median ex-ante asset size and those above the median. Bottom panel of Figure 11 shows that long term borrowings from banks increase for firms with lower ex-ante wealth but likely has no effect on those above median.

While the graph shows that the total long term borrowing has a positive and increasing elasticity over time with respect to court congestion among smaller firms, I cannot conclude that the lending threshold from banks decreased. I present the estimates using a dummy on borrowing to examine whether there are extensive margin effects with respect to borrowing from banks in favor of smaller firms in Table 15. On an average, 23 percent of small firms borrow every year compared to 40 percent among large firms. However, I find that extensive margin borrowing decreases with lower court congestion similarly across small and large firms. The point estimates are almost identical. Therefore, there is no differential effect on smaller firms with respect to the extensive margin of borrowing as a result of improved court functioning.

Table 16 presents the intensive margin effects, i.e., results on the borrowing levels (Column 1), borrowing trend or change in borrowing relative to past year (Column 2), unconditional sales and profit (Columns 3 and 5, respectively), and sales and profits within the firm sub-sample that experience a change in borrowing relative to previous year (Columns 4 and 6). Panel A of Table 16 reports the estimates for the sub-sample of firms with below median asset size whereas Panel B reports the estimates for the larger firms. I note that both level and trend for borrowing increases significantly for smaller firms when court congestion decreases by 1 percent whereas I fail to reject the null of no effect for larger firms. For these, while the coefficient is positive for the level of borrowing, it is negative for the trend. That is, it is likely that the larger firms borrow less relative to the past period as a result of lower congestion. While these are mainly intensive margin effects conditional on borrowing, the fact that the smaller firms experience a growth in borrowing from banks whereas the larger firms experience a likely reduction supports the hypothesis of a reduction in wealth threshold for borrowing when the courts function better.

Examining the estimates on sales revenue and profits among both types of firms across Columns 3-6, I find suggestive evidence that sales and profits increase with a reduction in court congestion when firms are able to borrow more. The estimates of the elasticities for smaller firms is similar in magnitude, although imprecise, as in the pooled sample of firms. Among larger firms, profits increase substantially in response to a lowering of congestion. This elasticity in profits is higher within the subsample of firms for whom borrowing increases.

**Visual IV** Figure A7 presents binned scatter-plots of the relationship between residualized firm outcomes and predicted court disposal rate, after partialling out the fixed effects. These plots show positive relationship across firm outcomes excluding capital and land investments.

## 7.1 Alternate Identification: Event Study

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

$$Y_{fdt} = \rho_d + \rho_{st} + \sum_{k=-5}^{k=5} \gamma_k \mathbb{1}\{t \geq k\} + \zeta_{fdt} \tag{16}$$

where event $t$ is defined as the first year of positive shock to judge occupancy, defined as at least 10 percent increase in judge occupancy over the preceding year's value. While this is not the same definition of "treatment" as defined in the main analysis, the results should be qualitatively similar if the hypotheses are true.

Figure A8 shows the event study graphs using the above specification. The results are qualitatively similar to the IV or reduced form estimation using court disposal rate and judge vacancy respectively. Bank lending increases after experiencing a positive shock (10 percent increase) in judge vacancy. Firm estimates are noisier but also exhibit an increasing response pattern after the district court experiences a positive judge shock for the first time. On the other hand, the effect on capital investment in the form of plant and machinery or land show no consistent pattern. Even with a different design and definition of "treatment", we continue to find similar qualitative effect of judicial capacity on bank lending and firm outcomes.

## 7.2 Firm Borrowing as a Causal Channel

One of the channels through which improved court performance affects firm production is through credit markets. In the sections above, I provided evidence in support of increased lending by banks towards manufacturing and consumption uses. Consistently, firm borrowing from banks also increased subsequently. However, to what extent does borrowing from formal financial institutions such as banks aid in firm production? How important is this channel relative to others? Following Imai et al. (2011), I estimate Average Causal Mediation Effect (ACME) through borrowing by instrumenting firms' borrowing with new bank branch openings in the district in the following linear model:

$$
\begin{aligned}
Y_{fdt+k} &= \psi_d + \psi_{st} + \omega_1 Borrow_{fdt+k} + \omega_2 Occup_{dt} + \mathbf{X'}_f\Gamma_1 + \epsilon_{fdt+k} \text{ ;} k \geq 0 \quad (17)\\
Borrow_{fdt+k} &= \alpha_d + \alpha_{st} + \beta_1 Bank\ Shock_{dt+j} + \beta_2 Occup_{dt} + \mathbf{X'}_f\Gamma_2 + \mu_{fdt+k} \text{ ;} k \geq j \geq 0 \quad (18)
\end{aligned}
$$

The idea behind ACME estimation is to establish the causal chain flowing through the credit channel. Coefficient $\omega_1$ in Equation (17) would provide a causal estimate under the sequential ignorability assumption, which requires not just conditional independence of the potential outcomes of firm production variables and the mediator (borrowing) variable but also requires the potential outcomes of production to be conditionally independent of the potential mediator outcomes. One way to ensure that this assumption holds is to instrument $Borrow_{fdt+k}$ in Equation (17) with $Bank\ Shock_{dt}$, which is only correlated with firm borrowing and not with any unobserved determinants of firm production, judge vacancy, or other post-intervention variables along the causal path to firm outcomes.

$Bank\ Shock_{dt}$ is defined as follows. I use data on new bank branch opening in the study districts since 2005 provided by the Reserve Bank of India. I define the shock as a dummy variable that takes the value of 1 (but 0 otherwise) when the share of total new bank branches opened in a given year that are located in rural areas is above 75th percentile of the within district distribution of the share of rural branch openings. To serve as a valid instrument, the bank shock should be conditionally independent of the potential outcomes of not only firm production outcomes and firm borrowing (mediator) but also independent of judge vacancy. This design is akin to the alternative research design proposed by Imai et al. (2011), when the sequential ignorability assumption is unlikely to hold. That is, when it is unlikely to preclude other post-treatment variables that influence both firm borrowing and firm production. Therefore, I instrument firm borrowing with bank branch shock. Bank branch expansion is determined by public policy since a large share of the banks are public sector banks and require branch licensing approval from the Reserve Bank of India. These decisions are orthogonal to within district variation in judge vacancy as well as firm level variables, and therefore, the bank shock as defined likely satisfies the exclusion restriction. Consistent with this, I do not find any significant correlation between bank shock and judge vacancy, firm borrowing, and firm production outcomes.

Table 17 presents the results of this estimation. Column 1 presents the regression coefficient on lagged judge occupancy on current period bank shock. This suggests that judicial capacity concerns does not affect the decision of banks to open relatively more new branches in rural areas. Column 2 presents the first stage relationship between bank shock and firm borrowing. The coefficient on bank shock indicates that the borrowing increases by 14 percent. All the regressions on mediation analysis accounts for judge occupancy. The coefficient on judge occupancy in Column 2 is the effect of judicial capacity on firm borrowing through lending decisions of banks that is independent of lending from a newly opened bank branch. The first stage results imply that the effect of judicial capacity on firm borrowing is 3.6 percent of bank shock when the judge occupancy increases by 1 percentage points. So, reducing vacancy marginally by adding one judge generates an increase in firm borrowing equivalent to more than the bank shock (5.5 percent increase in judge occupancy per judge added x 3.6 $\approx$ 20). Columns 3 - 6 presents the coefficients with firm production variables on the left hand-side. The coefficient on judge occupancy in these columns imply the effect of judge occupancy through channels other than credit market channels on firms' production decisions and outcomes. The coefficient on firm borrowing in the IV specifications multiplied by the coefficient on judge occupancy in the first stage provides the average causal mediation effect on the complier population. For example, the mediation effect of a one percentage point increase in judge occupancy through firms' borrowing from bank increases firm sales by 0.3 percent, wage bill by 0.2 percent, and the value of plants and machinery by 0.3 percent. On the other hand, the effect of judicial capacity through channels other than the credit markets are statistically insignificant and sometimes negative. Figure A9 depicts the reduced form estimates of bank shocks on lags and leads of the dependent variables, after controlling for judge occupancy.

Through this analysis, I show the entire causal chain of the importance of well functioning courts on firm outcomes mediated through the credit market channel. Timely enforcement of debt recovery trials enable banks to reduce their stressed assets and circulate recovered debt back as fresh credit towards productive uses.

### 7.3 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, mainly through increase in borrowings and less likely through other channels. 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 and showing 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 as 0.178.[17] 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 congestion 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 a follow-up paper, I examine the interaction of court congestion with introduction of laws, including changes in India's bankruptcy law, to identify the complementarity between legal and judicial institutions.

# 8 Conclusion

To conclude, I present the first causal estimates of the timeliness of adjudication through district courts on formal sector firm growth using trial level data. Judge occupancy is an important factor determining the effectiveness of courts as an institution for the enforcement of credit 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 23 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.

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

[17]The authors' measure of congestion is measured as log backlog per judge. Therefore, the backlog appears in the numerator in their variable 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.

informal justice administration institutions and selection into formal sector for production. This would be a natural next question to explore in subsequent research using this dataset and context.

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.

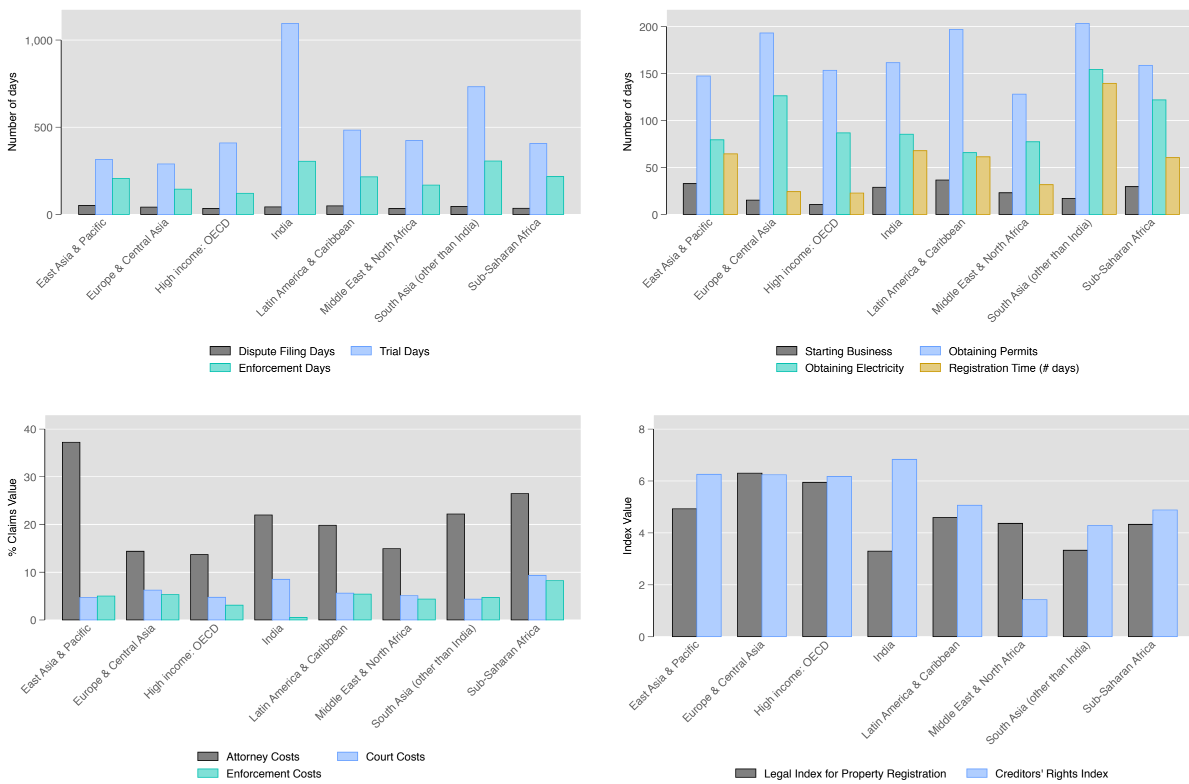
Further, I show the importance of court performance for the functioning of formal credit markets, highlighting the channel of contract enforcement. The mediation analysis helps isolate the credit channel from other mechanisms to establish the relative importance of contract enforcement in credit markets for firm growth. This is because banks litigate more intensively and initiate litigation against defaulting borrowers, which is a necessary step before taking collateral into possession or initiating bankruptcy proceedings. Timeliness of the litigation proceedings increases the extent of loans made by banks, enables recovery of outstanding loans, allowing them to allocate more loans to 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.

As a result, firms in the district experience lowering of credit constraints, increasing their borrowings from banks. Banks' lending is also supplemented by increased lending from other sources such as inter-firm lending. A flush of credit relaxes credit constraints firms face, leading to an expansion in production. Profits increase on an average, and specifically among credit unconstrained firms, for whom improved institutional environment likely lowers transaction costs.

This indicates that the problem of vacancy in district courts has meaningful economic repercussions, which is consistent with the current demand by legal experts for addressing the issue of vacancy and strengthening 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 increased tax collection and an expansion in employment. 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.

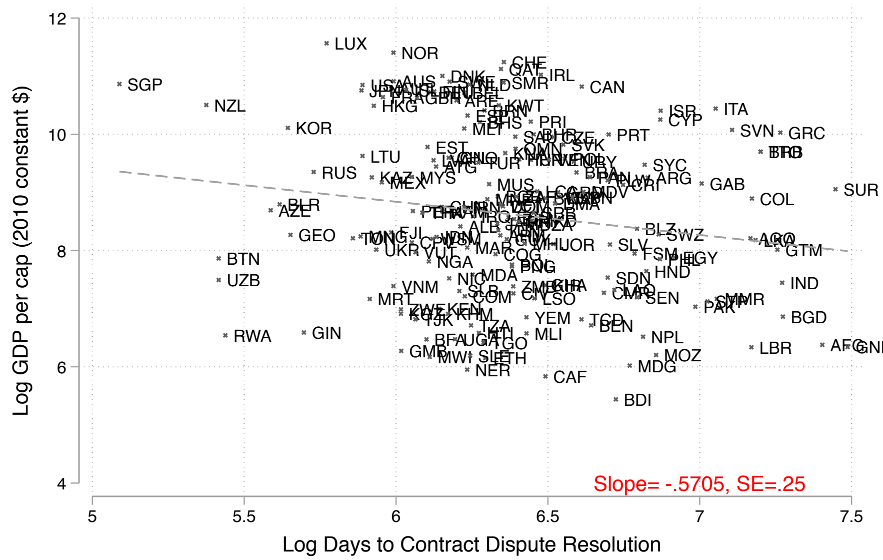
# 9 Figures

Figure 1: World Bank Doing Business Survey Database



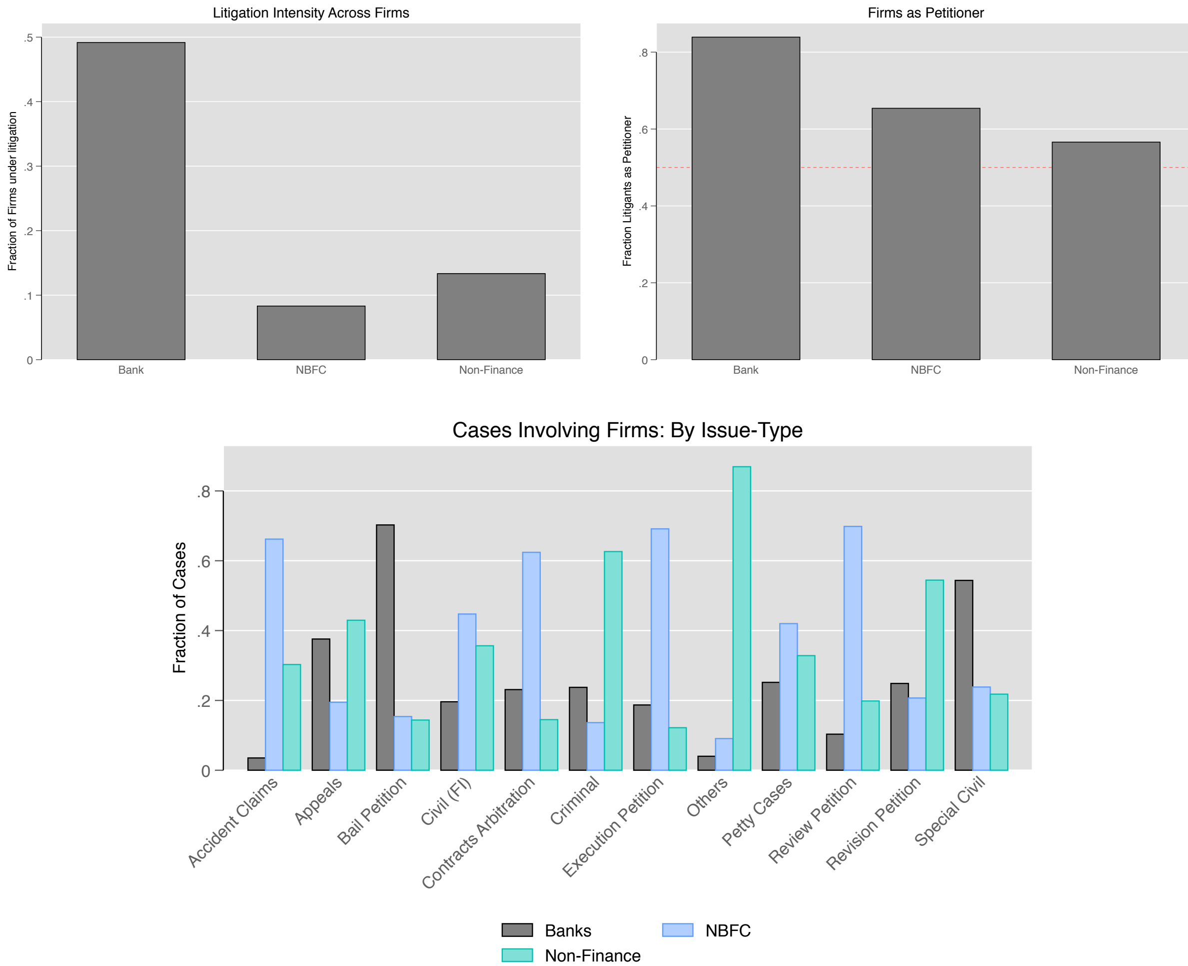

Notes: Data source: Doing Business database, World Bank. All contract enforcement variables are calculated from the perspective of the court of first instance. Figure on the top-left graphs time delays in filing, adjudication, and judgement enforcement concerning contractual disputes. Top-right figure graphs time delays in other aspects of starting a business other than dispute resolution, particularly those concerning the bureaucracy. Figure on the bottom-left presents the costs of resolving contractual disputes in courts of first instances, measured as a percentage of claims value. Finally, the figure on bottom-right presents measures on legal protection of rights, separated by creditor rights and rights to land as property.

Figure 2: GDP per capita and Contract Enforcement



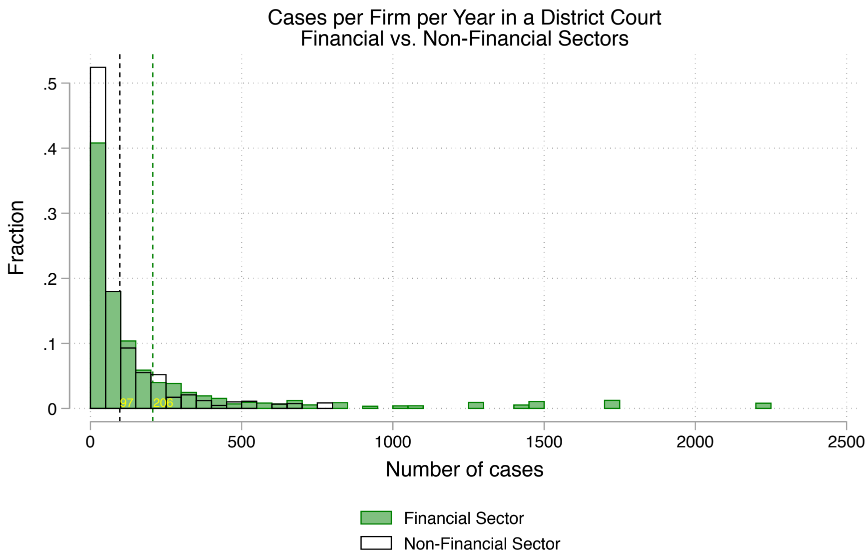

Notes: Data source: Doing Business and WDI databases, World Bank. Variable on the x-axis measures the log transformation of trial duration. Variable on the y-axis measures the log transformation of GDP per capita. Country codes are presented as value labels of the scatter plot.

Figure 3: 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).

Figure 4: 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. Financial sector firms, such as banking and NBFCs, have a large number of cases per firm per court in the sample.

Figure 5: Model: Lender-Borrower Game

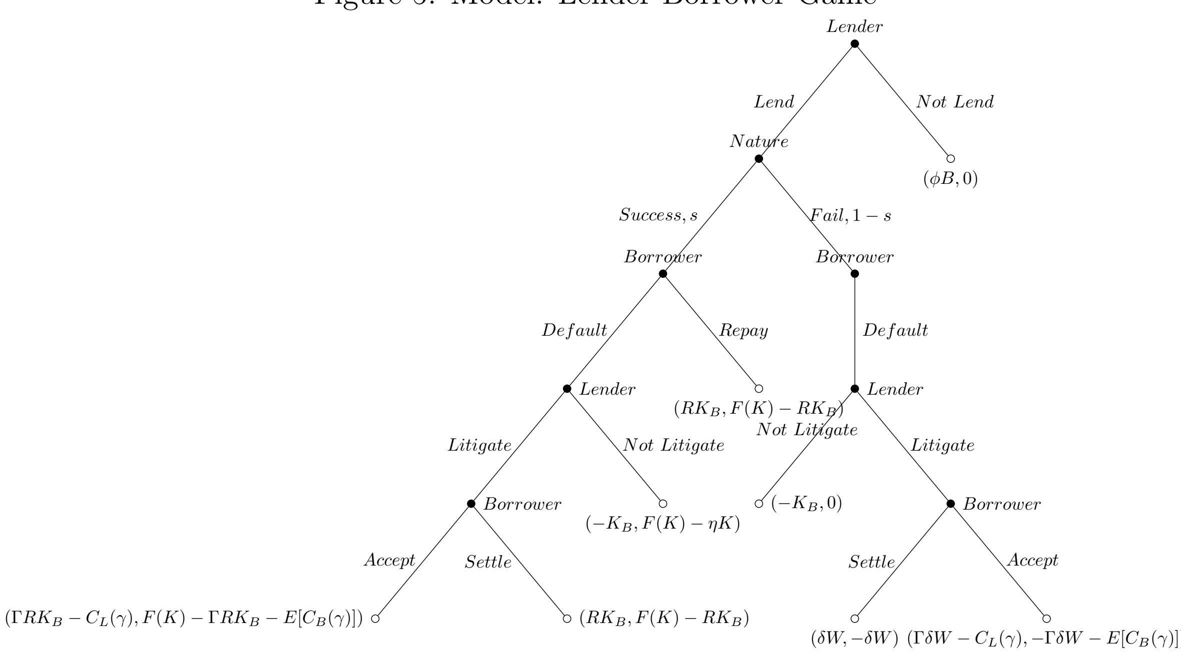


Figure 6: Model: Credit Contract

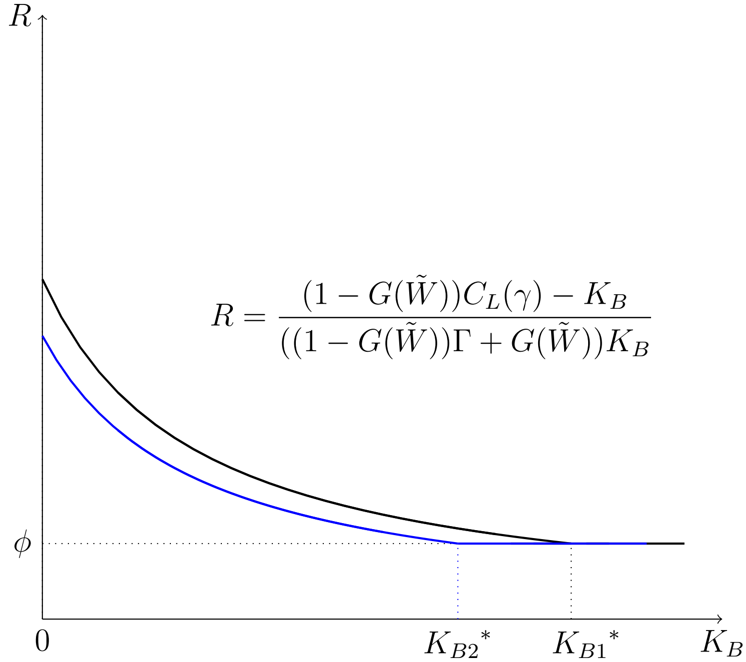
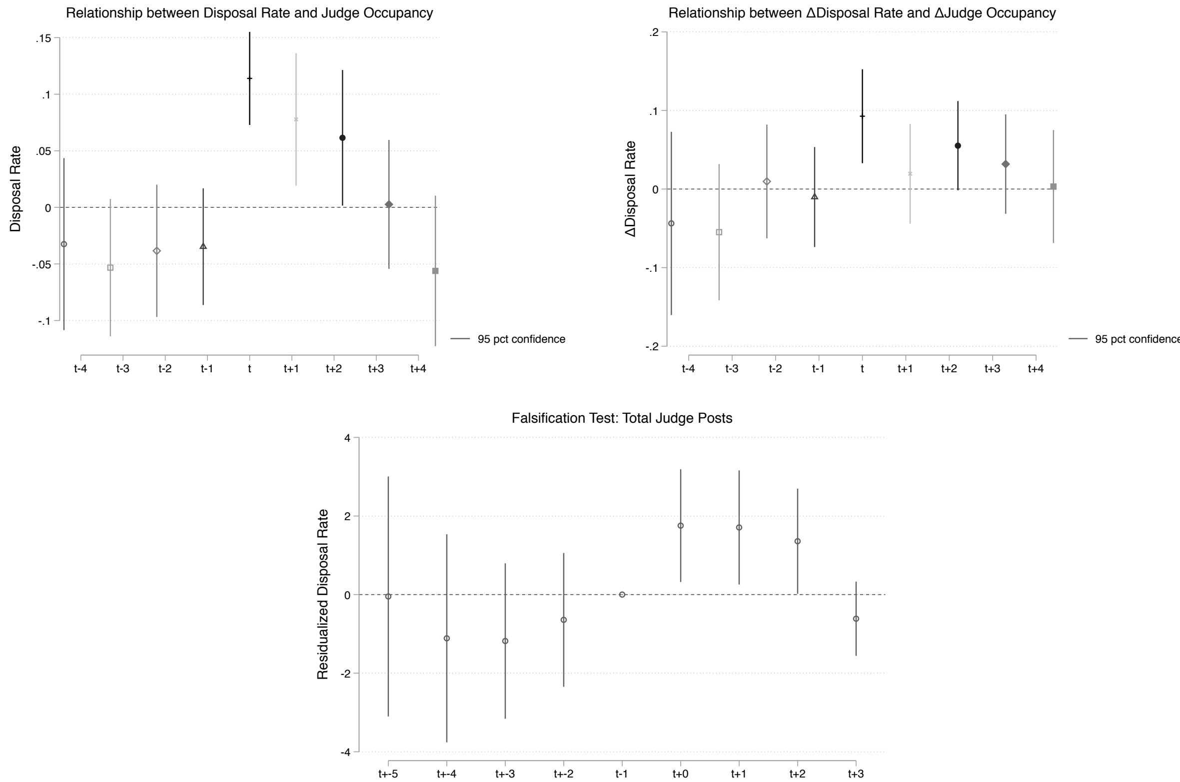
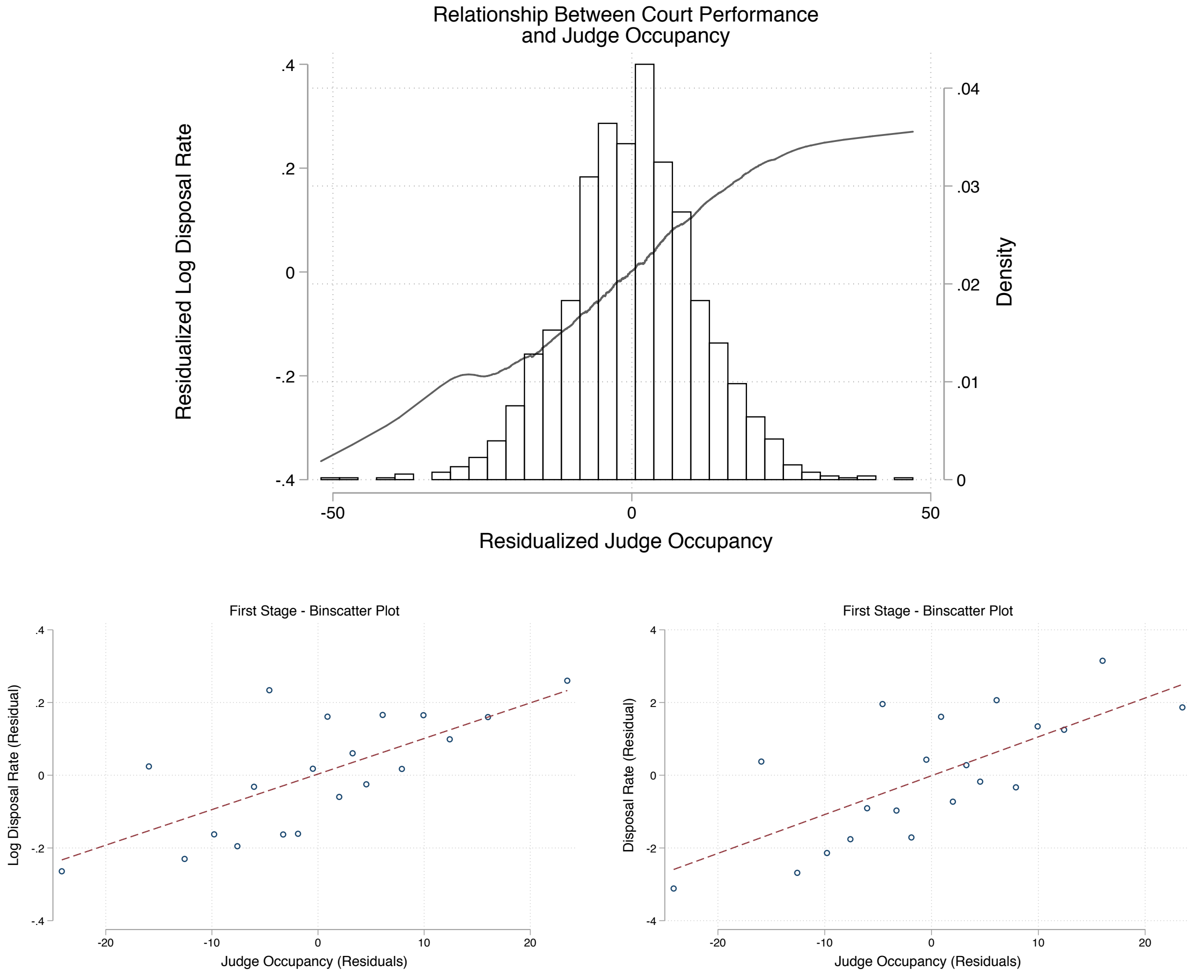


Figure 7: Exogeneity of Judge Occupancy With Respect to Past Court Congestion



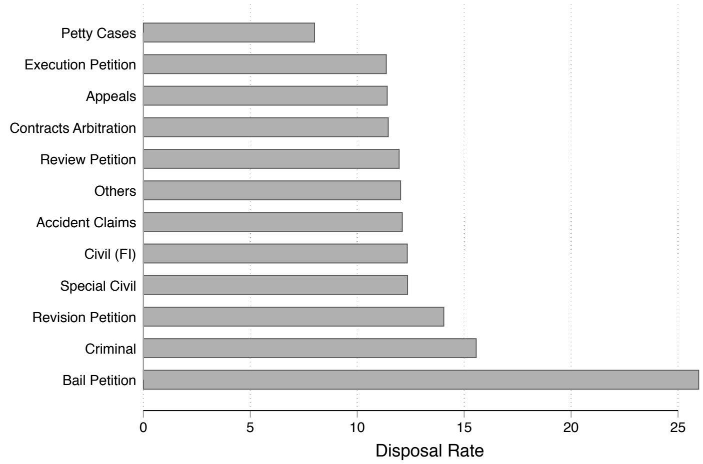

Notes: The figures on the top panel plot the relationship between both levels and changes in judge occupancy at time $t$ with respect to levels and changes in disposal rate, respectively, residualized of all fixed effects. The graph in the bottom panel plots time coefficients of an event study design around the year of full occupancy (numerator = total judge post in the district). The base year considered is the year prior to full occupancy ($t-1$). Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district year.

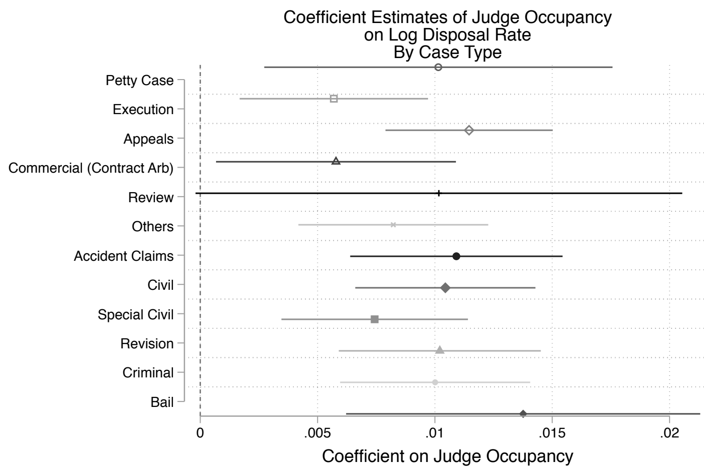
Figure 8: Court Performance and Judge Occupancy: First Stage




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

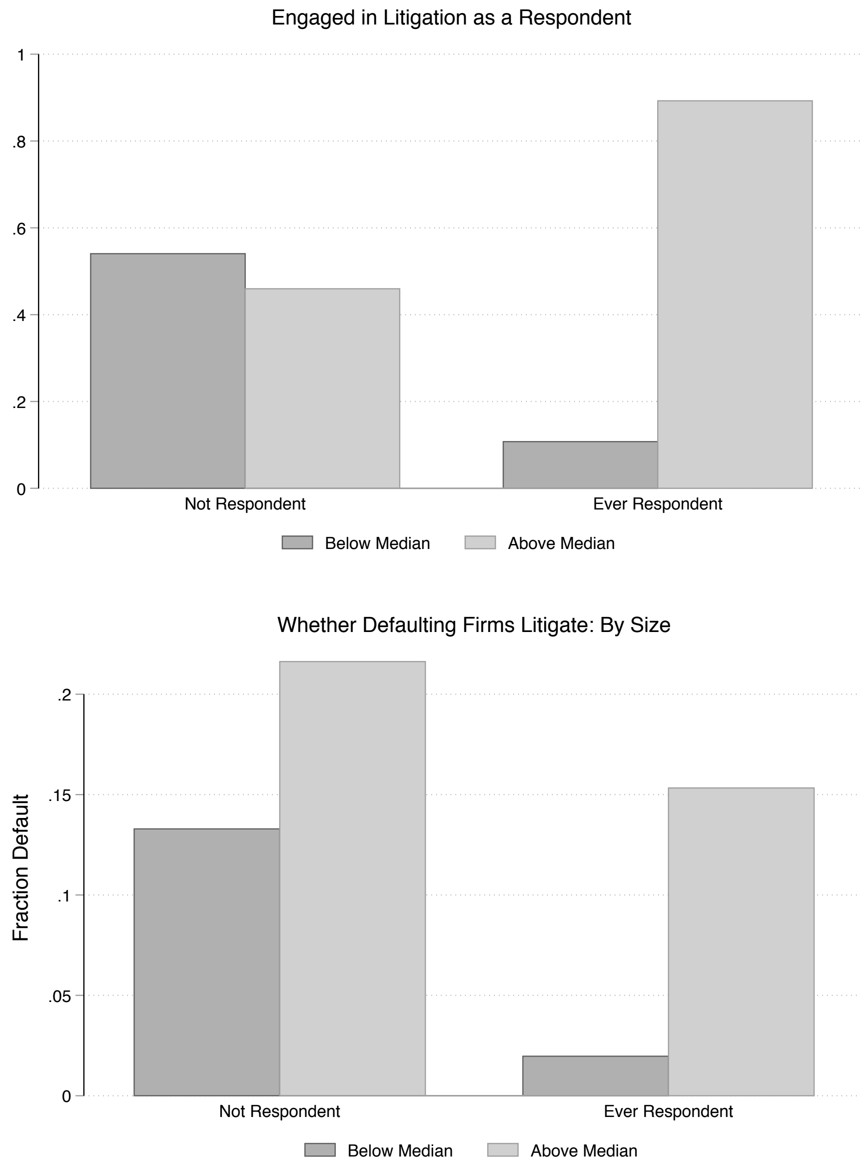
Figure 9: Court Performance and Judge Occupancy: Estimates Across Case-Types



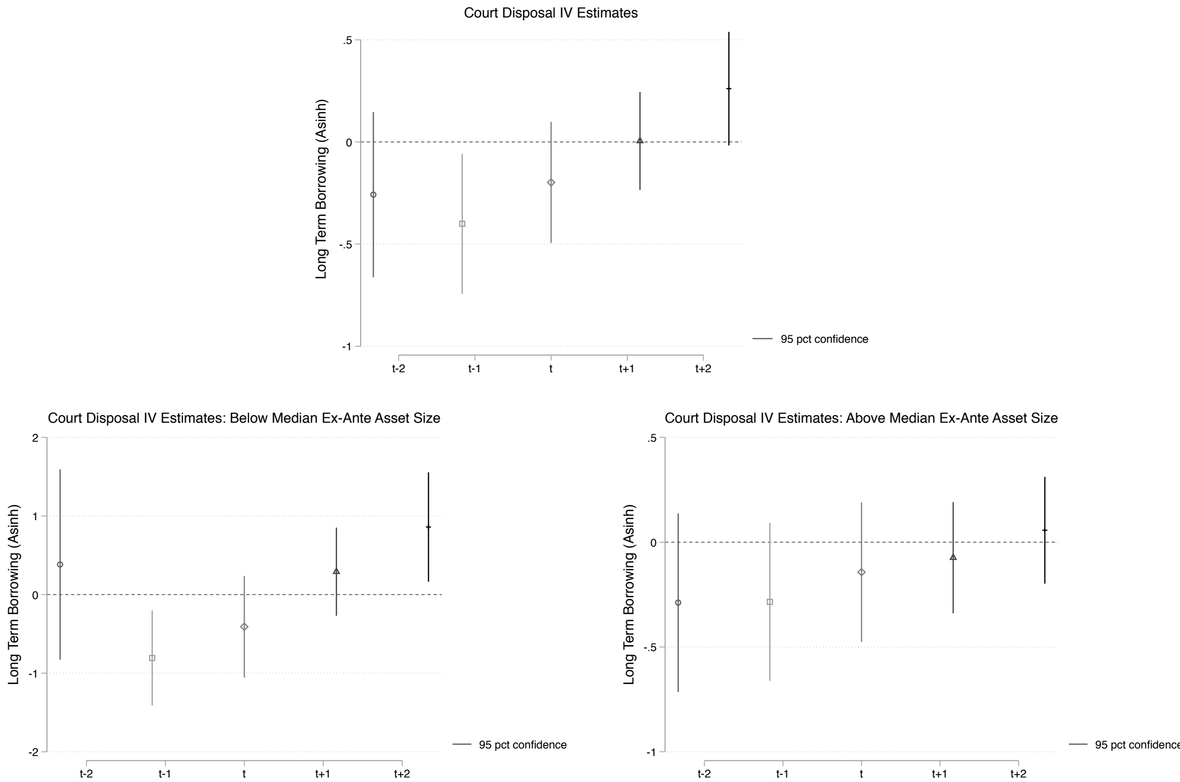

Notes: Top graph presents average disposal rate by broad case-type buckets. Bottom graph presents the first stage estimates by each of these buckets. I coded many specific case-types - there were over 2000 unique issues under conflict - that I binned into above mentioned buckets based on related nature of dispute. All standard errors are clustered by district-year.

Figure 10: Firm as Respondent By Asset Size Distribution and Defaulting Status



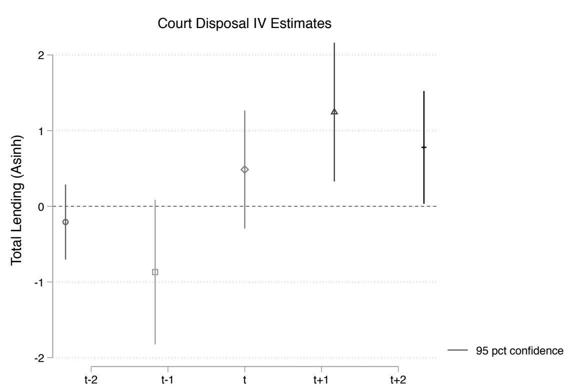

Notes: "Ever Respondent" is a binary variable, coded as 1 if a firm in the Prowess data has ever appeared as a respondent in the court sample during the study period. The figure in the bottom panel depicts litigation rate among defaulting firms by asset size. Firms are classified as defaulters based on their credit rating by credit rating agencies. Firms that missed any repayment or have defaulted on loans in the past receive a bad rating.

Figure 11: Effects on Firm's Borrowing from Banks



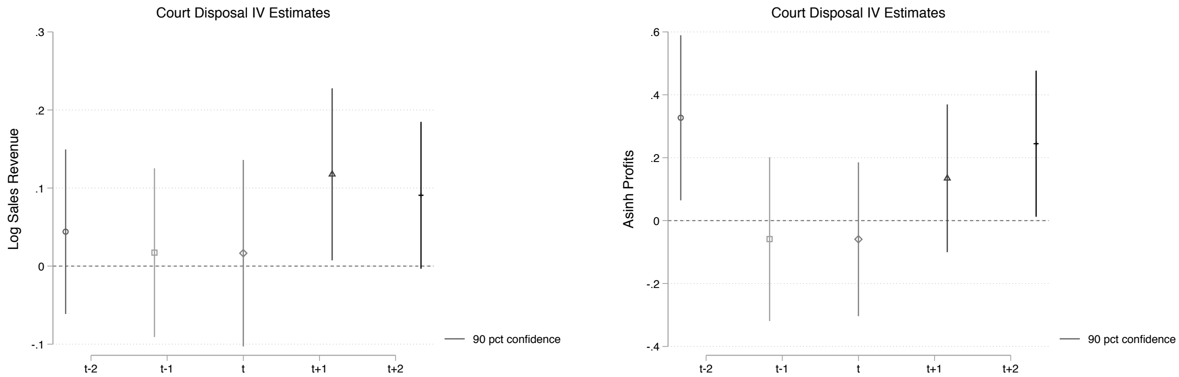

Notes: The graphs above plot the IV coefficients from regressing lags and leads of the long term borrowing from banks on disposal rate, respectively. The bottom panel presents heterogeneity by ex-ante asset size distribution. All standard errors are clustered by district-year.

Figure 12: Lending by Firms Located in Court Jurisdiction



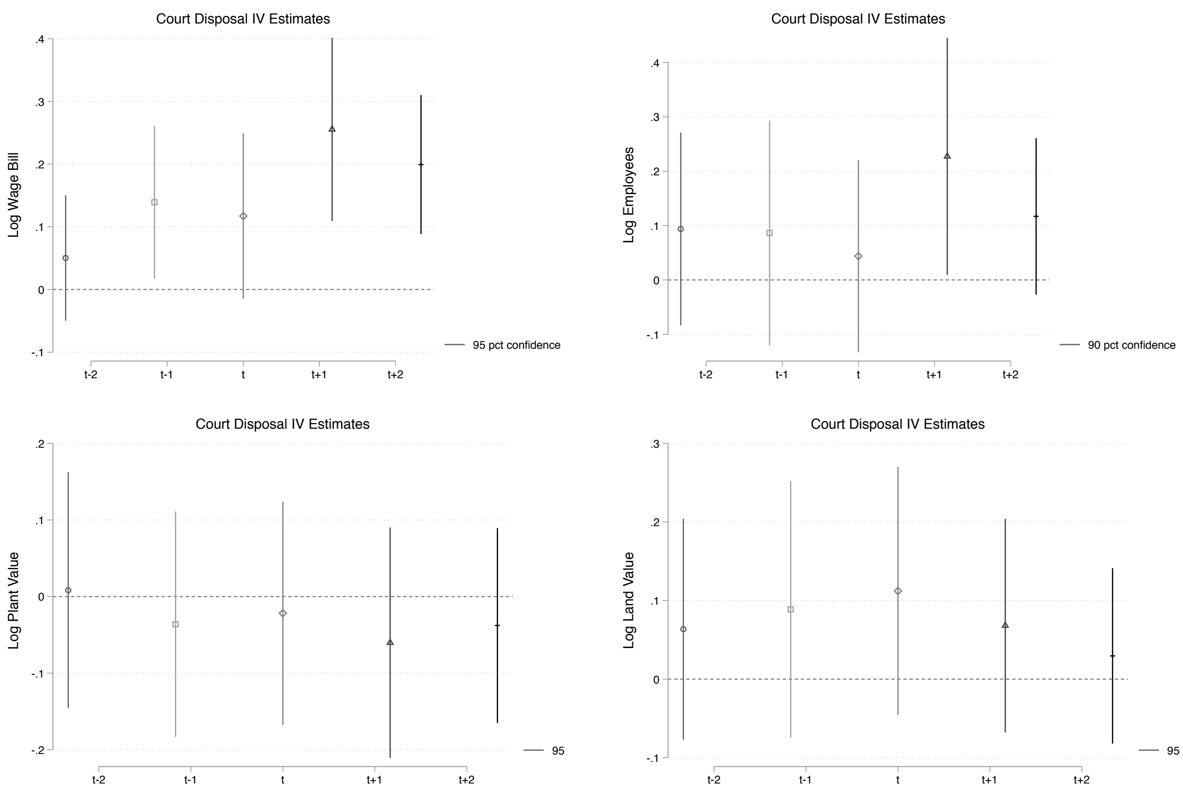

Notes: The graphs above plot the IV coefficients from regressing lags and leads of lending by firms on disposal rate. The sample firms engaged in lending are those with registered offices in the same district as the corresponding court. All standard errors are clustered by district-year.

Figure 13: Effects on Sales and Profits




Notes: The graphs above plot the IV coefficients from regressing lags and leads of sales revenue (left) and profits (right) on disposal rate, respectively. The sample includes all firms whose registered offices are co-located in the same district as the corresponding court. All standard errors are clustered by district-year.

Figure 14: Effects on Input-Use




Notes: The graphs above plot the IV coefficients from regressing lags and leads of wage bill and employment (top panel) and capital - plant and land value (bottom panel) on disposal rate, respectively. The sample includes all firms whose registered offices are co-located in the same district as the corresponding court. All standard errors are clustered by district-year.

# 10 Tables

Table 1: Summary Statistics

| | (1) | | | | | |
|---|---|---|---|---|---|---|
| | No. of Units | Observations | Mean | Std Dev | Min | Max |
| Panel A: Court Variables | | | | | | |
| Total Judge Posts | 195 | 1755 | 18 | 19 | 1 | 108 |
| Percent Judge Occupancy | 195 | 1723 | 77 | 21 | 10 | 100 |
| Disposal Rate (percent) | 195 | 1755 | 14 | 12 | 0 | 86 |
| Speed (percent) | 195 | 1723 | 76 | 102 | 0 | 2580 |
| No. Filed | 195 | 1723 | 3312 | 3712 | 1 | 34427 |
| No. Resolved | 182 | 1504 | 3341 | 3693 | 1 | 37994 |
| Percent Lower Court Judgement Appealed | 195 | 1723 | 19 | 16 | 0 | 100 |
| Percent Cases Dismissed | 182 | 1504 | 22 | 17 | 0 | 100 |
| Case Duration (days) | 195 | 5706852 | 420 | 570 | 0 | 4022 |
| Panel B: Firm Variables | | | | | | |
| Revenue from Sales (real terms, million INR) | 4189 | 20029 | 5452 | 23513 | 0 | 796688 |
| Profits (in real terms, million INR) | 4618 | 24010 | 184 | 4003 | -144347 | 158634 |
| Wage Bill (in real terms, million INR) | 4454 | 21847 | 417 | 2104 | -0 | 70354 |
| No. of Workers ('000) | 1095 | 4075 | 2 | 7 | 0 | 154 |
| Land value (real terms, million INR) | 3154 | 16243 | 309 | 1713 | 0 | 50578 |
| Plant value (real terms, million INR) | 3580 | 18124 | 2889 | 16736 | 0 | 878342 |
| Long Term Borrowing (real terms, million INR) | 2460 | 9313 | 1866 | 9284 | 0 | 251188 |
| Inter-firm Lending (real terms, million INR) | 69 | 297 | 419962 | 733941 | 9 | 4595152 |
| NBFC Lending (real terms, million INR) | 238 | 631 | 8298 | 26556 | 0 | 306740 |

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

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.

Table 3: Balance on district and firm time-varying characteristics

| | (1)<br>Percent Judge Occupancy | (2)<br>Percent Judge Occupancy | (3)<br>Percent Judge Occupancy | (4)<br>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) | | |
| Borrowing (t-1) | | | -0.00758* | |
| | | | (0.00441) | |
| Borrowing (t-2) | | | -0.000903 | |
| | | | (0.00522) | |
| Sales (t-1) | | | | 0.000451 |
| | | | | (0.00156) |
| Sales (t-2) | | | | 0.00103 |
| | | | | (0.00159) |
| Profit (t-1) | | | | 0.00229 |
| | | | | (0.00371) |
| Profit (t-2) | | | | 0.00210 |
| | | | | (0.00373) |
| Wage Bill (t-1) | | | | 0.00307** |
| | | | | (0.00126) |
| Wage Bill (t-2) | | | | -0.0000648 |
| | | | | (0.00125) |
| Employees (t-1) | | | | -0.0000317 |
| | | | | (0.00154) |
| Employees (t-2) | | | | -0.000454 |
| | | | | (0.00169) |
| P-value(joint test) | 0.580 | 0.790 | 0.66 | 0.46 |

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

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

Table 4: Exogeneity of Judge Occupancy: By Levels and Changes in Congestion

| | (1) | (2) |
|---|---|---|
| | Percent Judge Occupancy | $\Delta$ Judge Occp |
| Disposal Rate (t-1) | -0.0146 | |
| | (0.0410) | |
| Disposal Rate (t-2) | -0.0444 | |
| | (0.0392) | |
| $\Delta$ Disposal Rate (t-1) | | -0.0148 |
| | | (0.0443) |
| $\Delta$ Disposal Rate (t-2) | | 0.00575 |
| | | (0.0368) |
| Observations | 1329 | 1135 |
| District Fixed Effects | Yes | Yes |
| Other Fixed Effects | State, State-Year FE | State, State-Year FE |
| Adj R-Squared | 0.710 | 0.0900 |

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

Notes: This table presents estimates of regressing judge occupancy (Column 1) and change in judge occupancy (Column 2) on past period disposal rate and change in disposal rates, respectively. Since past period judge occupancy are correlated with current period judge occupancy, as well as the corresponding period disposal rates, the specifications include lagged judge occupancy/change in judge occupancy as additional controls. Standard errors are clustered at the district-year level.

Table 5: First Stage: Judge Occupancy and Court Congestion

| | (1) Log Disposal Rate | (2) Index | (3) Log Case Duration at Disposal | (4) Log Share Dismissal | (5) Log Appeal | (6) Log New Filing | (7) Log New Disposed | (8) Log Disposal Rate |
|---|---|---|---|---|---|---|---|---|
| Percent Judge Occupancy | 0.00978*** | 0.00745*** | 0.000726 | -0.000679 | 0.00172 | 0.0169*** | 0.00964*** | |
| | (0.00182) | (0.00231) | (0.00148) | (0.00183) | (0.00153) | (0.00165) | (0.00228) | |
| Percent Judge Occupancy Alt | | | | | | | | 0.00624*** |
| | | | | | | | | (0.00139) |
| Observations | 1714 | 1478 | 1478 | 1485 | 1714 | 1714 | 1485 | 1701 |
| 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 | 0 | 616.8 | 21.76 | 19.09 | 3312.2 | 3340.6 | 14.33 |
| F-Stat | 28.81 | 10.43 | 0.240 | 0.140 | 1.270 | 104.8 | 17.86 | 20.06 |
| R-Squared | 0.750 | 0.790 | 0.660 | 0.670 | 0.690 | 0.910 | 0.850 | 0.750 |

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

Notes: This table presents the first stage estimates of regressing judge occupancy on court variables, including congestion. I present 7 different ways of measuring the timeliness of adjudication process in these courts, including an index combining all these measures (Column 2). Row 2 presents an alternate method of constructing judge occupancy, where I fix the denominator as the total number of posts towards the start of the study period. 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: In the table above, I compare the overall first stage estimates of judge occupancy on disposal rate with those estimated using different sub-samples of the district courts. Columns 2-4 present the first stage by terciles of court size and Columns 5-7 by terciles of district population density. All standard errors are clustered at the district-year level.

## 10.1 Tables: Litigating Firms

Table 7: Banks' Loan Behavior

| | (1) OLS | (2) 2SLS | (3) RF | (4) Log Disp (First Stage) |
|---|---|---|---|---|
| | | Panel A: Log Loan Accounts | | |
| 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 |
| | | Panel B: Log Outstanding Loan | | |
| 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: Results presented in this table focuses only on Scheduled Commercial Banks, for which the data is provided by the Reserve Bank of India. Panel A reports specifications using log total number of loan accounts as the dependent variable whereas Panel B reports specifications using log outstanding loan as depending variable. Column 4 reports the first stage. All standard errors are clustered at the district-year level.

Table 8: Banks' Loan Behavior: Public Sector Banks

| | Panel A: Log Loan Accounts | | | Panel B: Log Outstanding Loan | | |
|---|---|---|---|---|---|---|
| | OLS | IV | Reduced Form | OLS | IV | Reduced Form |
| Log Disposal (t-1) | -0.0129 | 0.225** | | -0.00516 | -0.296** | |
| | (0.0164) | (0.110) | | (0.0233) | (0.138) | |
| Judge Occupancy (t-1) | | | 0.00175** | | | -0.00230** |
| | | | (0.000765) | | | (0.000977) |
| Observations | 4279 | 4279 | 4279 | 4279 | 4279 | 4279 |
| District Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Case Type Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 6805.5 | 6805.5 | 6805.5 | 3483.4 | 3483.4 | 3483.4 |
| F-Stat | 0.620 | 4.160 | 5.200 | 0.0500 | 4.580 | 5.530 |
| Adj R-Squared | 0.940 | -0.370 | 0.940 | 0.960 | -0.330 | 0.960 |

Standard errors in parentheses

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

Notes: Results presented in this table focuses only on public sector banks, for which the data is provided by the Reserve Bank of India. These banks are either partially or completely owned by the state. Panel A reports specifications using log total number of loan accounts as the dependent variable whereas Panel B reports specifications using log outstanding loan as depending variable. All standard errors are clustered at the district-year level.

Table 9: Banks' Loan Behavior: Sectoral Allocation

| | (1) | (2) | (3) |
|---|---|---|---|
| | OLS | IV | Reduced Form |
| | | Panel A: Manufacturing | |
| Log Disposal (t-1) | -0.0327* | 0.286** | |
| | (0.0185) | (0.140) | |
| Judge Occupancy (t-1) | | | 0.00222** |
| | | | (0.000933) |
| Observations | 4279 | 4279 | 4279 |
| 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 | 12553.4 | 12553.4 | 12553.4 |
| F-Stat | 3.110 | 4.180 | 5.670 |
| Adj R-Squared | 0.930 | -0.410 | 0.930 |
| | | Panel B: Consumption | |
| Log Disposal (t-1) | 0.0278** | 0.167** | |
| | (0.0123) | (0.0647) | |
| Judge Occupancy (t-1) | | | 0.00130*** |
| | | | (0.000452) |
| Observations | 4279 | 4279 | 4279 |
| 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 | 131343.9 | 131343.9 | 131343.9 |
| F-Stat | 5.100 | 6.650 | 8.230 |
| Adj R-Squared | 0.970 | -0.220 | 0.970 |
| | | Panel C: Agriculture | |
| Log Disposal (t-1) | 0.00417 | 0.0594 | |
| | (0.00851) | (0.0505) | |
| Judge Occupancy (t-1) | | | 0.000461 |
| | | | (0.000383) |
| Observations | 4279 | 4279 | 4279 |
| 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 | 178683.4 | 178683.4 | 178683.4 |
| F-Stat | 0.240 | 1.380 | 1.450 |
| Adj R-Squared | 0.980 | -0.120 | 0.980 |

Standard errors in parentheses

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

Notes: Results presented in this table focuses only on Scheduled Commercial Banks, for which the data is provided by the Reserve Bank of India. Panel A reports specifications using log total number of loan accounts allocated to the manufacturing sector as the dependent variable. Panel B reports the estimates using log total number of loans allocated for consumption, i.e. individual housing or vehicle purchase loans whereas Panel C reports the estimates using log total number of loans allocated for agriculture. All standard errors are clustered at the district-year level.

Table 10: Firms' Litigation Behavior as a Respondent

| | (1) Ever Litigate | (2) Ever Litigate (Among Defaulters) | (3) Litigate | (4) Litigate (Defaulters) | (5) Litigate | (6) Litigate (Defaulters) |
|---|---|---|---|---|---|---|
| Below Median x Judge Occupancy | | | 0.00123*** | 0.0000863 | 0.000110 | -0.000234 |
| | | | (0.000397) | (0.000390) | (0.000146) | (0.000331) |
| Percent Judge Occupancy | | | -0.000866*** | -0.000912** | -0.000336* | -0.000557 |
| | | | (0.000250) | (0.000378) | (0.000198) | (0.000405) |
| Below Median Assets | -0.219*** | -0.120*** | -0.122*** | -0.0439 | 0 | 0 |
| | (0.0179) | (0.0156) | (0.0271) | (0.0351) | (.) | (.) |
| Observations | 141252 | 18536 | 38461 | 5669 | 37796 | 5587 |
| District Fixed Effects | Yes | Yes | Yes | Yes | | |
| Firm Fixed Effects | | | | | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 0.130 | 0.140 | 0.0300 | 0.0300 | 0.0300 | 0.0300 |
| F-Stat | 149.4 | 59.41 | 15.22 | 13.28 | 1.520 | 2.360 |
| Adj R-Squared | 0.180 | 0.290 | 0.0800 | 0.100 | 0.210 | 0.160 |

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

Notes: Dependent variable in Columns 1-2 is a binary variable, coded as 1 if a firm in the Prowess data has ever appeared as a respondent in the court sample. Dependent variables in Columns 3 - 6 are also binary variables representing respondent status, but coded as 1 or 0 for each year in the sample dataset. Below Median is coded as 1 if the firm is below median in the distribution of asset sizes of all firms before 2010. The firm sample in Column 1 includes all firms in the Prowess dataset whereas firms in Columns 3-6 are those that map onto the court dataset. Further, sample in Columns 2, 4, and 6 is restricted to the set of defaulters based on credit rating by credit rating agencies. Standard errors are clustered by district-year.

Table 11: 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 |
|---|---|---|---|---|---|---|---|
| | | | Panel A: OLS | | | | |
| Log Disposal Rate | -0.0329 | -0.106 | -0.00177 | 0.0292** | -0.00854 | 0.0276** | |
| | (0.0377) | (0.103) | (0.00592) | (0.0115) | (0.00778) | (0.0134) | |
| | | | Panel B: IV | | | | |
| Log Disposal Rate | -0.0554 | -1.655* | -0.000265 | 0.0976 | 0.0247 | 0.0838 | |
| | (0.288) | (0.940) | (0.0393) | (0.0611) | (0.0574) | (0.117) | |
| | | | Panel C: Reduced Form | | | | |
| Judge Occupancy | -0.000385 | -0.0109** | -0.00000174 | 0.000771* | 0.000171 | 0.000581 | 0.00651*** |
| | (0.00200) | (0.00522) | (0.000257) | (0.000450) | (0.000395) | (0.000792) | (0.00146) |
| 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: The sample of firms above are the litigating respondent firms found in the court sample that are other than NBFCs or banks. Panels A, B, and C report OLS, IV, and reduced form estimates, respectively. Standard errors are clustered by district-year.

## 10.2 Tables: All Firms

Table 12: Court Congestion and Firm Borrowing/Lending

| | Asinh Long Term Borrowing | Total Lending |
|---|---|---|
| **Panel A: Unbalanced** | | |
| **OLS** | | |
| Log Disposal Rate (t-2) | 0.0257 | 0.212*** |
| | (0.0350) | (0.0738) |
| **IV** | | |
| Log Disposal Rate (t-2) | 0.385* | 0.979** |
| | (0.208) | (0.428) |
| **Reduced Form** | | |
| Percent Judge Occupancy (t-2) | 0.00502** | 0.0238*** |
| | (0.00227) | (0.00557) |
| Observations | 9297 | 227 |
| District Fixed Effects | Yes | Yes |
| Other fixed effects | Year, State-Year | Year, State-Year |
| Mean Dependent Variable | 1865.7 | 423505.8 |
| Adj R-Squared | 0.140 | 0.400 |
| **Panel B: Balanced Unweighted** | | |
| **OLS** | | |
| Log Disposal Rate (t-2) | 0.0399 | 0.141 |
| | (0.0386) | (0.150) |
| **IV** | | |
| Log Disposal Rate (t-2) | 0.692** | 0.712 |
| | (0.305) | (0.622) |
| **Reduced Form** | | |
| Percent Judge Occupancy (t-2) | 0.00747*** | 0.0203 |
| | (0.00261) | (0.0203) |
| Observations | 6347 | 126 |
| District Fixed Effects | Yes | Yes |
| Other fixed effects | State, Year, State-Year | State, Year, State-Year |
| Mean Dependent Variable | 2548.3 | 60051.8 |
| Adj R-Squared | 0.110 | 0.580 |
| **Panel C: Balanced Weighted** | | |
| **OLS** | | |
| Log Disposal Rate (t-2) | 0.0430 | 0.186 |
| | (0.0423) | (0.149) |
| **IV** | | |
| Log Disposal Rate (t-2) | 0.460 | 0.810** |
| | (0.338) | (0.406) |
| **Reduced Form** | | |
| Percent Judge Occupancy (t-2) | 0.00752* | 0.0482*** |
| | (0.00392) | (0.0166) |
| Observations | 6347 | 126 |
| District Fixed Effects | Yes | Yes |
| Other fixed effects | State, Year, State-Year | State, Year, State-Year |
| Mean Dependent Variable | 2548.3 | 60051.8 |
| Adj R-Squared | 0.0600 | 0.300 |

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

Notes: The table above reports OLS, IV, and reduced form estimates on the intermediate firm level outcomes of long term borrowing from banks and inter-firm lending. The explanatory variables trail the dependent variables by 2 years. All these estimates are reported by different samples of incumbent firms, incorporated before the study period. Panel A represents the estimates on an unbalanced panel of firms located in the same district as the court. Panel B restricts the sample to a balanced panel. Panel C reports the estimates on the balanced panel, with the regressions weighted by the overall number of firms in the district at the start of the study period. All standard errors are clustered at the district-year level.

Table 13: Court Congestion and Interest Rate

| | Interest Rate (All Firm) | Interest Rate (Below Median Asst) | Interest Rate (Above Median Asst) |
|---|---|---|---|
| | | Panel A: Unbalanced Panel | |
| | | OLS | |
| Log Disposal Rate (t-2) | -0.00255 | -0.0323 | 0.0119 |
| | (0.0166) | (0.0292) | (0.0186) |
| | | IV | |
| Log Disposal Rate (t-2) | 0.0879* | -0.0348 | 0.102** |
| | (0.0466) | (0.0811) | (0.0507) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | 0.000603 | -0.00210 | 0.00115 |
| | (0.00108) | (0.00185) | (0.00120) |
| Observations | 19505 | 4642 | 14849 |
| 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 |
| Mean Dependant Var (Raw) | 15.756 | 10.481 | 17.41 |
| F-Stat | 103.07 | 34.65 | 29.15 |
| Adj R-Squared | .07 | .1 | .06 |
| | | Panel B: Balanced Unweighted | |
| | | OLS | |
| Log Disposal Rate (t-2) | -0.00133 | -0.0236 | 0.00981 |
| | (0.0103) | (0.0197) | (0.0112) |
| | | IV | |
| Log Disposal Rate (t-2) | -0.0221 | -0.0906 | -0.0239 |
| | (0.0430) | (0.0813) | (0.0524) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | -0.000453 | -0.00182 | -0.000489 |
| | (0.000863) | (0.00166) | (0.00104) |
| Observations | 13000 | 3582 | 9418 |
| 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 |
| Mean Dependant Var (Raw) | 17.153 | 10.209 | 19.795 |
| Adj R-Squared | .09 | .13 | .08 |
| | | Panel C: Balanced Weighted | |
| | | OLS | |
| Log Disposal Rate (t-2) | 0.0135 | -0.0246* | 0.0285** |
| | (0.00915) | (0.0139) | (0.0111) |
| | | IV | |
| Log Disposal Rate (t-2) | 0.0446 | -0.0562 | 0.0786* |
| | (0.0297) | (0.0393) | (0.0407) |
| | | Reduced Form | |
| Percent Judge Occupancy (t-2) | 0.00188 | -0.00249 | 0.00326** |
| | (0.00123) | (0.00179) | (0.00164) |
| Observations | 13000 | 3582 | 9418 |
| 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 |
| Mean Dependant Var (Raw) | 17.153 | 10.209 | 19.795 |
| Adj R-Squared | .05 | .04 | .03 |

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

Notes: The table above reports OLS, IV, and reduced form estimates on the intermediate firm level outcomes of implied interest rate, computed as the ratio between annual interest expenditure and average borrowing. The explanatory variables trail the dependent variables by 2 years. All these estimates are reported by different samples of incumbent firms, incorporated before the study period. Panel A represents the estimates on an unbalanced panel of firms located in the same district as the court. Panel B restricts the sample to a balanced panel. Panel C reports the estimates on the balanced panel, with the regressions weighted by the overall number of firms in the district at the start of the study period. Column 1 represents the average effect across all firms. Columns 2 and 3 break the sample by firms below and above median ex-ante asset size (i.e. indicator of wealth). All standard errors are clustered at the district-year level.

## Table 14: Court Congestion and All Firm Outcomes

| | Log Revenue from Sales | Asinh Profit | Log Wage Bill | Log Employees | Log Plant Value | Log Land Value |
|---|---|---|---|---|---|---|
| | | | **Panel A: Unbalanced Panel** | | | |
| | | | 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 |
| | | | **Panel B: Balanced Unweighted** | | | |
| | | | 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 |
| | | | **Panel C: Balanced Weighted** | | | |
| | | | 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 table above reports OLS, IV, and reduced form estimates on the final firm level production outcomes. The explanatory variables trail the dependent variables by 2 years. All these estimates are reported by different samples of incumbent firms, incorporated before the study period. Panel A represents the estimates on an unbalanced panel of firms located in the same district as the court. Panel B restricts the sample to a balanced panel. Panel C reports the estimates on the balanced panel, with the regressions weighted by the overall number of firms in the district at the start of the study period. All standard errors are clustered at the district-year level.

Table 15: Hetergeneous Effects of Court Congestion on the Extensive Margin of Borrowing

| | (1)<br>Borrow Dummy<br>Below Median (OLS) | (2)<br>Borrow Dummy<br>Above Median (OLS) | (3)<br>Borrow Dummy<br>Below Median (IV) | (4)<br>Borrow Dummy<br>Above Median (IV) | (5)<br>Borrow Dummy<br>Below Median (RF) | (6)<br>Borrow Dummy<br>Above Median (RF) |
|---|---|---|---|---|---|---|
| Log Disposal Rate (lagged) | -0.00131 | 0.00274 | -0.0564** | -0.0549** | | |
| | (0.00506) | (0.00490) | (0.0266) | (0.0277) | | |
| Percent Judge Occupancy (lagged) | | | | | -0.00117*** | -0.00110*** |
| | | | | | (0.000436) | (0.000420) |
| Observations | 6750 | 10403 | 6750 | 10403 | 6750 | 10403 |
| 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) | .231 | .399 | .231 | .399 | .231 | .399 |
| Adj R-Squared | .11 | .09 | .11 | .08 | .12 | .09 |

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

Notes: The table above reports OLS, IV, and reduced form estimates estimates on the firm level outcomes of on the sub-samples generated by firms below and above ex-ante asset size. The explanatory variables trail the dependent variables by 2 years. All standard errors are clustered at the district-year level.

Table 16: Hetergeneous Effects of Court Congestion: By Asset Size

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Panel A: Below Median | | | |
| | Asinh Long Term Borrowing | Δ Asinh Long Term Borrowing | Log Revenue from Sales | Log Revenue from Sales (Sample Δ Borrowing) | Asinh Profits | Asinh Profits (Sample Δ Borrowing) |
| | | | OLS | | | |
| Log Disposal Rate (lagged) | 0.107** | 0.104** | 0.0429* | 0.0593** | -0.0498 | -0.0481 |
| | (0.0448) | (0.0429) | (0.0251) | (0.0301) | (0.0502) | (0.0498) |
| | | | IV | | | |
| Log Disposal Rate (lagged) | 0.601** | 0.312** | 0.0897 | 0.157 | -0.124 | 0.123 |
| | (0.262) | (0.152) | (0.110) | (0.144) | (0.208) | (0.217) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (lagged) | 0.00982*** | 0.00291 | 0.00167 | 0.00298 | -0.00268 | 0.00269 |
| | (0.00362) | (0.00284) | (0.00207) | (0.00272) | (0.00456) | (0.00467) |
| Observations | 1560 | 1159 | 4469 | 3741 | 6136 | 5342 |
| 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) | 328.726 | -.076 | 507.831 | 488.979 | 507.831 | 507.831 |
| Adj R-Squared | .22 | 0 | .29 | .29 | .04 | .04 |
| | | | Panel B: Above Median | | | |
| | | | OLS | | | |
| Log Disposal Rate (lagged) | -0.0117 | -0.0593 | 0.0255 | 0.0400* | 0.199*** | 0.215*** |
| | (0.0364) | (0.0368) | (0.0177) | (0.0239) | (0.0677) | (0.0766) |
| | | | IV | | | |
| Log Disposal Rate (lagged) | 0.248 | -0.0940 | -0.0386 | 0.0738 | 0.745** | 1.052*** |
| | (0.191) | (0.102) | (0.0787) | (0.0881) | (0.311) | (0.392) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (lagged) | 0.00459 | -0.00297 | -0.000744 | 0.00144 | 0.0150*** | 0.0217*** |
| | (0.00310) | (0.00206) | (0.00145) | (0.00184) | (0.00576) | (0.00619) |
| Observations | 4159 | 3193 | 9573 | 7521 | 10412 | 8296 |
| 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) | 3,318.24 | -.102 | 9,875.99 | 10,009.4 | 326.264 | 392.209 |
| Adj R-Squared | .09 | 0 | .29 | .3 | .07 | .08 |

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



Notes: The table above reports OLS, IV, and reduced form estimates estimates on the firm level outcomes of on the sub-samples generated by firms below and above ex-ante asset size. The explanatory variables trail the dependent variables by 2 years. All standard errors are clustered at the district-year level.

Table 17: Mediation Effects of Increased Bank Borrowing

| | (1) Bank Shock | (2) First Stage | (3) Asinh Sales | (4) Asinh Profit | (5) Asinh Wage Bill | (6) Asinh Employees | (7) Asinh Land Value | (8) Asinh Plant Value |
|---|---|---|---|---|---|---|---|---|
| Percent Judge Occupancy (t-2) | -0.00148 | 0.00528** | -0.00218 | -0.00463 | -0.000825 | 0.00505 | 0.000683 | -0.00147 |
| | (0.00251) | (0.00264) | (0.00211) | (0.0105) | (0.00146) | (0.0351) | (0.00246) | (0.00173) |
| Bank Branch Shock (t-1) | | 0.141*** | | | | | | |
| | | (0.0536) | | | | | | |
| Asinh Borrowing | | | 0.584* | 1.569 | 0.367* | -0.340 | 0.0245 | 0.594** |
| | | | (0.308) | (1.486) | (0.189) | (2.937) | (0.566) | (0.251) |
| Observations | 7726 | 7726 | 7737 | 7737 | 7543 | 1696 | 6286 | 7079 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Court-State Time Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Court District FE | Yes | Yes | 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 | Firm Level Controls | Firm Level Controls |
| Mean Dependant Var (Raw) | .349 | 1,647.26 | 5,798.29 | 13.618 | 341.106 | 2.286 | 328.957 | 3,716.8 |
| F-Stat | 1.15 | 53.21 | 426.21 | 1,489.13 | 689.09 | 105.47 | 421.23 | 490.13 |
| Adj R-Squared | .6 | .15 | .4 | -.66 | .45 | -.49 | .21 | .58 |

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



Notes:

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# Appendix

## 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.

## 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.

## Model Proofs

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

**Proof for Proposition 2: Credit Market Response to Court Performance** Differentiating (2) and (5) with respect to $\gamma$ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as follows:

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

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

**Constrained Optimization:**

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

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

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

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

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

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

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

1. For large firms, $i = L$, the marginal benefit $0 - \frac{\partial m_L}{\partial \gamma}$ is mainly due to reduction in monitoring costs since there is no change in their borrowing from banks. If this reduction in monitoring costs is greater than the marginal increase in input costs due to higher optimal input use under better institutional quality, then the profits for such firms will increase.

2. For marginal small firms, $i = S$ and $W \approx W^* - \epsilon$, the marginal benefit $K_B - \frac{\partial m_S}{\partial \gamma}$ is due to both availability of borrowing from banks $K_B$ as well as a reduction in monitoring costs. I assume that the monitoring costs for small firms do not decrease substantially since a large share is fixed cost for these firms. If the increase in borrowing is large enough to offset the increase in input costs, then the profits for such firms will increase.

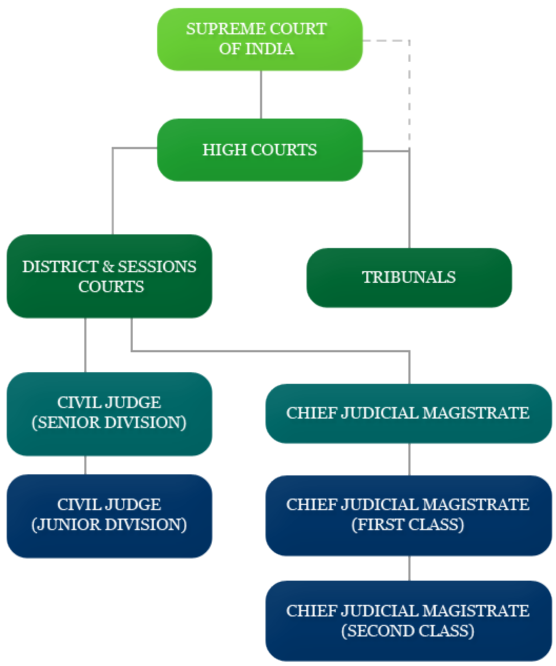
3. For inframarginal small firms, $i = S$ and $W << W^*$, neither their optimal inputs nor their profits change under improved institutional quality since $(\underbrace{\frac{\partial K_S}{\partial \gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial \gamma}}_{\approx 0}) \approx 0$.

### A0.1 Additional Robustness Checks

**Firm Fixed Effects** In all specifications above, the estimates are computed as the local average treatment effect of court congestion 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 congestion over time, I add firm fixed effects to the main specification. Table A11 presents the results on borrowing-lending outcomes and Table A12 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.

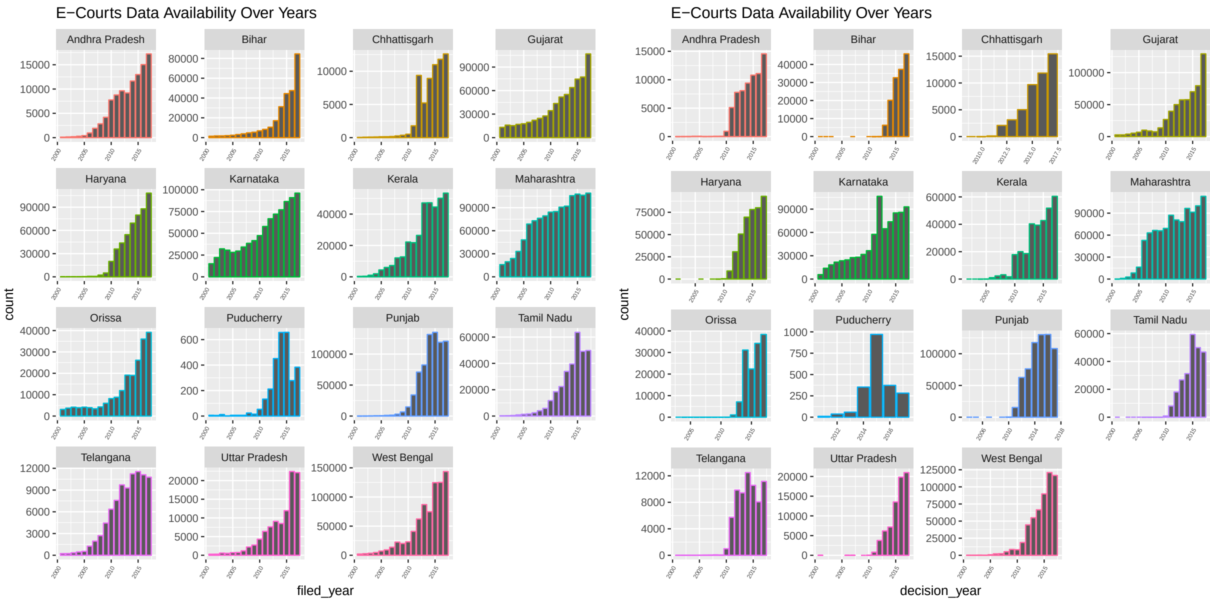
## Appendix: Figures

Figure A1: The Indian Judiciary Org-Chart




Source: Daksh, India.

Figure A2: 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 A3: 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 A4: Construction of Firm Sample

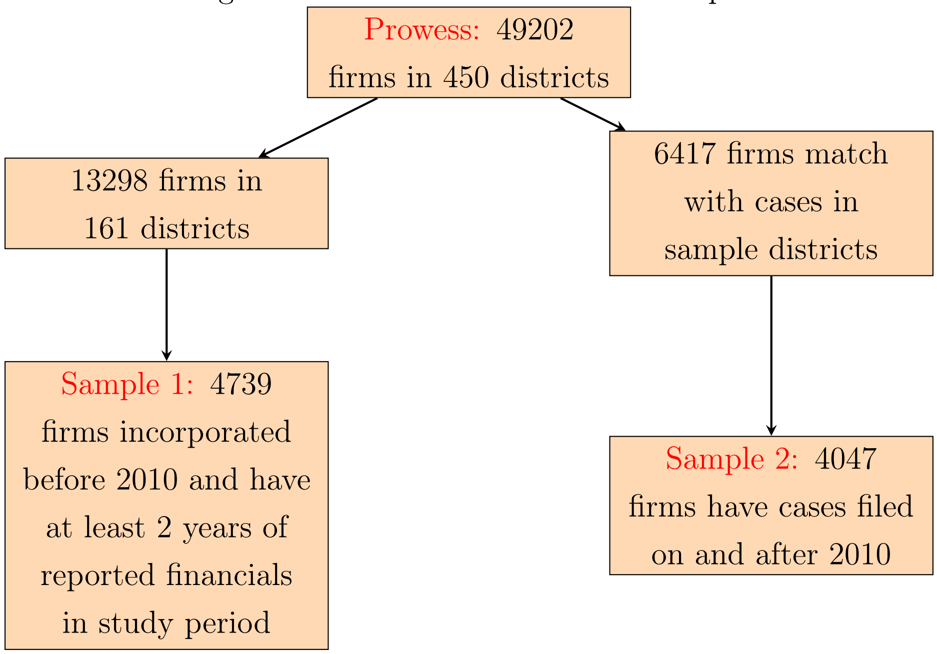



Figure A5: Correlation Between Judge Occupancy and District Population Change

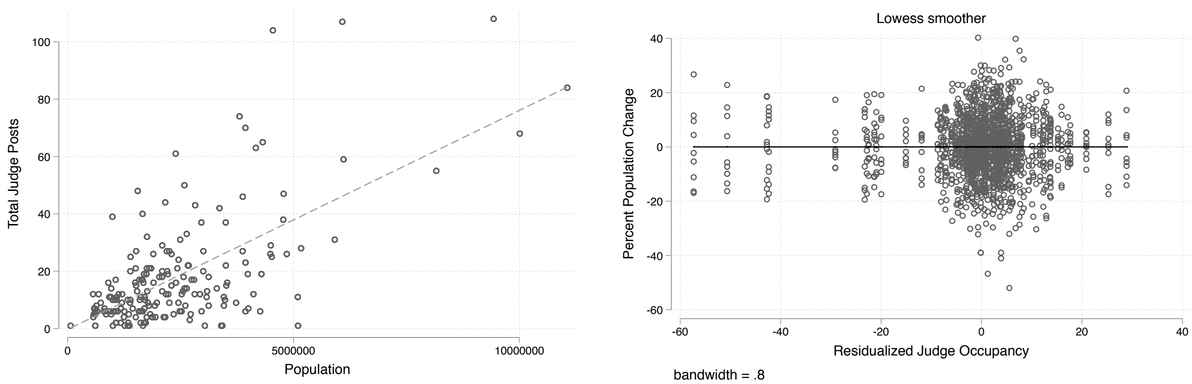
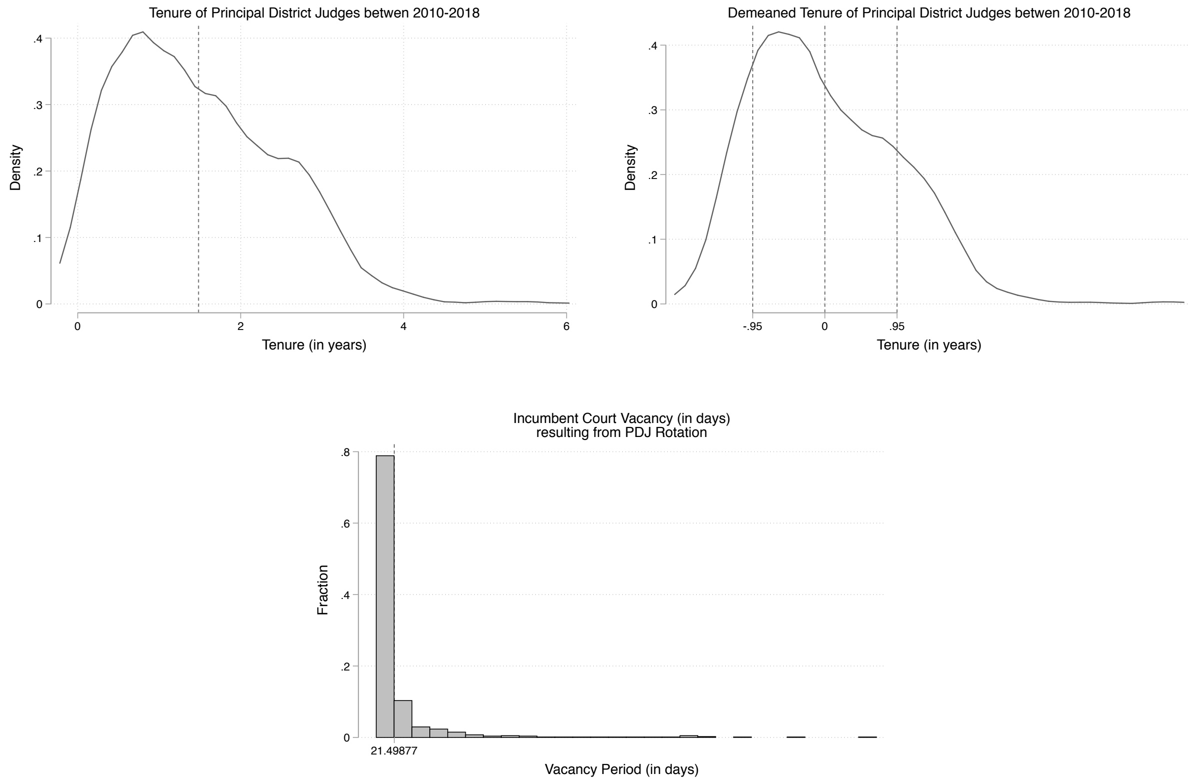
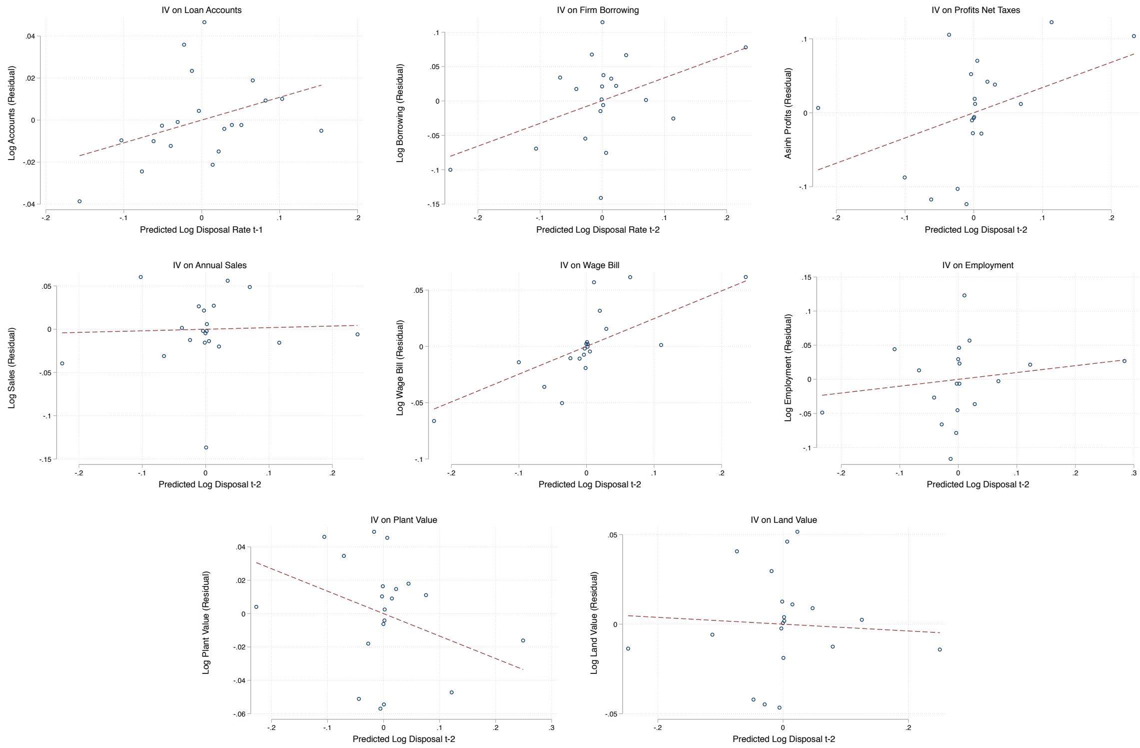


Figure A6: Judge Tenure: An Example of Principal District Judge



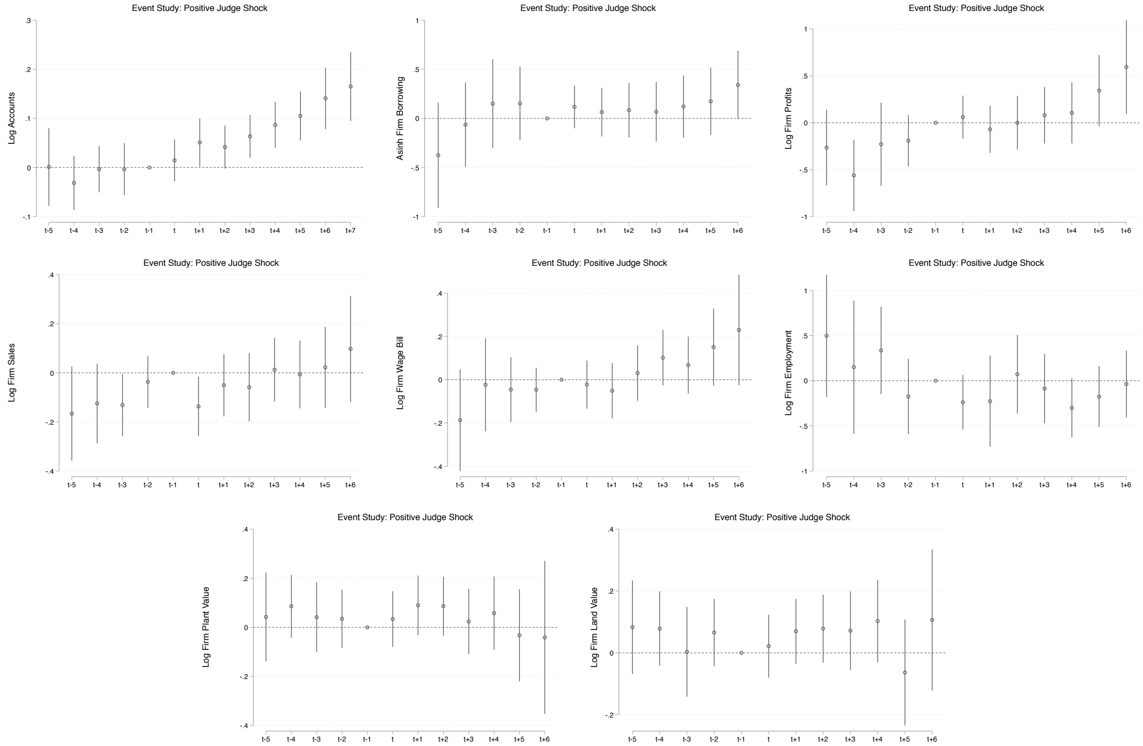

Notes: Above graphs show the distribution of turn-around and tenure of the highest position in the District and Session Court - the Principal District Judge.

## Figure A7: Visual IV Results



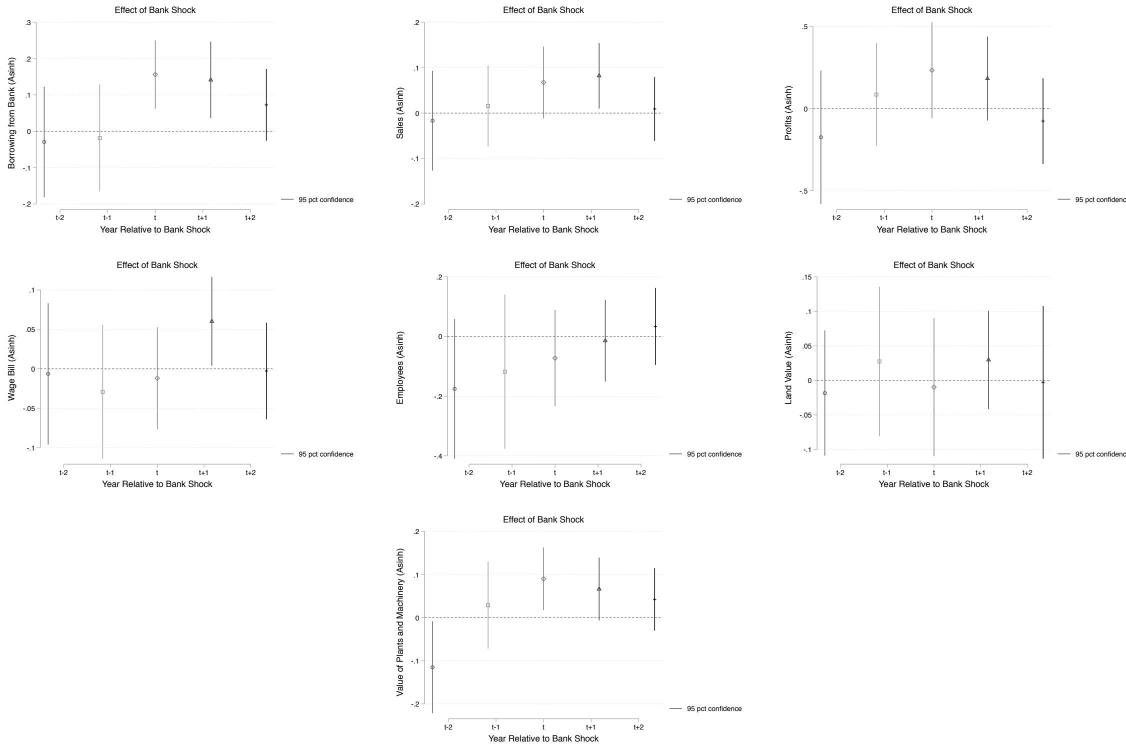

Notes: Above are binned scatters-plots depicting the relationship between various outcomes of interest and predicted log disposal rate.

Figure A8: Alternate Identification: Event Study Estimates




Notes: Above are event study estimates using the event of a positive judge shock, defined as the first occurrence of a 10% increase over previous year's judge occupancy, to identify the effects of judicial capacity on credit and firm outcomes.

Figure A9: Mediation Effects: Credit Channel




Notes: Above are estimates of mediation effect through firm borrowing. The x axis represents the time horizon of the outcome variable relative to bank shock occurring at time t. The regressions also control for judge occupancy, which is independent of bank shock, and therefore, these estimates are to be construed as the effects through the credit market channel.

# Appendix: Tables

Table A1: 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 A2: 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 A3: 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 A4: 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.

## A0.2 Appendix: Tables Testing Tenure Independence

Table A5: 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) |
| Log Judge Tenure (PDJ) | -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 A6: Independence: Past Firm Outcomes and Judge Tenure

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Log Sales (t-1) | Asinh Profit (t-1) | Log Wage Bill (t-1) | Log Plant Value (t-1) | 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 A7: 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) |
| 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 A8: 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) |
| 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 A9: Robustness Check Firm Outcomes: Clustering by State-Year

| | (2)<br>OLS | (3)<br>2SLS | (4)<br>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 A10: Robustness Check Firm Outcomes: Clustering by District

| | (2)<br>OLS | (3)<br>2SLS | (4)<br>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.

### A0.3 Tables: Firm Fixed Effects

Table A11: Court Congestion and All Firm Intermediate Outcomes: Firm Fixed Effects

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

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

Notes: The table above reports OLS, IV, and reduced form estimates on the intermediate firm level outcomes of long term borrowing and inter-firm lending. I account for firm fixed effects instead of district fixed effects to examine within firm response to changes in court congestion. The explanatory variables trail the dependent variables by 2 years. All these estimates are reported for the sample of balanced panel of firms located in the same district as the court. All standard errors are clustered at the district-year level.

Table A12: Court Congestion and All Firm Outcomes: Firm Fixed Effects

| | All Firms (Balanced Panel) | | | | | |
|---|---|---|---|---|---|---|
| | Log Revenue from Sales | Asinh Profit | Log Wage Bill | Log Employees | Log Plant Value | 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 |
| | | | Below Median Assets | | | |
| | | | OLS | | | |
| Log Disposal Rate (t-2) | -0.0312 | -0.0490 | -0.0354** | -0.111** | 0.00610 | -0.0719*** |
| | (0.0286) | (0.0958) | (0.0161) | (0.0475) | (0.0210) | (0.0216) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | -0.210 | -0.0872 | -0.0114 | -0.700 | -0.105 | -0.138 |
| | (0.142) | (0.372) | (0.0861) | (0.493) | (0.0867) | (0.126) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | -0.00309 | -0.00137 | -0.000167 | -0.00721** | -0.00159 | -0.00224 |
| | (0.00192) | (0.00597) | (0.00127) | (0.00314) | (0.00122) | (0.00207) |
| Observations | 3381 | 4627 | 4171 | 650 | 2658 | 2386 |
| 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) | 7,071.22 | 228.479 | 433.929 | 1.967 | 4,057.09 | 415.29 |
| F-Stat | | | | | | |
| Adj R-Squared | .88 | .39 | .94 | .98 | .94 | .87 |
| | | | Above Median Assets | | | |
| | | | OLS | | | |
| Log Disposal Rate (t-2) | -0.0593** | -0.00743 | 0.00382 | -0.0237 | -0.0262 | -0.00657 |
| | (0.0234) | (0.109) | (0.0116) | (0.0250) | (0.0183) | (0.0198) |
| | | | IV | | | |
| Log Disposal Rate (t-2) | -0.0816 | 0.919* | 0.0803 | -0.273* | -0.0952 | -0.190* |
| | (0.0962) | (0.518) | (0.0524) | (0.152) | (0.0853) | (0.102) |
| | | | Reduced Form | | | |
| Percent Judge Occupancy (t-2) | -0.00116 | 0.0135** | 0.00114* | -0.00448** | -0.00141 | -0.00271** |
| | (0.00134) | (0.00676) | (0.000669) | (0.00223) | (0.00116) | (0.00124) |
| Observations | 9625 | 10526 | 10110 | 3020 | 9018 | 8565 |
| 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) | 7,071.22 | 228.479 | 433.929 | 1.967 | 4,057.09 | 415.29 |
| F-Stat | | | | | | |
| Adj R-Squared | .91 | .48 | .94 | .93 | .92 | .89 |

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

Notes: The table above reports OLS, IV, and reduced form estimates on the final firm level production outcomes. I account for firm fixed effects instead of district fixed effects to examine within firm response to changes in court congestion. The explanatory variables trail the dependent variables by 2 years. All these estimates are reported by different samples of incumbent firms, incorporated before the study period. Panel A represents the estimates on the balanced panel of firms located in the same district as the court. Panel B restricts the sample to firms below median ex-ante asset size distribution. Panel C reports the estimates for firms above median ex-ante asset size distribution. All standard errors are clustered at the district-year level.