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Examining the role of Judicial Institutions in Economic Development

Author
Rao, Manaswini

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Examining the role of Judicial Institutions in Economic Development

by

Manaswini Rao

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Associate Professor Aprajit Mahajan, Chair
Professor Elisabeth Sadoulet
Professor Frederico Finan

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Abstract

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Courts are considered important in the functioning of markets, and yet, there is limited causal evidence showing this. In my dissertation, I explore the causal role of judicial institutions in facilitating economic development outcomes. In the first chapter of my dissertation, I estimate the causal effects of courts' effectiveness in backlog resolution 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 chapter. 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.

In the second chapter, I discuss the interaction between legal reforms in bankruptcy resolution and judicial capacity through the enforcement of creditor rights in trial courts on credit allocation in local markets. Poor creditor rights constrain the functioning of credit markets, that subsequently affects the availability of credit for productive uses. Can well-functioning courts facilitate the enforcement of creditor rights? How does this affect credit allocation? To study this, I use a difference in difference research design by comparing districts with high judge occupancy and those with low occupancy, before and after the 2016 national legislation on bankruptcy resolution in India that increased the rights of the creditors over stressed assets. There are three key findings. First, banks reduce lending towards unproductive uses such as lending to defaulting firms and increase lending based on capital efficiency in districts with better judicial capacity. Second, improved creditor rights coupled with better judicial capacity increases repayment. Third, banks are more likely to initiate and witness resolution of debt recovery related litigation in districts with better judicial capacity after the bankruptcy reform, suggesting that enforcement of creditor rights in well functioning trial courts plays an important complementary role. Finally, the chapter concludes by examining credit misallocation, showing that good quality formal institutions are insufficient to fully

address existing misallocation.

How does judge vacancy affect trial-level and litigant outcomes? Emerging economies like India suffer from state capacity constraints that affect economic outcomes. While insufficiency in the number of public teachers and doctors in providing human capital development services has received increasing attention in economics, capacity constraints in the judiciary has rarely been discussed. In the third chapter, I examine the role of judge vacancy on the proceedings of ongoing trials and subsequent effects on litigant outcomes in India. The system of annual judge assignment to district courts shifts the existing high level of vacancies across courts that varies orthogonally to existing trial and litigant outcomes, enabling causal identification. There are following main findings: first, the duration of trial increases when an ongoing trial experiences judge vacancy relative to other trials in the same court that do not. Second, this shock negatively affects wage bill and decreases the asset value of plaintiff firms whereas the effects are smaller and statistically indistinguishable from zero for defendant firms. Third, the large negative effect for plaintiff firms is likely to occur due to increase in the number of dismissals resulting from vacancy. Given that smaller firms are more likely to use the formal judicial system as a plaintiff in the case of transactional disputes relative to larger firms, weaker judicial capacity disproportionately affects them leading to equity concerns.

Through these chapters, I show that judicial institutions play an important role in an economy. My approach to answering these macro questions involves using disaggregated and rich administrative data that enable me to shed light on the underlying mechanisms linking institutional quality and economic outcomes.

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Chapter 1

Introduction

In this dissertation, I examine the role and importance of judicial institutions - primarily of ordinary trial courts - in shaping economic development outcomes in the context of an emerging economy. Courts resolve disputes arising out of violation of contracts and infringement of rights, which are essential to the development of formal financial sector and subsequently in increasing investment and economic growth. Lags in timely resolution can introduce uncertainty and transaction costs, that weaken not just the immediate outcomes of the litigators but also have potential ramifications for the functioning of the entire economy. The first chapter examines the effect of backlog resolution in trial litigations in local district courts on local economic outcomes, measured in terms of economic production by formal sector firms. In doing so, I demonstrate the importance of ex-post contract enforcement in debt recovery process for commercial banks. I use disaggregated administrative data on the universe of trials in 195 district courts to construct measures of court-level backlog resolution as well as identify exogenous factors that determine the rate of backlog resolution, using instrumental variables design for causal inference. By matching the court-level data with annual balance sheet data of a sample of formal sector firms registered within the courts' jurisdiction, I show large market-level effects on firms' production outcomes, which are mainly driven by an increased access to bank credit.

Why do banks lend more to firms when courts function better? How does this interact with the strength of creditor rights? High judge occupancy in a district court determines the ability to resolve litigation in a timely manner relative to a context when the court experiences a large number of judge vacancies. However, the effects of well-functioning courts are likely limited when the creditors do not have rights over capital lent, particularly during corporate bankruptcies. On the other hand, in a context where creditors have clear rights over their stressed assets, well-functioning courts are important to enforce the rights in a timely manner to enable recovery through either liquidation or restructuring. In my second chapter, I examine the interaction between the strength of creditor rights, when it comes to recovering unpaid debt, and the judicial capacity of local trial courts. I use a difference in difference research design by comparing districts with high judge occupancy and those with low occupancy, before and after the 2016 national legislation on bankruptcy resolution in India that increased the rights of the creditors over stressed assets. This chapter sheds light on the complementary role played by policies and institutions in reducing potential misallocation in credit markets.

Judicial capacity is an important component of overall state capacity, which has been argued as crucial for economic development. However, not much is known about how the judiciary functions in any context, let alone in the context of a developing economy. In the third and final chapter, I demonstrate the immediate effects of judicial capacity on the welfare outcomes of litigants engaged in ongoing trials. By using a combination of existing under-capacity in Indian courts and the system of frequent judge reassignments, I show that a random subset of trials witness judge vacancy in their lifetimes. Specifically, I compare such trials that encounter a vacancy to those in the same court that do not. Subsequently, I identify the reduced form effects of judge vacancy on the subset of litigants for whom I was able to obtain annual balance-sheet and production data.

Through this dissertation, I provide empirical evidence on the importance of legal and judicial institutions for firm growth both directly through the process of litigation as well as indirectly by facilitating the functioning of local credit markets. The first chapter presents the causal effects of courts as an institution on firm growth through increased credit availability. The second chapter shows that both policies establishing creditor rights and well functioning courts are important for banks in increasing the efficiency of their lending. Finally, the third chapter demonstrates that judicial capacity constraints, measured in terms of judge vacancy, increase the duration of trials that negatively impact litigants' asset value and production decisions.

Chapter 2

Judges, Lenders, and the Bottom Line: Court-ing Firm Growth in India[1]

2.1 Introduction

Enforcement of contracts and property rights have strong implications for the development of formal financial sector, investment, and growth (Coase 1960; Glaeser, Johnson, and Shleifer 2001; Johnson, McMillan, and Woodruff 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, 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.

[1]I am indebted to my advisors Aprajit Mahajan, Elisabeth Sadoulet, Frederico Finan, and mentors Emily Breza and Arun Chandrasekhar for their constant guidance and feedback through this project. I thank Michael Anderson, Abhay Aneja, Sam Asher, Johannes Boehm, Benjamin Bushong, Alain de Janvry, Kwabena Donkor, Ben Faber, Marco Gonzalez-Navarro, Sean Higgins, Andrew Hultgren, Larry Karp, Supreet Kaur, Erin Kelley, Ben Krause, Greg Lane, Megan Lang, Ethan Ligon, John Loeser, Jeremy Magruder, Ted Miguel, Yusuf Neggers, Matthew Pecenco, Jeffery Perloff, Jim Sallee, Bilal Siddiqi, Vaishnavi Surendra, David Zilberman, Shaoda Wang, and all participants at Development Workshop and Dev Lunch at U C Berkeley. A huge shout-out to Kishore Mandyam, Harish Narasappa, Surya Prakash, and members at DAKSH for help with court data extraction and insightful discussions. Special thanks to former members of the Indian judicial system as well as S.K. Devanath, Suhrid Karthik, Vinay Venkateswaran, and Madhav Thattai who helped me understand the context better. I acknowledge the generous funding support from International Growth Centre (IGC), State Effectiveness Initiative and UC Berkeley Library for acquiring the Prowess database. All errors are my own.

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.[2]

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 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 Lilienfeld-Toal, Mookherjee, and Visaria (2012).[3] 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

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[2]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 2.1 and Figure 2.2 show the problem of lengthy trial duration in India and the negative association between per capita GDP and trial duration.

[3]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.

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.[4] 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 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 -

[4]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.

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.[5]

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 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.

[5]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.

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.[6]

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 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, 2009b, 2012), lending behavior (Visaria 2009; Ponticelli and Alencar 2016), and firms (Lilienfeld-Toal, Mookherjee, and Visaria 2012; Ahsan 2013; Ponticelli and Alencar 2016; Amirapu 2017; Boehm and Oberfield 2018; 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.

2.2 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

[6] 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 of 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.

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 2.1 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 2.2). 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.

2.2.1 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.[7] 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 A.1 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 A.2 in the appendix provides the details on the distribution of

[7]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.

firm types across sample and excluded districts. Appendix Figure A.2 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.[8]

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 "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.[9] Since all these measures, except duration, are highly correlated with disposal rate as shown in Appendix Table A.4, 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

[8]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.

[9]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.

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 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.[10]

Summary Stats: Panel A of Table 2.1 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.

2.2.2 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

[10]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.

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 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).

2.2.3 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.[11]

2.2.4 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 A.4 describes the firm sample construction process in detail.

[11] 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.

Summary Stats: Table 2.1 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 credit outcomes, annual total long term (repayment > 1 year) borrowing from banks average at INR 1866 million (≈ 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 (≈ USD 6 billion). Finally, the average lending by non-banking lenders called the non-banking finance companies (NBFC) is INR 8.3 billion (≈ USD 120 million).[12]

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 A.4 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.[13]

2.2.5 A Descriptive Analysis of Litigation Behavior

Table 2.2 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.

[12]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 headcount. 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.

[13]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.

Panels in Figure 2.3 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 suit. NBFCs, also lenders, are also more likely to initiate litigation (over 60 percent) conditional on litigation choice. The bottom panel in Figure 2.3 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.

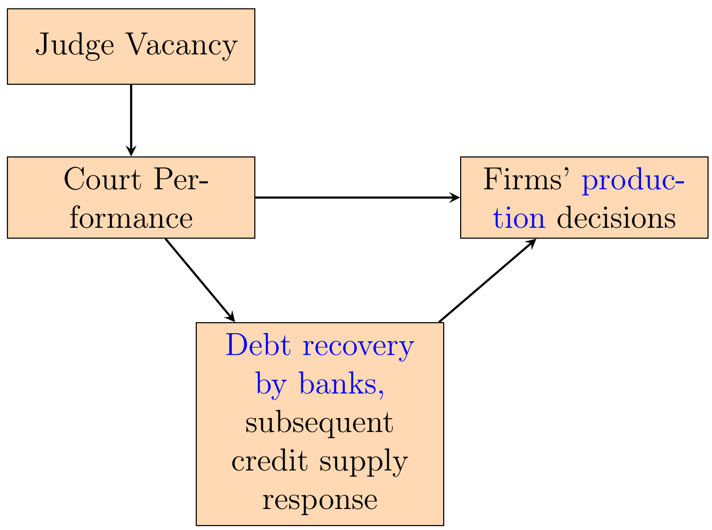
2. They use the district court systems for all manners of civil suits, especially those involving credit defaults and other types contract breaches (dishonoring of cheques under the Negotiable Instruments Act).

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.

2.3 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.



2.3.1 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 ηK in the process, with remaining payoff at $f(K) - \eta K$. The lender loses the entire principal, $-K_B$. Repayment results in $f(K) - RK_B$ as payoff to the borrower and the lender earns RK_B. On the other hand, the borrower automatically defaults under failure, in which case the lender chooses to litigate or not to monetize borrower's assets to recover their loan. The game is depicted in Figure 2.5. Under default, the lender can choose to litigate, incurring a cost $C_L(\gamma) > 0, \frac{\partial C_L}{\partial \gamma} < 0$, where γ is 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. [14]

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

$$\Gamma\delta W - E[C_B(\gamma)] \geq -\delta W \implies W \geq \frac{E[C_B(\gamma)]}{(1-\Gamma)\delta} = \tilde{W} \tag{2.1}$$

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

$$(1 - F(\tilde{W}))(\Gamma\delta W - C_L(\gamma)) + F(\tilde{W})\delta W \geq -K_B \implies W \geq \frac{(1 - F(\tilde{W}))C_L(\gamma) - K_B}{((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta} = W^* \tag{2.2}$$

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

$$f(K) - \Gamma RK_B - E[C_B(\gamma)] \geq f(K) - RK_B \implies RK_B \geq \frac{E[C_B(\gamma)]}{(1-\Gamma)} = \delta\tilde{W} \tag{2.3}$$

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

$$(1 - G(\tilde{W}))(\Gamma RK_B - C_L(\gamma)) + G(\tilde{W})RK_B \geq -K_B \implies R \geq \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} \tag{2.4}$$

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

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:

$$R = \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} \tag{2.5}$$

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

$$\begin{aligned} s\Big(G(\tilde{W})RK_B + (1 - G(\tilde{W}))(\Gamma RK_B - C_L(\gamma))\Big) + \\ (1 - s)\Big((1 - F(\tilde{W}))(\Gamma\delta W - C_L(\gamma)) + F(\tilde{W})\delta W\Big) \geq \phi K_B \end{aligned} \tag{2.6}$$

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 2.5.

- 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 η is fraction of capital used to evade.
- T3a The borrower then decides to accept and litigate, or settle. If they litigate, then the lender almost certainly wins (or has a relatively high probability of winning) but incurs a cost $C_L(\gamma)$. Borrower also incurs litigation costs, that is unknown ex-ante. The payoff in this situation is $(\Gamma RK_B - C_L(\gamma), f(K) - \Gamma RK_B - E[C_B(\gamma)])$. If lender chooses to settle, the payoffs are $(-K_B(W), f(K) - RK_B)$.
- T1b If the project fails, the borrower automatically defaults.

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

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

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

Proposition 1: Litigation Response of Borrowers As the inverse court congestion, γ, 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 2.6.

Proposition 2: Credit Market Response to Court Congestion As the inverse court congestion, γ, 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.

2.3.2 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:

$$\text{Max}_{X_1,X_2}(\Pi = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - \phi m_i(\gamma)) \tag{2.7}$$

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

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

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

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

Proof: See Appendix.

2.3.3 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.

2.4 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:

$$Y_{fdt+k} = \phi_d + \phi_{st} + \theta D_{dt} + \mathbf{X'}_f \Delta + \epsilon_{fdt+k} \;; k \geq 0 \tag{2.8}$$

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 ϵ_{fdt+k} is the idiosyncratic error. I account for all time-varying unobserved factors at the state level by including state-year fixed effects, ϕ_{st}, and time-invariant district unobserved characteristics by including district fixed effects, ϕ_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:

$$D_{dt} = \gamma_d + \gamma_{st} + \psi Occup_{dt} + \mathbf{X'}_f \Pi + \nu_{fdt+k} \tag{2.9}$$

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, Duflo, and Mullainathan 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 $\Omega = 0$.

$$District\ Char_{dt-k} = \nu_d + \nu_{st} + \rho Occup_{dt} + \eta_{dt-k};\ k > 0 \tag{2.10}$$

$$Y_{fdt-k} = \kappa_d + \kappa_{st} + \Omega Occup_{dt} + \mathbf{X'}_f \Gamma + \epsilon_{fdt-k};\ k > 0 \tag{2.11}$$

   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.

$$Occup_{dt} = \nu'_d + \nu'_{st} + \rho' D_{dt-k} + \eta'_{dt};\ k > 0 \tag{2.12}$$

$$\Delta Occup_{dt} = \kappa'_d + \kappa'_{st} + \Omega' \Delta D_{dt-k} + \epsilon'_{dt};\ k > 0 \tag{2.13}$$

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 2.3, Columns 1-2). Further, I also find that judge occupancy is uncorrelated with prior period firm outcomes (Table 2.3, 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 2.4 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 2.7 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 A.6, top panel) and that the system of rotation leads to "gap days" before the successor judge takes charge (Figure A.6, 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 A.5 and Table A.6 in the appendix show this result.

2. **First Stage and Monotonicity:** Figure 2.8 and Table 2.5 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 2.5 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.[15] 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 2.6). These patterns suggest that the monotonicity assumption likely holds. The interpretation of the 2SLS estimates as LATE implies that the estimated effects are applicable only for the "treatment compliers" in the sample. That is, judge occupancy has an effect on courts as an institution and subsequently on firm growth in district-years where court 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 2.6 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.

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

2.5 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

$$Y_{dt+s} = \delta_d + \delta_{st} + \delta_c + \beta D_{dt} + \upsilon_{dt};\ \ s \geq 0 \tag{2.14}$$

$$D_{dt} = \alpha_d + \alpha_{st} + \alpha_c + \lambda Occup_{dt} + \xi_{dt} \tag{2.15}$$

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.[16]

Panel A of Table 2.7 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

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

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 2.7 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 2.8 shows the results on loan account and outstanding loan for public sector banks by district-year. The IV estimates indicate that the loan accounts 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 2.9 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.

2.6 Effects on Respondent Firms

2.6.1 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 2.10 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 2.10 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.

2.6.2 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 2.11 presents the first stage for this sample, which is of similar sign and relative magnitude.

Columns 1-3 of Table 2.11 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.

2.7 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 2.11 and Column 1, Panel A of Table 2.12 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 2.12) as well as after weighting the regression by the number of incumbent firms per district (Column 1, Panel C Table 2.12).

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 2.12 and Figure 2.12. 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 2.12, 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 2.13 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 2.13). 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 [17]. Figure 2.14 and Panel A Columns 3-6 Table 2.14 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 ≈ 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 2.14). 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 2.14 reveals a positive and significant coefficient on the value of plant and machinery as well as weakly on land.

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

Firm Sales Revenue and Profits: The IV estimates on firms' sales revenue as shown in the left panel of Figure 2.13 is positive and significant. Panel A Column 1 of Table 2.14 presents OLS, IV, and the reduced form estimates for sales revenue using lagged court variables. The elasticity suggests that the sales increases by 0.1 percent for 1 percent increase in disposal rate. This remains stable across specifications using balanced panel of firms with and without weights (Column 1, Panel B and Panel C of Table 2.14) but is imprecisely estimated.

The panel on the right in Figure 2.13 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 2.14). 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 2.14.

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 2.11 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 2.15. 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 2.16 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 2.16 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 A.7 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.

2.7.1 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.

$$Y_{fdt} = \rho_d + \rho_{st} + \sum_{k=-5}^{k=5} \gamma_k \mathbb{1}\{t \geq k\} + \zeta_{fdt} \tag{2.16}$$

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 A.8 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.

2.7.2 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:

$$Y_{fdt+k} = \psi_d + \psi_{st} + \omega_1 Brw_{fdt+k} + \omega_2 Occup_{dt} + \mathbf{X'}_f \Gamma_1 + \epsilon_{fdt+k} \;;k \geq 0 \tag{2.17}$$
$$Brw_{fdt+k} = \alpha_d + \alpha_{st} + \beta_1 Bank\ Shock_{dt+j} + \beta_2 Occup_{dt} + \mathbf{X'}_f \Gamma_2 + \mu_{fdt+k} \;;k \geq j \geq 0 \tag{2.18}$$

The idea behind ACME estimation is to establish the causal chain flowing through the credit channel. Coefficient ω_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 Brw_{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 2.17 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 A.9 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.

2.7.3 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.[18] In the context of this study, this estimate is slightly higher at 0.385. The effect on

[18]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.

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.

2.8 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 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 Survey, 2017 An Introduction* (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.

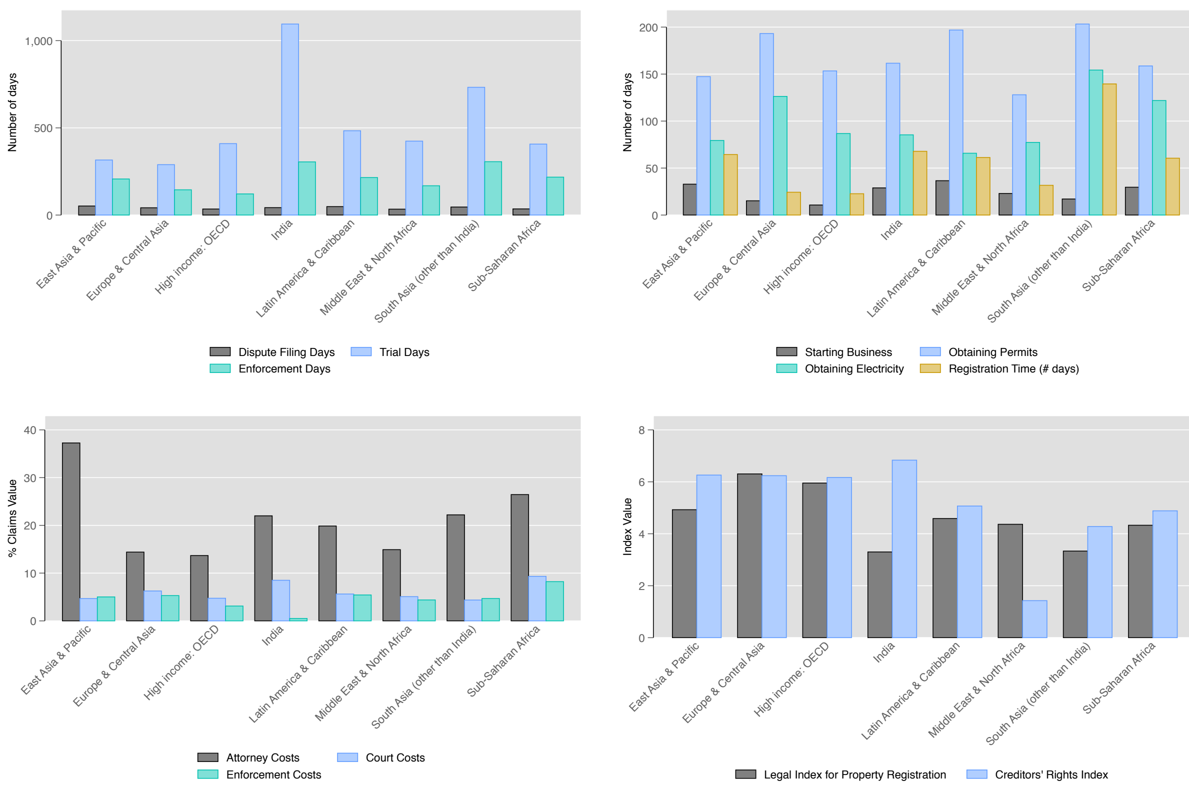
Further, I show the importance of court performance for the functioning of formal credit markets, highlighting the channel of contract enforcement. The mediation analysis helps isolate the credit channel from other mechanisms to establish the relative importance of contract enforcement in credit markets 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.

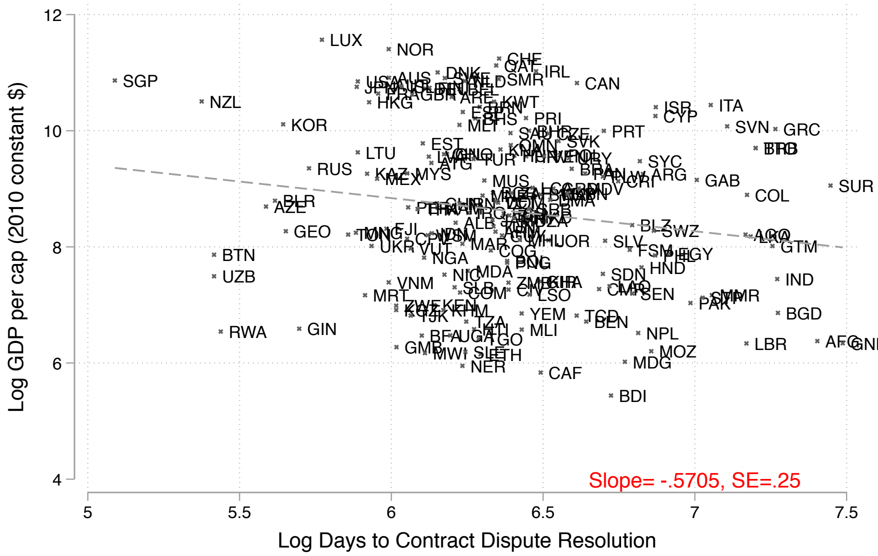
2.9 Figures

Figure 2.1: World Bank Doing Business Survey Database



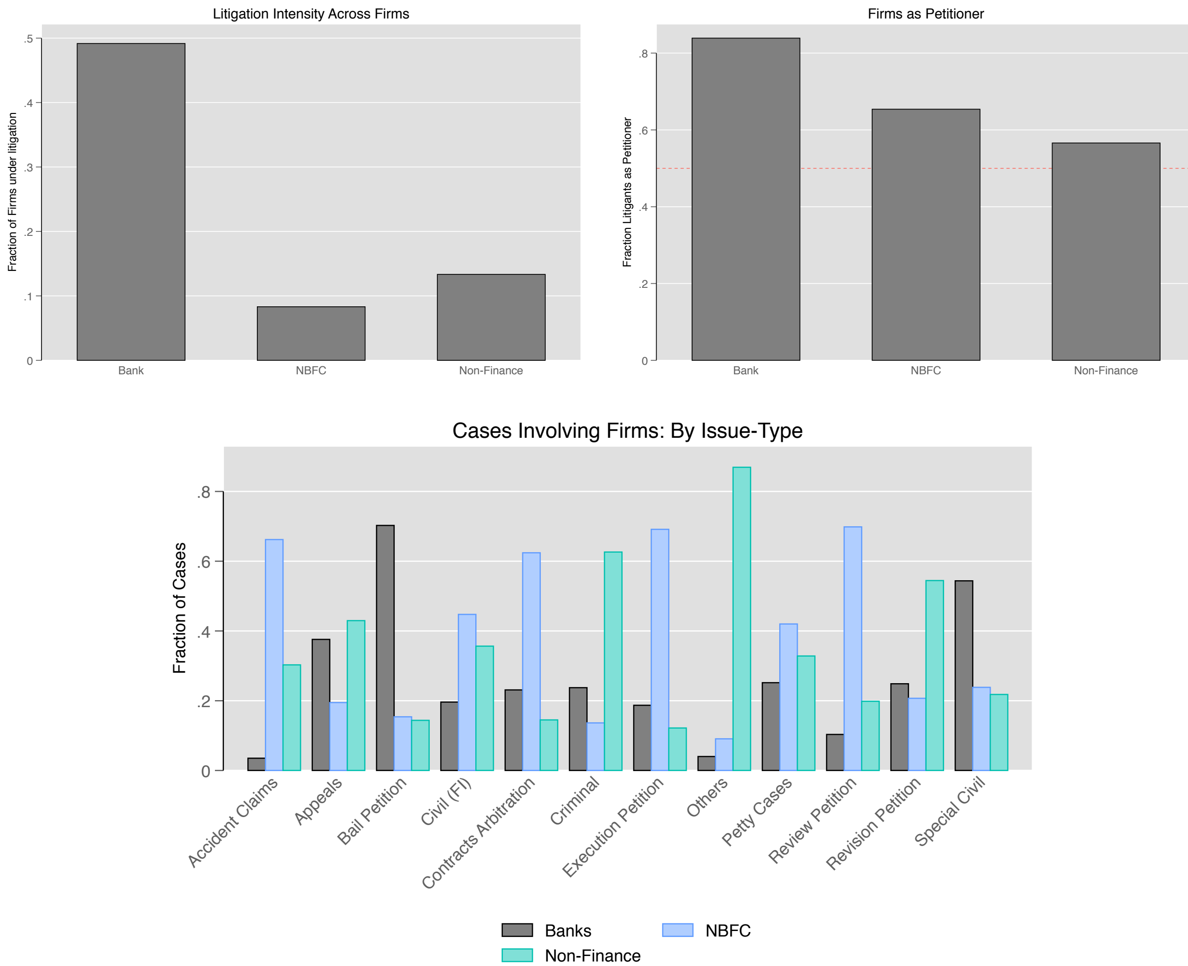
Notes: Data source: Doing Business database, World Bank. All contract enforcement variables are calculated from the perspective of the court of first instance. Figure on the top-left graphs time delays in filing, adjudication, and judgement enforcement concerning contractual disputes. Top-right figure 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 2.2: GDP per capita and Contract Enforcement



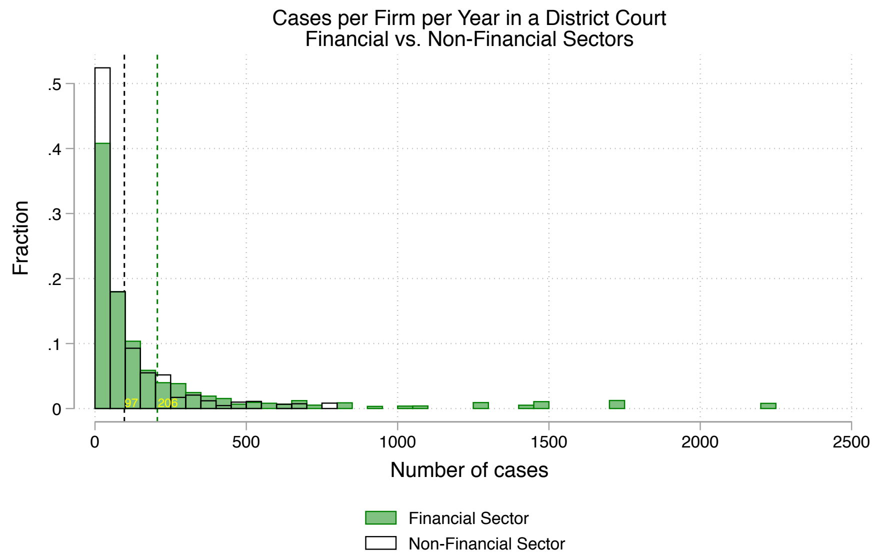
Notes: Data source: Doing Business and WDI databases, World Bank. Variable on the x-axis measures the log transformation of trial duration. Variable on the y-axis measures the log transformation of GDP per capita. Country codes are presented as value labels of the scatter plot.

Figure 2.3: 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 2.4: 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 2.5: Model: Lender-Borrower Game

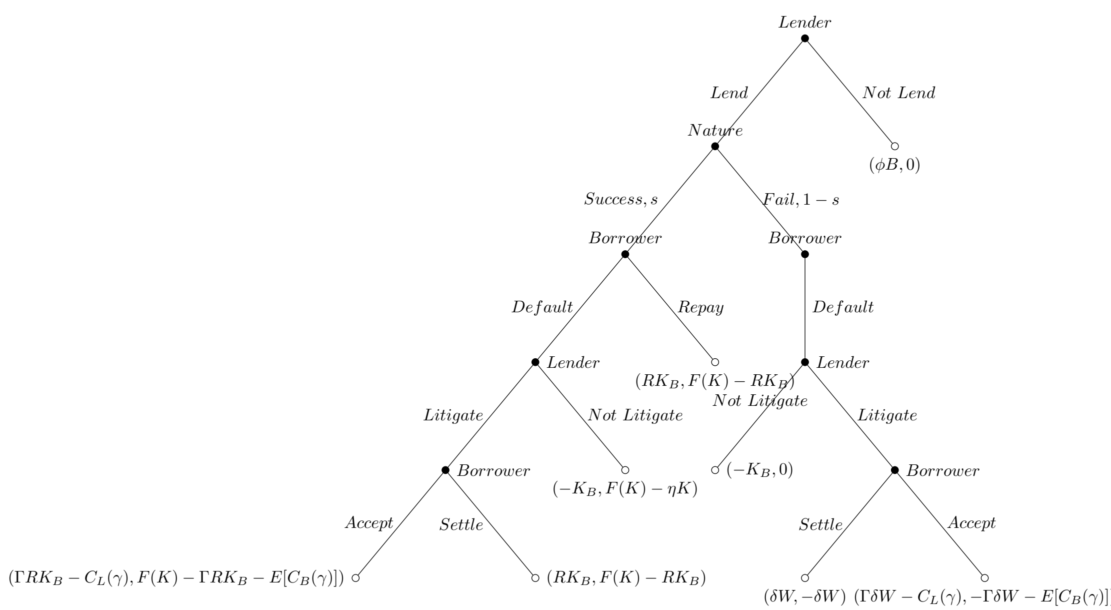


Figure 2.6: Model: Credit Contract

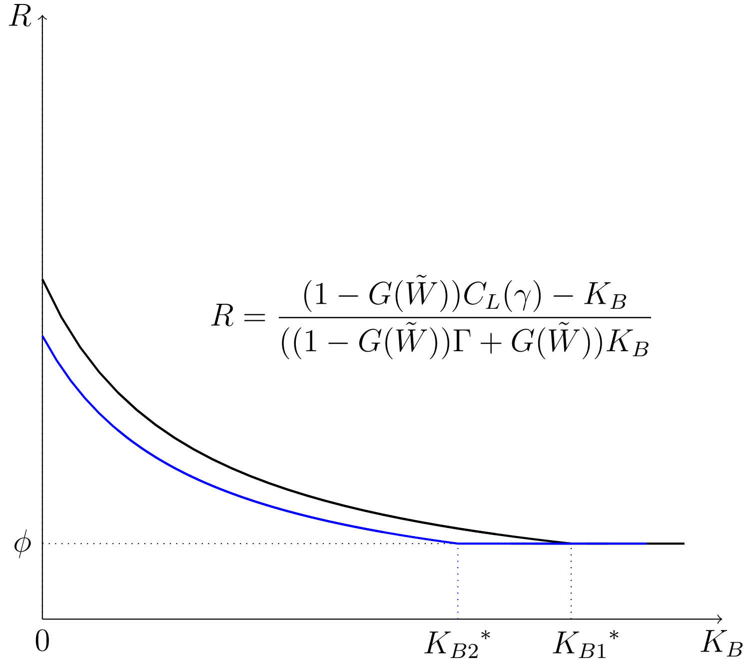
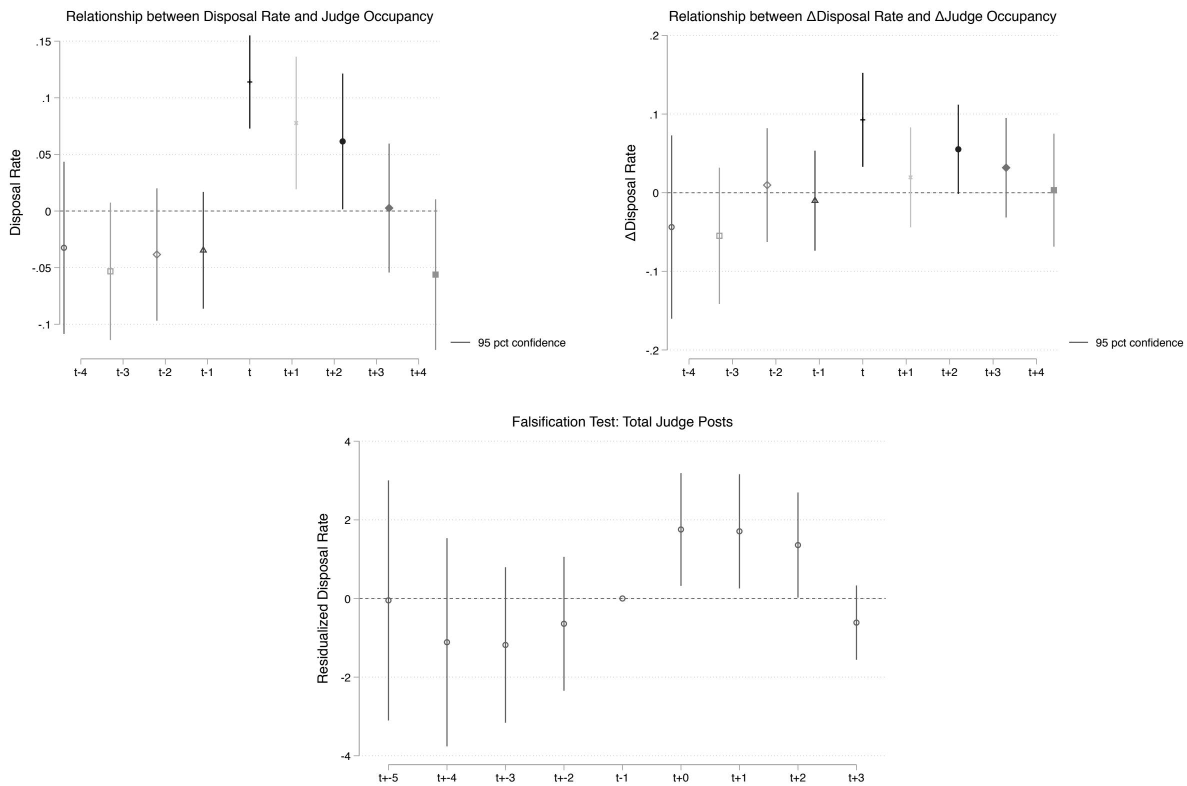
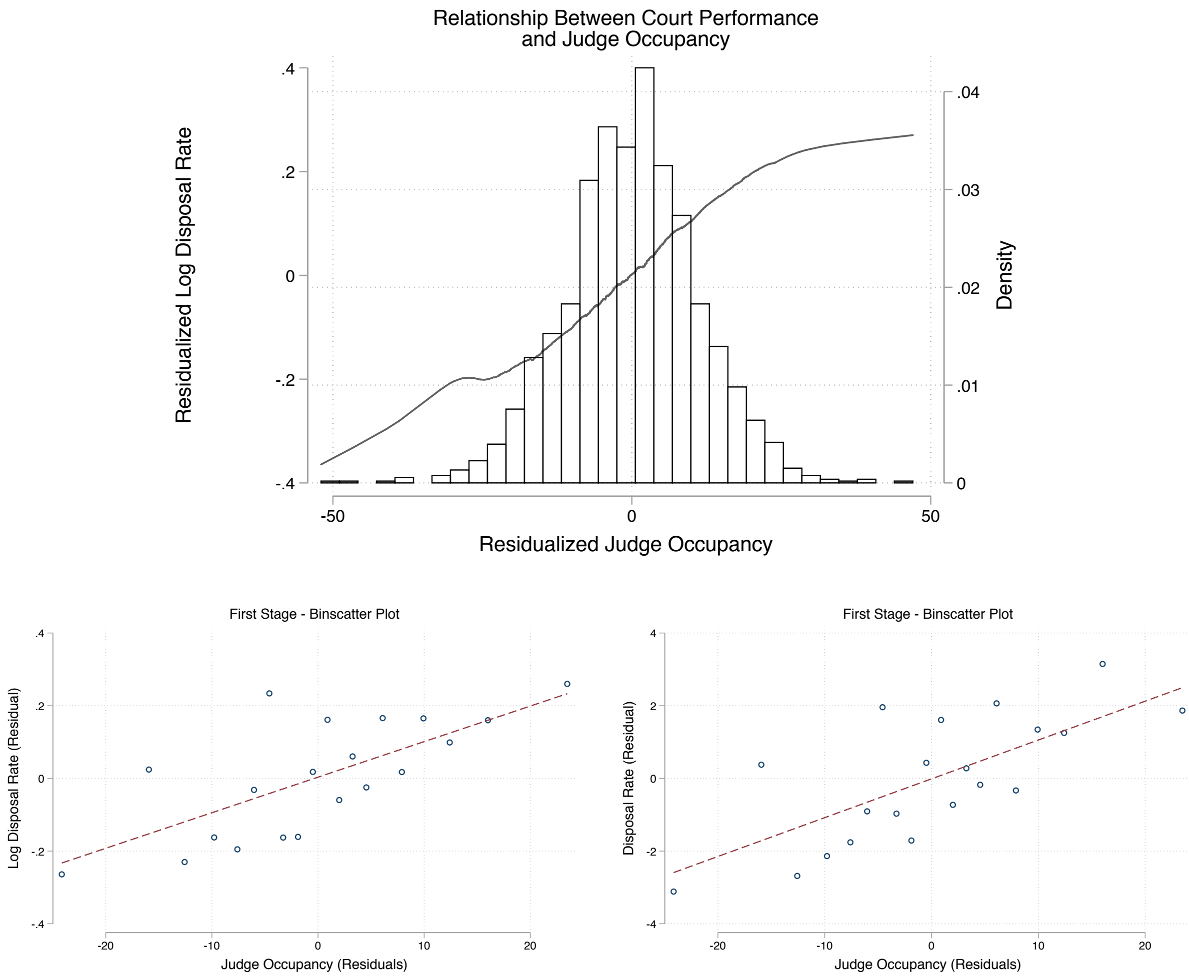


Figure 2.7: Exogeneity of Judge Occupancy With Respect to Past Court Congestion



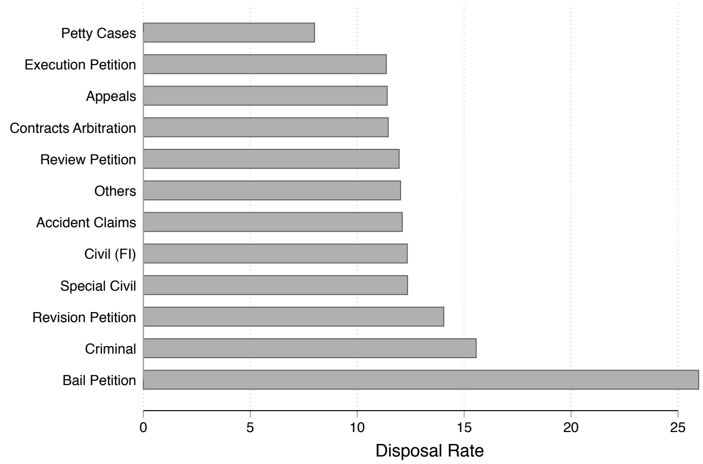
Notes: The figures on the top panel plot the relationship between both levels and changes in judge occupancy at time t with respect to levels and changes in disposal rate, respectively, residualized of all fixed effects. The graph in the bottom panel plots time coefficients of an event study design around 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.

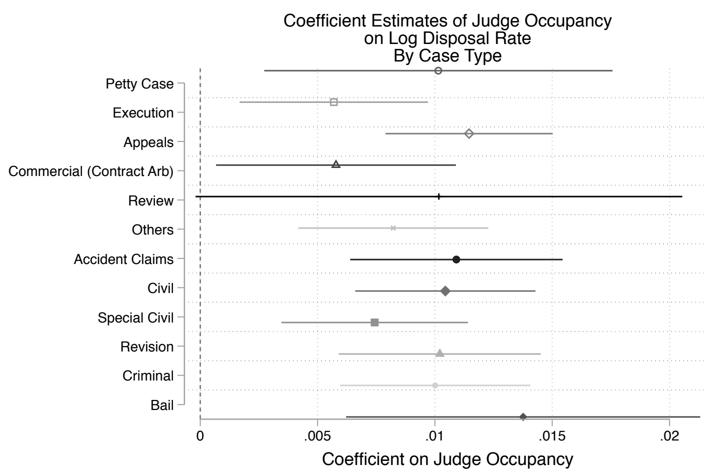
Figure 2.8: Court Performance and Judge Occupancy: First Stage



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.

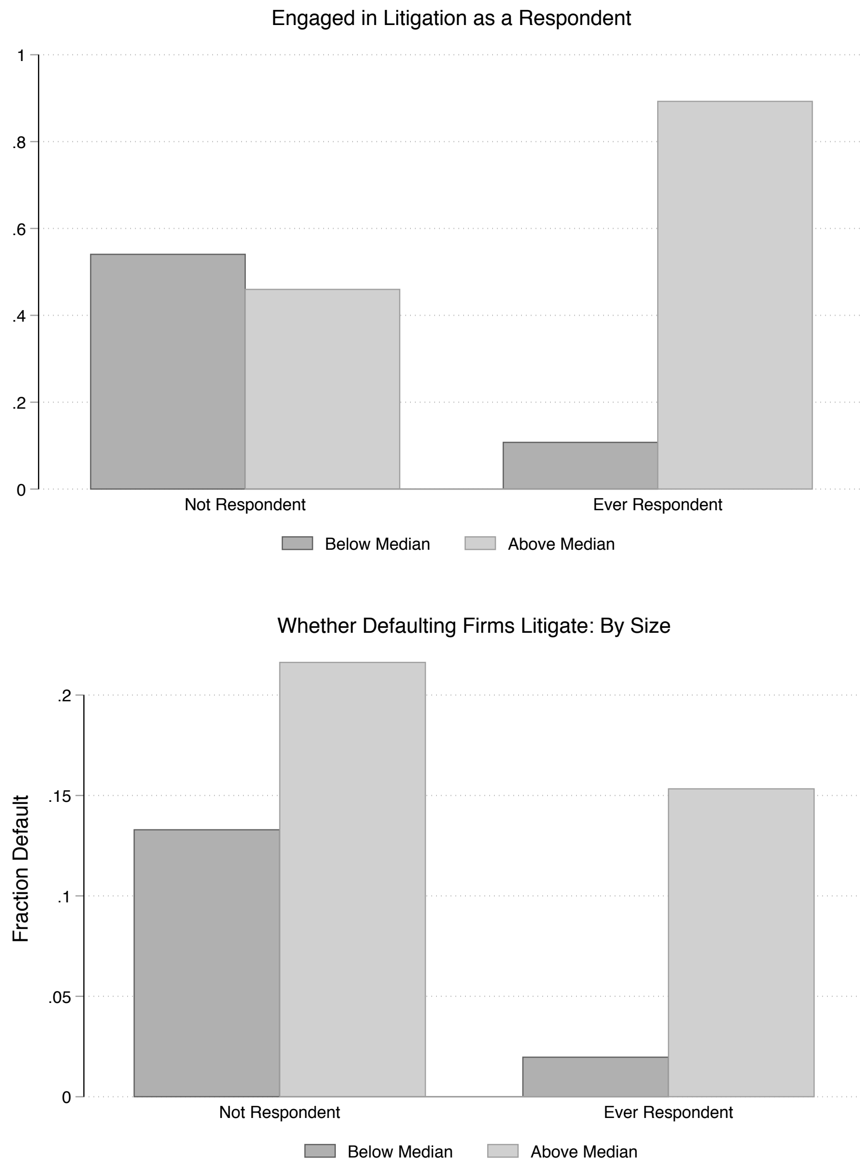
Figure 2.9: Court Performance and Judge Occupancy: Estimates Across Case-Types





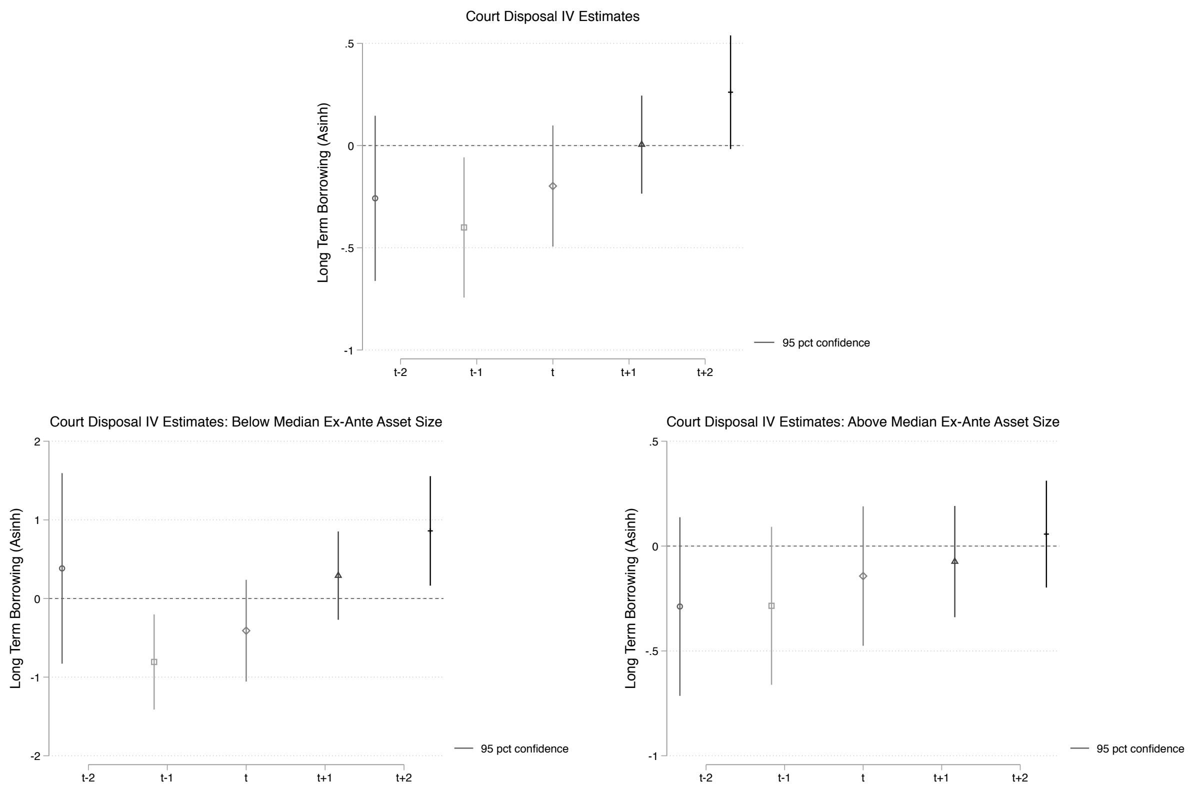
Notes: Top graph presents average disposal rate by broad case-type buckets. Bottom graph presents the first stage estimates by each of these buckets. I coded many specific case-types - there were over 2000 unique issues under conflict - that I binned into above mentioned buckets based on related nature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

Figure 2.10: Firm as Respondent By Asset Size Distribution and Defaulting Status



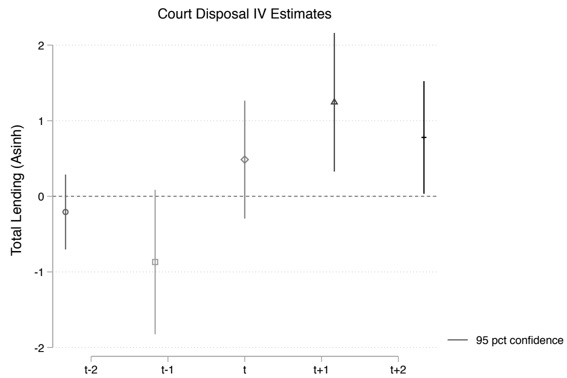
Notes: “Ever Respondent” is a binary variable, coded as 1 if a firm in the Prowess data has ever appeared as a respondent in the court sample during the study period. The figure in the bottom panel depicts litigation rate among defaulting firms by asset size. Firms are classified as defaulters based 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 2.11: Effects on Firm's Borrowing from Banks



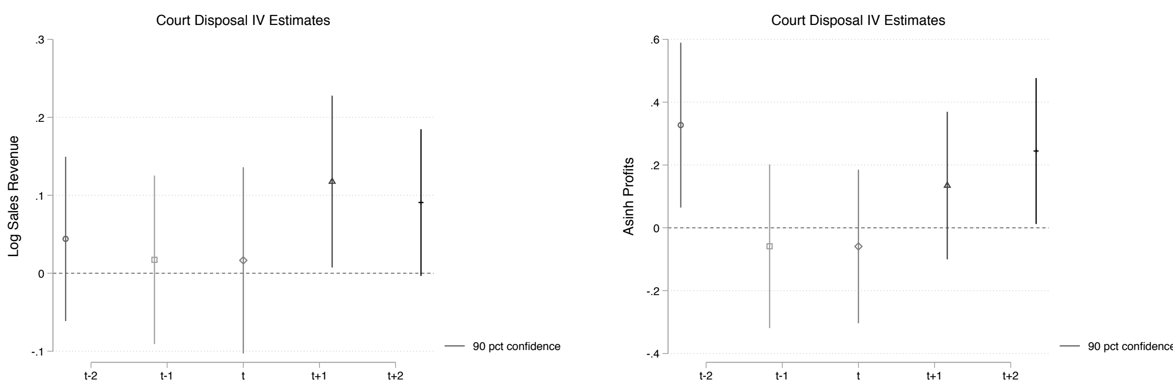
Notes: The graphs above plot the IV coefficients from regressing lags and leads of the long term borrowing from banks on disposal rate, respectively. The bottom panel presents heterogeneity by ex-ante asset size distribution. All standard errors are clustered by district-year.

Figure 2.12: Lending by Firms Located in Court Jurisdiction



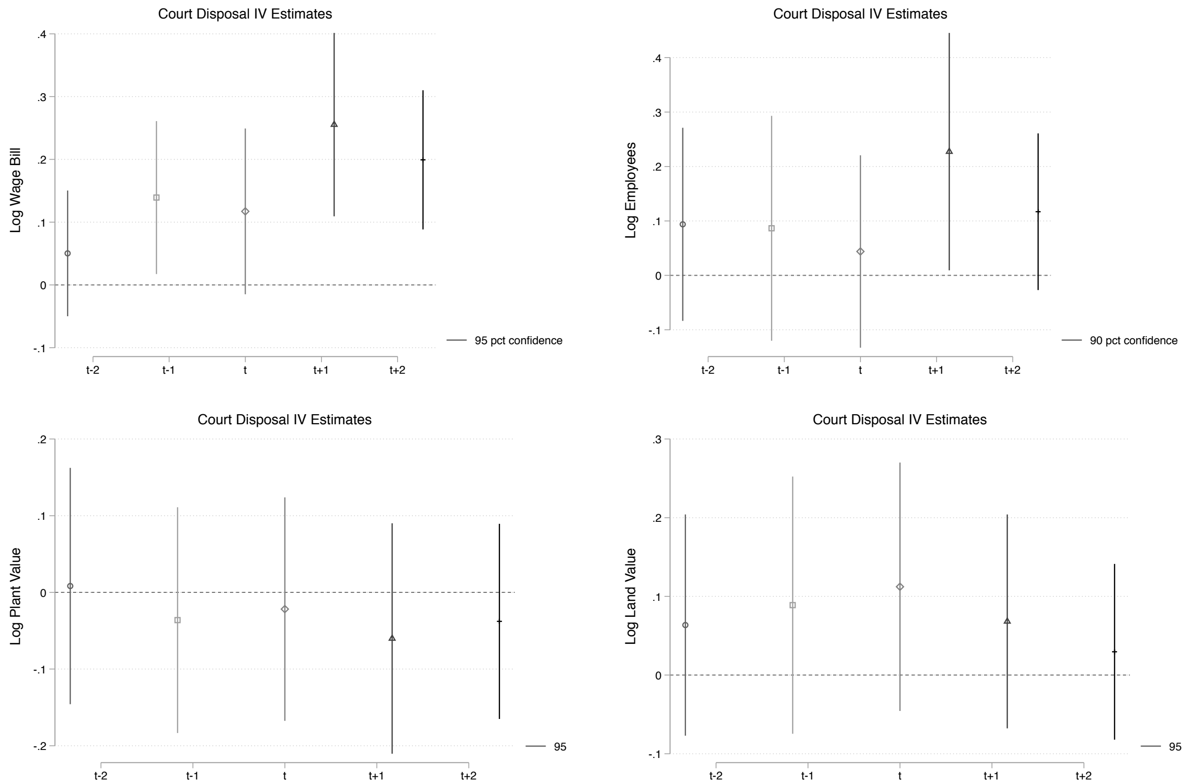
Notes: The graphs above plot the IV coefficients from regressing lags and leads of lending by firms on disposal rate. The sample firms engaged in lending are those with registered offices in the same district as the corresponding court. All standard errors are clustered by district-year.

Figure 2.13: 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 2.14: 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.

2.10 Tables

Table 2.1: 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 2.2: 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 2.3: Balance on district and firm time-varying characteristics

	(1) Percent Judge Occupancy	(2) Percent Judge Occupancy	(3) Percent Judge Occupancy	(4) 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 2.4: Exogeneity of Judge Occupancy: By Levels and Changes in Congestion

	(1) Percent Judge Occupancy	(2) Δ Judge Occp
Disposal Rate (t-1)	-0.0146 (0.0410)	
Disposal Rate (t-2)	-0.0444 (0.0392)	
Δ Disposal Rate (t-1)		-0.0148 (0.0443)
Δ 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 2.5: 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 2.6: 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.

2.10.1 Tables: Litigating Firms

Table 2.7: 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 2.8: 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 2.9: Banks' Loan Behavior: Sectoral Allocation

	(1) OLS	(2) IV	(3) 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 2.10: 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 2.11: 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.

2.10.2 Tables: All Firms

Table 2.12: Court Congestion and Firm Borrowing/Lending

	Panel A: Unbalanced	
	Asinh Long Term Borrowing	Total Lending
	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 2.13: 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 2.14: 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 2.15: Heterogeneous Effects of Court Congestion on the Extensive Margin of Borrowing

	(1) Borrow Dummy Below Median (OLS)	(2) Borrow Dummy Above Median (OLS)	(3) Borrow Dummy Below Median (IV)	(4) Borrow Dummy Above Median (IV)	(5) Borrow Dummy Below Median (RF)	(6) Borrow Dummy 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 2.16: Hetergeneous Effects of Court Congestion: By Asset Size

	(1)	(2)	(3)	(4)	(5)	(6)
	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)
			Panel A: Below Median			
			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 2.17: 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: Column 1 shows that the bank shock is uncorrelated with past period judge occupancy. Column 2 presents the first stage estimates of the two independent variables - judge occupancy and bank shock - on bank borrowing. Columns 3-8 show the IV estimates of bank borrowing on various firm outcomes, where bank borrowing is instrumented with bank shock. Significant coefficient on borrowing indicates that borrowing is a significant channel through which judicial institutions affect firm production outcomes.

Chapter 3

Institutional Factors of Credit Allocation: Examining the Role of Judicial Capacity and Bankruptcy Reforms[1]

3.1 Introduction

Economists have been interested in the role of institutions in explaining the current differences in economic growth and other development outcomes (La Porta et al. 1998; Djankov, Mcliesh, and Shleifer 2007). A recurrent theme of analysis in development economics has been the role of misallocation of resources arising out of statutory provisions and regulations in driving the differences in economic outcomes across countries (Restuccia and Rogerson 2017). On the other hand, there is limited evidence on the interplay between institutions such as the judiciary and distortions generated by statutes and policies, and other factors generating misallocation of factors of production. In this paper, I address three key questions contributing to the literature on macro development and growth. First, do statutes or laws either strengthen or weaken the incentives in factor markets? Second, do well-functioning courts play a role in enforcing such statutes? Third, how do these two contribute to misallocation of credit in formal financial markets?

Statutes such as bankruptcy code protect the rights of creditors and other stakeholders over their ownership of capital and other factors of production provided by them. The strength of such rights determine the nature of production across countries, including the ownership structure of firms (La Porta et al. 1998). This also generates frictions in the financial market

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limiting access to credit for productive uses by firms and individuals (Djankov, Mcliesh, and Shleifer 2007).

Merely the presence of statutes defining clear rights of ownership isn't sufficient. It requires a strong enforcement mechanism through well functioning judicial system. An institutional regime that combines protection of rights through necessary statutes and regulation along with strong enforcement mechanism through effective judicial capacity is considered optimal for economic progress (Glaeser and Shleifer 2003). Such complementary institutions are important to provide full effect to the rights envisaged by statutes, for example, in the case of bankruptcy reform in Brazil (Ponticelli and Alencar 2016). This is particularly important for financial sector, which not only requires a clear definition and protection of creditor rights but also swift enforcement of credit contracts. Other factors such as corporate governance structure of financial institutions, personnel incentives of bank officials, and market structure including state policies on credit allocation also play a critical role in the potential misallocation of credit. These could also interfere with the potency of the above two institutional factors in reducing misallocation and expansion of financial markets.

To study the role of institutions on credit allocation and aggregate credit supply and repayment rates, I exploit cross-sectional variation in judicial capacity in 195 district courts in India and a one time bankruptcy reform in 2016 using a difference in difference research design. The bankruptcy reform strengthened creditor rights by prioritizing payments to financial creditors during restructuring or liquidation process which was hitherto in favor of the borrowers. I measure judicial capacity as the average judge occupancy in district courts in years prior to the reform. Causal identification requires the assumption that credit allocation and repayment behavior trend similarly across districts with varying judicial capacities in the absence of the reform. I include district and state-year fixed effects to account for any unobserved time-invariant and time-varying factors at these geographic levels. First, I examine credit allocation to firms based on their past default status and prior period factor productivities using detailed annual borrowing data from a sample of formal sector firms. Next, I examine aggregate number of loans and repayment rate at the district-level - local credit market - to examine how changes in the institutional environment affects market level outcomes. Finally, I examine the effect on credit allocation to the agriculture sector, which is considered a priority sector under the state's directed lending policy, to understand how institutions interact with potentially distortionary policies.

In support of the hypothesis informed by a simple model of credit allocation in the presence of varying institutional quality and incentives faced by bank officials, I find that under weaker creditor rights, average lending to defaulting firms - as classified based on their prior period credit rating by independent rating agencies - is twice as much as average lending to non-defaulting firms. This suggests that the incentives faced by bank officials likely play an important role in resulting allocation in favor of such firms. This phenomena is generally referred to as "ever-greening" phenomena in the context of the banking sector in India. As the creditor rights improve post reforms, I find that the lending to defaulting firms significantly decreases. The decrease in lending is economically meaningful when restricting the sample to high judge occupancy districts. The decrease is smaller in low judge occupancy districts relative to high capacity districts, though I cannot reject the null hypothesis of equivalence. In all, I can conclude that an improvement in creditor rights decreases lending to known defaulter across districts with varying judicial capacities.

A second dimension of credit allocation I focus on is lending by ex-ante factor productivity. By classifying the sample of formal sector firms as above and below median by their prior period marginal revenue products of capital (MRPK) and labor (MRPL), I find that the banks allocate loans by MRPL and not by MRPK at baseline. However, the allocation increases in favor of high MRPK firms post reform, which is driven by an increase in lending in high judicial capacity districts. On the other hand, there is no change in lending to such firms in low capacity districts.

Next, I examine the overall local credit market-level (district-level) aggregate lending and repayment outcomes and how they respond to an improvement in creditor rights differentially by the underlying district judicial capacity. I find modest negative effects on overall lending as judge occupancy increases. When I restrict the bank sample to only public sector banks, I find no effects on aggregate lending. Public sector banks form 80% of the banking sector in India and are in the center of the bad loan (NPA) crisis. Therefore, I focus on these subset of banks in analyzing the overall market level effects. On the other hand, I find a significant increase in repayment, measured as a decrease in the total outstanding loans, across all banks as well as among public sector banks. The estimates imply that a one percentage point increase in the average prior period judge occupancy decreases outstanding loan by 0.5 %. This translates to an increase in repayment between 2.5-3 % in districts with one more available judge in the prior period. Disaggregating lending and repayment by the sector, I find that the increase in repayment in better judicial capacity districts is mainly driven by the manufacturing sector whereas there is no effect either on lending to or repayment from the agriculture sector.

Finally, I study market level allocation to specific sectors such as the agriculture sector driven by directed lending policy to identify the role played by institutional factors in credit allocation. The results suggest that the allocation arising out of directed lending policies, measured as percentage of total credit limit allocated to the agriculture sector, decreases in low judicial capacity districts whereas it is unaffected in high judicial capacity districts. Percentage of loans due from the agriculture sector also follows a similar pattern, revealing a decrease in low judicial capacity districts. Using average judge occupancy in the prior period as a continuous measure of judicial capacity, the point estimates suggest that an increase in occupancy by one percentage point increases percentage lent and pending from the agriculture sector. This suggests that at lower judicial capacities, an improvement in both enforcement capacity and creditor rights increases credit allocation to the sector favored by state policy. Taken together with the results on credit allocation to formal sector firms, this suggests that institutions at least partially but not completely determine credit allocation and that judicial capacity play an important role in the enforcement of creditor rights and contracts. Further, state policies and other distortions continue to influence credit allocation that need to be examined along with the role of institutions.

To show how judicial institutions enforce creditor rights and credit contracts, I find that banks increase litigation through filing of new plaints in high judicial capacity districts immediately after the reform. In contrast, filing of new suits drop in low judicial capacity district. This likely indicates that banks, under the new regime with stronger rights, are more likely to identify delinquent borrowers by filing suits that would complement their subsequent filing of bankruptcy proceedings to recover their assets. Thus, the mechanism behind credit allocation and the functioning of local credit markets imply a complementary role played by judicial institutions.

This paper contributes to many strands of the academic literature. First, it provides microeconomic evidence on the role of judiciary and legal institutions in shaping credit market outcomes, supporting the cross-country literature on the importance of institutions for financial markets (La Porta et al. 1998; Acemoglu and Johnson 2005; Djankov, Mcliesh, and Shleifer 2007). To show this, I use first of its kind disaggregated trial-level data to identify judicial capacity at the level of local (district) trial courts and exploit one-time reform in bankruptcy process to demonstrate the complementary role played these two institutions in affecting credit allocation as well as local credit market response in a large, emerging economy like India.

Second, this adds to the literature on credit misallocation by identifying institutional factors of misallocation. Credit allocation to borrowers is determined by state lending and bailout policies (Banerjee and Duflo 2014; Giné and Kanz 2018), and incentives faced by banking officials (Cole, Kanz, and Klapper 2015). Banks allocate more loans to larger or politically connected borrowers when faced with negative shocks (Khwaja and Mian 2008) in weaker bankruptcy regimes (LilienfeldToal and Mookherjee 2016). This paper demonstrates that a stronger bankruptcy regime requires complementary investment in judicial capacity to reduce potential misallocation but isn't enough to completely eliminate all other sources of misallocation.

Third, the paper shows the importance of well-functioning courts for bankruptcy reform to have teeth. Statutes embodying legal rules protecting creditor and investors' interests is shown to be positively associated with a diverse and competitive credit markets (La Porta et al. 1998; Rajan and Zingales 1998), credit availability for firms (Vig 2013) and subsequent expansion in firm production (Ponticelli and Alencar 2016) and trade (Paravisini et al. 2015). However, this requires timely enforcement of credit contracts for debt recovery (Visaria 2009) and creditor rights in the case of bankruptcy (Giné and Love 2010; Ponticelli and Alencar 2016). This paper provides evidence in support of enforcement of both contracts and creditor rights through a combination of legal reform and local judicial institutions that increases aggregate repayment rates in the local credit markets.

Finally, the paper is well-timed for policy action. By using recent data from 2010-2018, the paper provides policy lessons to address the ongoing banking crisis in India. The discussion surrounding the bankruptcy environment and addressing the problem of NPAs only refer to the role played by the higher judiciary - High Courts and Supreme Courts - in interpreting the constitutionality of the new bankruptcy law and provide jurisprudential clarification for its implementation. On the other hand, early detection and redressal of debt non-repayment through ordinary trial courts in key to provide timely diagnosis of any troubles in the health of local credit markets before they become a national-level problem. For this, investment in building the capacities of local courts is apposite.

Rest of the paper is structured as follows. Section 2 describes the banking sector and the evolution of creditor rights and enforcement mechanism in India. I describe the datasets and variables used in Section 3. Section 4 sketches a simple model of credit allocation to draw testable hypotheses on credit allocation as a function of bankruptcy regime and local enforcement capacity, which I estimate using empirical strategy laid out in Section 5. In section 6, I present and discuss the results and conclude in section 7.

3.2 Banking in India

The banking sector in India is characterized by a dominant share of public sector banks for commercial operations - Scheduled Commercial Banks or SCBs, regulated by the Reserve Bank of India (RBI), as well as Regional Rural Banks and cooperative banks with operations primarily directed towards agriculture, regulated by NABARD. The state has always played a key role in the evolution of the sector through varying systems of controls on the sector's operation including nationalization or the dominant public ownership but also controls over lending operations through priority sector lending norms, liquidity, and cash reserves requirement (Demetriades and Luintel 1996).

Despite economic liberalization of the 1990s, lending controls in the form of priority sector lending continues even till this date. These norms are not limited to public sector banks but also apply to any bank registered for operations in India including private sector and foreign banks. The priority sector largely consists of the agriculture sector including agro-industries as well as small and medium enterprises (SME) that have a state mandated loan allocation close to 40% of all lending by banks. Lending to this sector has also frequently encountered bail-outs by the government as political agenda, eroding timely repayment behavior (Gine and Kanz, 2018). Figure 4.1 depicts directed lending to priority sector (Panel A) and public sector enterprises (Panel B), disaggregated by public sector and private sector banks. Public sector banks have a large share of lending exposed to these directed lending norms in contrast to private banks. Additionally, many large corporate loans made prior to the global financial crisis of 2008 has turned bad in its aftermath, with banks only starting to recognize them as bad loans or non-performing assets (NPA) as highlighted by Dr. Raghuram Rajan in his speech as the RBI governor in 2016.

Typically, a fraction of all lending goes bad, i.e. don't get repaid and the banks are unable to recover. This happens when the debtor becomes insolvent after facing significant negative shock(s) or is untraceable. In developed countries such as the Unites States, the percentage of total lending that is deemed as an NPA is typically under 1% as per the Federal Reserve. Even during the height of the 2008-2010 financial crisis, the total NPA was slightly above 3%. In contrast, the NPAs in India have historically been over 2% and steadily increasing since 2012, peaking to 11% (Panel A Figure 4.1). Panel B Figure 4.2 plots log value of NPA from 2005 to 2018. These show that the NPAs have been increasing until the reform and only showing a modest declining trend starting 2017.

Easy debt recovery and bankruptcy process play an important role in keeping NPA under check. This requires both unambiguous laws as well as strong enforcement institutions that enable timely recovery of unpaid debt and facilitate restructuring or liquidation of delinquent borrowers.

3.2.1 Bankruptcy Process

The bankruptcy process in India until 2016 favored debtor and shareholder rights over creditor rights during either restructuring or liquidation proceedings. The 2016 Insolvency and Bankruptcy Code (IBC 2016) is a new consolidated law on bankruptcy process that provides for a market based mechanism for time-bound bankruptcy resolution, either through restructuring or liquidation. At the same time, it strengthened the rights of the creditors, particularly financial creditors including banks and financial institutions, in the recovery of NPAs and any unpaid debt from the debtor.

Figure 3.3 provides the timeline of the reform. Up until 2016, codes governing bankruptcy proceedings were fragmented across many statutes. Company Law, which lays down the rules governing incorporated entities, was amended in 2013 in an attempt to streamline the process. An all encompassing bankruptcy statute under IBC 2016 was tabled in the Parliament in the winter session of 2015, was voted on and became a law by May 2016. The first set of bankruptcy resolutions were passed in 2017 that heralded a new regime of debtor-creditor relation. These events divide the time period into pre-reform period when the rights of financial creditors were weak and post-reform when the creditors were made key stakeholders in resolving debt defaults, particularly large scale corporate debt defaults. They made the key decisions on restructuring or liquidation as the appropriate next step.

3.2.2 Role of the Judiciary in Bankruptcy

The judiciary, along with specific adjudicating authority (National Company Law Tribunal or NCLT) under IBC 2016, are responsible for implementing the code and for providing clarity over both the process and outcomes for debtors and creditors. In addition to providing an interpretation of the law, the judiciary - especially ordinary trial courts - are important in recognizing a loan as a non-performing asset or classify a debtor as delinquent through litigation initiated by the creditors.

Up until the 2016 reform, debt recovery related cases were either filed in local district courts or in the specialized Debt Recovery Tribunals (DRT) depending on the monetary limit of the debt claim. The reform set up an adjudication system (NCLT) outside of the formal judicial system to enable creditors and debtor firms to initiate bankruptcy proceedings in the event of non-payment of large corporate loans that required either liquidation or restructuring.

However, insolvency proceedings related to liabilities from criminal offense, fraud and family disputes, personal insolvency, anti-trust and intellectual property, and property related disputes such as tenancy and eviction continue to be litigated within the formal judiciary including trial courts until now. Additionally, financial creditors such as banks and financial institutions can claim their ownership of securitized assets during liquidation process by filing claims under laws specific to financial creditors within the ordinary trial courts and DRTs. Therefore, formal judicial institutions play an important and complementary role in the enforcement of creditor rights under the new bankruptcy regime.

3.2.3 Banker's Incentives

In addition to institutions governing enforcement of credit contracts, other sources of potential credit misallocation arise from poor monitoring and incentives of bank officials. Since employees of public sector banks are tenured officials, who are subject to frequent transfers to different branch locations, their incentives to sanction loans do not align with the objective for efficient credit allocation but rather to maximize their own personal incentives (i.e. career concerns).

3.3 Data

In this section, I describe the datasets I use for the analyses. I combine district-level bank credit operations data aggregated across all Scheduled Commercial banks with district-level judicial capacity data that I assembled by scraping publicly available case records across 195 District and Session Courts in India. In addition, I use formal sector firm balance sheet and borrowing data from Prowess to examine access to credit from formal financial institutions and credit allocation based on past default status as well as ex-ante marginal revenue product of labor and capital. I describe each of these datasets in detail below.

3.3.1 Credit Outcomes

The main outcomes pertain to how banks allocate credit across various needs and whether and how the allocation process changes due to changes in the judicial capacity in the corresponding local credit market, i.e. district. To study this, I use district-level credit summary data over 2010-2018 period across all Scheduled Commercial Banks as provided by the Reserve Bank of India (RBI). This dataset contains annual summary on total number of loan accounts, total outstanding loan amount, and total sanctioned credit limit. The summary is disaggregated by the sector of allocation as well as by whether the region is rural or urban.

3.3.1.1 Formal Sector Firm Borrowing

In order to examine credit allocation to specific firms, I use CMIE Prowess dataset to study long term borrowing by formal sector firms from banks. Since the dataset also provides annual credit rating and other balance sheet information on total assets and labor expenditure, I classify firms based on their ex-ante (i.e. prior to bankruptcy reform) default status based on credit rating as well as their ex-ante marginal revenue product of capital and labor

(MRPK and MRPL) for the subset of manufacturing firms, respectively. These classifications enable analyses to test the presence of credit misallocation and study how misallocation varies by district judicial capacity after the reform.

I compute MRPK and MRPL by assuming Cobb-Douglas production function for the subset of formal sector firms in manufacturing following Bau and Matray (2019). The assumptions regarding the functional form of production and exogeneity of output and factor prices enables computation of MRPK and MRPL as sales revenue per unit of asset value and sales revenue per unit of wage expenditure. As the firm level data is available from 1986, I use period prior to 2010 to classify firms as high MRPX ($X \in \{K, L\}$) and low depending on whether their average marginal product across 1986-2009 is above or below median within a specific production sector as per the corresponding 2 digit NIC code.

3.3.2 Judicial Capacity

In order to understand banks' credit allocation patterns by the judicial capacity of the corresponding local credit market, I classify districts as low capacity or high capacity if the average judge occupancy in the district courts in the years prior to the reform are below or above median value, respectively. I also use the average prior period judge occupancy - a continuous variable - to examine variation in judicial capacity in-lieu of the dummy variables. I calculate judge occupancy using data from case records across the universe of trials active between 2010-2018 in 195 District and Session courts. Each of the case record indicates the judge name or the courtroom where the case is pending. This allows me to create aggregate measures of court performance at the level of a courtroom and also help identify which courtrooms are vacant for at least a year or more. In the absence of publicly available judge roster with dates of joining and retirement/separation for every court served, this approach generates the incidence of vacancy in the absence of roster data. The vacancy figures thus generated match with the aggregate vacancy numbers mentioned in the Law Commission of India reports, government documentation, and media reports.

3.4 Model: Credit Allocation

In this section, I sketch a simple two-period model of credit allocation in an environment dominated by the presence of the public sector in the banking system. The system creates an incentive against detection and reporting of loan defaults by the bank officials, who continue to provide fresh loans to the potential defaulter to prevent labeling any current loan as a bad loan. This extends the model in Banerjee and Duflo (2014) by making the incentive of bailout by the bank official (default avoidance) as a function of institutional quality.

I consider a representative bank official, who has L units of credit to allocate to borrowers in each period. Borrowers are of two types in the population - Type H with a share ϕ in the population and Type L constituting the remaining $1-\phi$. Type H borrower has a deterministic production function with probability of success, $s_H = 1$ whereas type L faces a non-zero probability of production failure $1-s$ such that $s_L = s < 1$. The borrower type is unknown to both bank official and borrower in the initial period, which gets revealed with the outcome of production. So in the first round of allocation, the official equally distributes total credit L among the borrowers such that each borrower gets l units of credit.

At the end of period 1, the official receives a signal that the borrower is of type H conditional on observed production success. This signal probability is $S_H = \frac{\phi}{\phi+(1-\phi)s}$. Among type L borrowers, $(1-\phi)(1-s)$ fail. In period 2, the official can either declare loan provided to type L as default and face a penalty $P_1(l,\Gamma)$ or provide fresh loan for L to continue production, which would lead to a bigger default at the end of period 2 with probability $1-s$. Penalty in period 1 is a function of loan size, l, and local court quality Γ, such that $\frac{\partial P_1}{\partial \Gamma} > 0$, i.e. well functioning courts generate a larger penalty and $\frac{\partial P_1}{\partial l} > 0$. The official will bail out type L borrower by lending l_L in period 2 such that $sf(l_L - l) \geq l_L$, where l due from period 1 is paid out of l_L and the rest is put into production. Rationality implies that $l_L^* = sf(l_L^* - l)$, that is, the official lends the minimum amount to type L borrower to hedge the risk of default at the end of period 2. Therefore, the official compares the option of bailing the period 1 defaulter by declaring a default, which costs him $P_1(l,\Gamma)$. So, bailing will be the dominant strategy if the penalty from default at the end of period 2 is less than the penalty from default at the end of period 1. Penalty in period 2 has an additional institutional parameter, Θ - a measure of creditor (bank's) rights in the form of redressal through bankruptcy process, and is much larger in magnitude, $P_2 >> P_1$. Further $\frac{\partial P_2}{\partial \Gamma} > 0$, $\frac{\partial P_2}{\partial \Theta} > 0$ and $\frac{\partial^2 P_2}{\partial \Gamma \partial \Theta} > 0$. That is, penalty in period 2 is higher due to the complementary effects of default detection through courts as well as protection of creditor rights under bankruptcy reform.

$$(1-s)P_2(l_L^*, \Theta, \Gamma) \leq P_1(l, \Gamma)$$
$$P_2(l_L^*, \Theta, \Gamma) \leq \frac{P_1(l, \Gamma)}{1-s}$$

Assuming that the penalty can be expressed as a share of the loan amount, $P_1(l,\Gamma) = lP_1(\Gamma)$ and $P_2(l_L^*, \Theta, \Gamma) = l_L^* P_2(\Theta, \Gamma)$. Therefore, the bailout loan can be expressed as:

$$l_L^* \leq \frac{lP_1(\Gamma)}{(1-s)P_2(\Theta, \Gamma)} \tag{3.1}$$

The right hand side of the above expression for period 2 bailout loan varies both the quality of local courts, Γ, as well as the overall environment of creditor rights Θ. The bankruptcy reform increases Θ where as higher judge occupancy (lower judge vacancy) increases Γ. Without further assumptions on the functional form of the penalty functions, I get the following results:

Result 1: The bailout loan, l_L^*, decreases as both institutional parameters Θ and Γ increase, i.e. $\frac{\partial l_L^*}{\partial \Theta \partial \Gamma} < 0$. That is, bailout lending is lower to type L borrowers in credit markets (districts) with higher judicial capacity after the bankruptcy reform.

Proof

$$\frac{\partial l_L^*}{\partial\Theta\partial\Gamma} = \frac{l}{1-s}\left(\frac{-1}{P_2^2}\frac{\partial P_1}{\partial\Gamma}\frac{\partial P_2}{\partial\Theta} - \frac{P_1}{P_2^2}\frac{\partial^2 P_2}{\partial\Theta\partial\Gamma} + \underbrace{\frac{2P_1}{P_2^3}}_{\to 0}\frac{\partial P_2}{\partial\Gamma}\frac{\partial P_2}{\partial\Theta}\right) < 0$$

Result 2: In the absence of strong creditor rights through the bankruptcy reform, the effect of higher judicial capacity on bailout loan is ambiguous or likely positive.

Proof

$$\frac{\partial l_L^*}{\partial\Gamma} = \frac{l}{1-s}\left(\frac{1}{P_2}\frac{\partial P_1}{\partial\Gamma} - \frac{P_1}{P_2^2}\frac{\partial P_2}{\partial\Gamma}\right) > \text{ or } < 0$$

Implication Given this framework, the following section presents the empirical strategy to test the hypotheses on credit allocation generated by the above results. Specifically, I examine whether lending to "riskier" borrowers diminishes after the bankruptcy reform in districts with better judicial capacity.

3.5 Empirical Strategy

India enacted an overarching reform addressing the process of bankruptcy to strengthen creditor's rights. The policy focus of this reform was to enable business environment and aid creditors' recovery of bad loans by easing the process of liquidation and/or reinvestment in defaulting companies. This departs from the then extant bankruptcy regulation by providing greater rights to the creditors rather than to the borrowers and their shareholders. Improved creditor rights requires complementary improvement in the local judicial capacity that enables faster debt recovery and helps recognize stressed assets in a timely fashion. An important measure of judicial capacity is the percentage of judge seats that are occupied and not vacant. Since judges are central to the judicial production function, availability of judges is an indicator of trials progressing within the adjudication process.

In this section, I present empirical strategies to estimate the effect of an improvement in institutional environment on credit allocation based on borrower characteristics as well as overall credit market outcomes including total number of loans and loan repayment.

3.5.1 Credit Allocation

An important aspect of improved creditor rights is that the credit markets should function more efficiently from the perspective of credit allocation. The banking sector in India is subject to policy directive to reserve 40% of total lending to the "priority sector", as defined by government policy. This sector includes all agricultural loans, consumption loans towards low cost housing and education, and loans to small and medium enterprises based on asset size. Evidence thus far suggest that such a policy itself leads to misallocation of credit

(Lilienfeld-Toal, Mookherjee, and Visaria 2012; Banerjee and Duflo 2014). Additionally, the banking sector in India has been facing increased number of non-performing assets (NPA) from unchecked lending to finance long term infrastructure in the early years of the 21st century in the run-up to the global financial crisis (Rajan 2016). In order to understand the evolution of credit allocation when part of institutional failures are addressed, I examine bank lending to formal sector firms categorized by their pre-period default status based on credit rating and marginal factor productivity, in a difference in difference research design.

3.5.1.1 Lending to Firms by Past Default

I examine bank lending to formal sector firms using Prowess dataset which provides firm level panel data on annual borrowing from banks. Additionally, the data also provides credit rating of the borrower firms, which I use to classify whether a firm defaulted on borrowing in the period prior to the reform - a measure of "riskiness" of the borrower. In the following specification, I compare bank lending between defaulting firms relative to non-defaulters before and after the reform.

$$Y_{fdt} = \delta_d + \delta_{st} + \beta_1 Default_{fd} \text{ x } Post_t + \beta_2 Default_{fd} + \mathbf{X}_{fd}\Gamma + \epsilon_{fdt} \tag{3.2}$$

where Y_{fdt} represents bank lending to firm f registered in district d in year t. Firms are classified as defaulters with $Default_{fd} = 1$ if their credit rating indicates past default, and as non-defaulter otherwise. $Post_t$ is the dummy indicating whether year $t \geq 2016$ (i.e. period after reform), defined as $Post_t = 1$, for $t > 2016$ and 0 otherwise. To account for any unobserved time-invariant differences in district characteristics that could influence whether or not a district has above median judge occupancy, I include district fixed effects δ_d. To account for all time varying state level unobserved characteristics, such as changes in state policies and macro-economic indicators correlated with high judge occupancy, I include state-year fixed effects δ_{st}. In addition, I include firm level characteristics vector, $\mathbf{X}_{fd}$, that contains age, age-squared, and sectoral dummies. ϵ_{fdt} is the idiosyncratic error term. Since the "treatment" varies at the district level only, I cluster the standard errors by district. Additionally, I also compare lending to such firms in subsets of districts characterized by high and low judicial capacities, equivalent of triple differences design.

$$\begin{aligned} Y_{fdt} = \delta_d + \delta_{st} + \beta_1 Default_{fd} \text{ x } High\ Judge\ Occp_d \text{ x } Post_t + \beta_2 Default_{fd} \text{ x } Post_t \\ + \beta_3 High\ Judge\ Occp_d \text{ x } Post_t + \beta_4 Default_{fd} \text{ x } High\ Judge\ Occp_d \\ + \beta_5 Default_{fd} + \mathbf{X}_{fd}\Gamma + \epsilon_{fdt} \end{aligned} \tag{3.3}$$

In addition to variables common to equation 1, $High\ Judge\ Occp_d = 1$ represents districts with above median judge occupancy in the prior period. I exclude districts that are close to 50th percentile in order to create groups that are distinct in their judicial capacities.

In order to test the complementary role of judicial capacity in enforcing creditor rights influencing credit allocation, I examine whether the coefficient $\beta_1 = 0$ in equation 2 above. A negative coefficient implies that lending to defaulting firms decreases more in better judicial capacity districts post reform. This test examines whether the banks efficiently allocate credit by reducing lending to defaulting firms. Coefficient β_2 of equation 2 or coefficient β_1 of equation 1 estimates the effect of reform on bank lending to defaulting firms after the reform. Finally β_2 of equation 1 or β_4 of equation 2 estimates borrowing by defaulting firm prior to the reform. $\beta_2 > 0$ and $\beta_4 > 0$ suggests presence of credit misallocation as it implies higher lending by banks to defaulting firms, consistent with the "ever-greening" phenomena employed by bank officials incentivized to prevent detection of defaults.

In these specifications, the underlying identifying assumption for causal inference requires that the lending to defaulting firms trend similarly to non-defaulting firms in the absence of the reform and variation in judicial capacity. I test whether I observe any significant departure in trends prior to the reform period since I don't observe the counterfactual outcomes to actually test for this assumption after the reform. An insignificant pre-trend or parallel trend between the two groups in the prior period is a suggestive evidence in support of the identifying assumption.

3.5.1.2 Lending to Firms by Factor Productivity

A key ramification arising out of weak creditor rights and local enforcement capacity is credit misallocation. For example, directed lending policies constrain creditors in lending based on maximizing marginal factor productivity by requiring lending to certain type of borrowers. Further, skewed incentives of bank officers, specially in public sector banks, that excessively penalizes them for any defaults in their portfolio leads to the above mentioned "ever-greening" phenomena, worsening credit misallocation in addition to poor rights and enforcement.

To test whether credit allocation by banks respond to incentives altered by the institutional features, I examine annual lending to formal sector manufacturing firms based on their factor productivity - an alternate measure of borrower "riskiness". I classify firms based on their ex-ante marginal revenue product of labor (MRPL) or high marginal revenue product of capital (MRPK) using data from period prior to the reform. The idea is that firms with better factor productivity are less likely to default on loans. In order to empirically examine the hypotheses laid out in the model section, I employ difference in difference specification as before:

$$(3.4) \qquad Y_{fdt} = \delta_d^{prod} + \delta_{st}^{prod} + \beta_1^{prod} MRPX_{fd} \text{ x } Post_t + \beta_2^{prod} MRPX_{fd} + \mathbf{X}_{fd}\Gamma^{prod} + \epsilon_{fdt}^{prod}$$

where Y_{fdt} represents bank lending to firm f registered in district d in year t. Firms are classified as relatively efficient with $MRPX_{fd} = 1$, $X \in \{L, K\}$ if the firm is above median in the distribution of marginal revenue product of labor or capital within the district and 2-digit industry group in the period prior to the reform. The remaining terms are the same as in equation 1. Further, as before, I also compare lending to such firms in subsets of districts characterized by high and low judicial capacities, equivalent of triple differences design.

$$Y_{fdt} = \delta_d^{prod} + \delta_{st}^{prod} + \beta_1^{prod} MRPX_{fd} \text{ x } High\ Judge\ Occp_d \text{ x } Post_t + \beta_2^{prod} MRPX_{fd} \text{ x } Post_t$$
$$+ \beta_3^{prod} High\ Judge\ Occp_d \text{ x } Post_t + \beta_4^{prod} MRPX_{fd} \text{ x } High\ Judge\ Occp_d$$
$$+ \beta_5^{prod} MRPX_{fd} + \mathbf{X}_{fd}\Gamma^{prod} + \epsilon_{fdt}^{prod}$$
(3.5)

Coefficient β_1^{prod} of equation 1 and coefficient β_2^{prod} of equation 2 estimate the effect of reform on bank lending to factor efficient firms after the reform. β_2^{prod} of equation 1 or β_4^{prod} of equation 2 estimates borrowing by efficient firm prior to the reform. $\beta_2^{prod} < 0$ and $\beta_4^{prod} < 0$ suggests presence of credit misallocation as it implies lower lending by banks to more efficient firms. As before, I test the complementary role of judicial capacity by examining whether the coefficient $\beta_1^{prod} = 0$ in equation 2 above. A positive coefficient implies that lending to efficient firms increases more in better judicial capacity districts post reform.

Given the design, causal inference requires that the lending to more efficient firms trend similarly to less efficient firms in the absence of the reform and variation in judicial capacity. I test for any violation in trends being parallel in the period prior to the reform as a suggestive test for the identifying assumption.

3.5.2 Credit Market Level Outcomes

The reform should likely have a positive effect on the overall credit markets by improving debt recovery for banks. To show that any reforms aimed at improving creditor rights requires complementary improvement in local judicial capacity, I compare districts with higher judge occupancy in the prior period with districts with lower judge occupancy before and after the reform in a standard difference in difference research design. The empirical specification is as follows:

$$Y_{dt} = \alpha_d + \alpha_{st} + \gamma Judge\ Occp_d \text{ x } Post_t + \zeta_{dt} \tag{3.6}$$

where Y_{dt} is district-level credit market outcomes, including total number of loans and total outstanding loan amount reflecting unpaid debt. $Judge\ Occp_d$ is a continuous variable denoting the percentage of judge seats that are occupied on average in district d in the pre-reform period. $Post_t$ is a dummy indicating post reform period. I include two-way fixed effects by including district fixed effects - α_d, and state-year fixed effects - α_{st}. ϵ_{dt} represents the idiosyncratic error term. I cluster the standard errors by district.

The sign and magnitude of the coefficients γ indicate the effect of the reform on bank lending and outstanding (unpaid) debt when judicial capacity, measured as the average prior period judge occupancy, increases by one percentage point. This coefficient represents the complementary role of judicial capacity with respect to the overall credit market when creditor rights improve. When the outcome is outstanding loans, $\gamma < 0$ indicates an improvement in repayment behavior as a result of better judicial capacity and improved creditor rights.

Additionally, I examine the market level outcome by bank-type, especially lending and repayment to public sector banks. As mentioned earlier, the public sector banks in India constitute close to 80% of the banking sector and has an overwhelming share of NPA. Therefore, examining credit outcomes among public sector banks is important to infer about the role of bankruptcy reform and judicial capacity in addressing the NPA problem.

Finally, as before, I examine pre-trends in outcome measures by the district judicial capacity as a suggestive test for the validity of the identifying assumption for causal inference.

3.5.2.1 Lending by Economic Sector

Lastly, I examine the credit market level outcomes by the sector of lending, grouped as agriculture sector and non-agricultural sectors for productive loans. I exclude lending outcomes made for consumption purposes such as personal loans, housing loans, etc. Agriculture sector in India is categorized as priority sector for lending purposes and has been subject to many bail-outs by the government, leading to high rates of defaults (Giné and Kanz 2018). Since priority sector lending norms dictate that at least 18% of all lending be directed to the agriculture sector, an efficient allocation conditional on this policy would imply that lending to the agriculture sector should likely be capped at 18% or minimize allocation in excess of 18%.

$$Y_{dt}^k = \alpha_d^k + \alpha_{st}^k + \phi Judge\ Occp_d \text{ x } Post_t + \zeta_{dt}^k \tag{3.7}$$

As before, Y_{dt}^k includes credit market level loan outcomes specific to non-consumption sector k. Additionally, with outcome constructed as percentage of total lending to sector k, the hypothesis testing for no change in credit allocation to the agriculture sector post reforms would imply $\phi = 0$. $\phi > 0$ implies that the agriculture sector experiences an increase in its share of the total credit relative to non-agricultural production sectors. This could potentially indicate a misallocation if the allocation is not based on which sector has a higher marginal production of capital.

3.6 Results

In this section, I discuss the results from the analysis based on the empirical strategy laid out in the previous section. I begin by examining credit allocation by banks to firm borrowers by firm characteristics, showing that allocation improves as a result of the bankruptcy reform. The improvement is more pronounced in districts with better judicial capacity. Following allocation based on borrower characteristics, I present the results of overall credit market response at the level of a district by examining the effect on total lending and repayment at the market level. I find that repayment significantly improves after the reform in better judicial capacity districts and find a modest decline in lending. I break down the results by public sector banks as well as by sectoral allocation of productive loans at the market level. Finally, I provide suggestive evidence to show that the improvement in credit market and allocation efficiency is driven by improved capacity of local judicial institutions through increased filing of litigation as well as higher rate of dispute resolution.

3.6.1 Credit Allocation

In this section, I discuss credit allocation by banks to a sample of formal sector firms from Prowess dataset based on whether the firm defaulted in the past as well as by firms' ex-ante marginal revenue product of labor and capital. This tests the hypotheses that the allocative efficiency improves when institutional quality - combination of credit rights and judicial capacity - improves, although I cannot conclude whether improvement in institutional quality is sufficient to eliminate misallocation entirely.

3.6.1.1 Lending by Borrowing Firms' Characteristics

Panel A Figure 3.4 represents the data visually and Column 1 Table 4.3 presents the difference in difference estimates on annual borrowing by formal sector firms from banks by their past default status. At baseline, banks lend more - almost twice as much - to defaulting firms relative to non-defaulters likely consistent with the "ever-greening" hypothesis resulting from the incentive structure faced by the bank officials. However, this declines post reform whereas lending to non-defaulting firms marginally improves. This decline in lending to defaulting firms is robust to accounting for unobserved time-invariant firm specific characteristics by including firm fixed effects (Column 2 Table 4.3), with point estimates fairly stable. The estimates suggest that the lending to past defaulters decreases between 28-35 percent post reform.

Columns 3 and 4 Table 4.3 present the estimates in subsets of districts characterized by judicial capacity. The estimates and pattern in data as seen in Panel B Figure 3.4 are similar to that of the pooled sample but loses precision. The estimates are marginally lower in low judicial capacity districts although I fail to reject the equivalence of the estimate with that from high judicial capacity district sub-sample.

Next, I examine credit allocation by manufacturing firms' prior-period factor productivity. Table 4.4 and Table 4.5 present the estimates on bank borrowing by firms' MRPK and MRPL, respectively. Figure 3.5 represents the data visually. At baseline, banks lend more to firms with low MRPK. In particular, firms with low MRPK are lent twice as much as firms with high MRPK at baseline. On the other hand, the differential based on MRPL is smaller, with high MRPL firms borrowing about 25% more than low MRPL firms at baseline. However, after the reform, lending increases to firms with higher MRPK, suggesting that banks begin to respond to the firms' capital productivity when their rights are stronger. Specifically, borrowing increases by 15-20% among high MRPK firms after the reform. The estimates are stable even after accounting for firm fixed effects (Column 2 Table 4.4). Borrowing by high MRPL firms decline after reform although the estimate reduces in magnitude and loses precision with firm fixed effects (Columns 1 and 2 Table 4.5).

The increase in lending to high MRPK firms is largely driven by higher judicial capacity districts whereas there is no significant change in low judicial capacity districts (Columns 3 and 4 Table 4.4). However, the decline in lending to high MRPL firms is likely driven by low judicial capacity districts whereas the decline is modest and statistically insignificant in high judicial capacity districts (Columns 3 and 4 Table 4.5).

The analysis suggests that banks become careful in credit allocation after the reforms, especially if the firm is a past defaulter, in which case the lending decreases consistently across all districts across the distribution of judicial capacities. At the same time, the evidence suggests that the allocative efficiency likely improves as banks increase lending to high MRPK firms but only in districts with better judicial capacity.

3.6.2 Credit Market Outcomes

In this section, I present the results on overall credit market (district-level) outcomes on aggregate lending by banks and loan repayment. An improvement in creditor rights and judicial capacity should have a positive impact on the overall credit market in addition to allocation behavior discussed earlier. The key outcome to measure this improvement is the extent of repayment of outstanding loan, which I find increases substantially post reform.

Panel A Figure 3.6 and Table 4.6 presents the difference in difference estimates on total number of bank loans and amount outstanding at the district-level. I find that total number of loans declines by 4% in high judicial capacity districts whereas increases by 3% in low judicial capacity districts after the reform. Using the average prior period judge occupancy variable, total number of accounts decline by 0.3 percent after the reform when judge occupancy increases by 1 percentage points. At the same time, outstanding loans decline by 4-6 % in high judicial capacity districts whereas it increases by 6% in low judicial capacity districts.

For the subset of banks that belong to the public sector, outstanding loans decline in districts with better judicial capacity after the reform whereas there is no significant effect on total loans. Panel B Figure 3.6 represents the event-study estimates of bankruptcy reform in high judicial capacity districts for public sector banks. Columns 1and 4 Table 4.7 presents the estimates by prior period judge occupancy. As with the pooled sample, outstanding loans by public sector banks declines considerably post reform with improvement in judicial capacity. Specifically, outstanding loan decreases by 0.5 % after the reform for every 1 percentage point increase in district judge occupancy. On the other hand, total number of loans does not change meaningfully or in a statistically significant fashion among this subset of banks.

Examining the outcomes by the sector of lending for productive uses grouped as agriculture and non-agri sectors, I find that the reduction in outstanding loans is mainly been driven by improved repayment by non-agri sector borrowers. Although repayment also improves among agriculture sector loans, the estimates are statistically insignificant and or lower magnitude. Figure 3.7 presents the event study estimates by the sectors respectively. Columns 2-3 and 5-6 of Table 4.7 presents the difference in difference estimates by average prior period district judge occupancy. The estimates imply that outstanding loans to non-agriculture sector decreases by 0.74 % after reform for every one percentage point increase in judge occupancy, whereas the decline in outstanding loans to agriculture sector is estimated as 0.09 % reduction for marginal improvement in the underlying judicial capacity.

The results taken together suggest that an improvement in the institutional quality that strengthens creditor rights and enforcement ability by local judicial institutions helps improve local credit market outcomes. This improvement is mainly driven by an improvement in repayment behavior, especially among non-agriculture sector borrowers of public sector banks. On the other hand, there is no significant change in total lending suggesting that good quality institutions improve the functioning of local credit markets.

3.6.2.1 Priority Sector Lending

Creditor rights detailed in bankruptcy laws and the quality of enforcement in local courts are not the only institutional factors affecting credit allocation and the overall functioning of the local credit markets. Banks in India are closely regulated by the Reserve Bank of India and given the large role played by public sector banks in the entire banking sector, both allocation and overall credit markets are significantly influenced by public policies, particularly with respect to directed lending to specific sectors termed as the priority sector. While creditor rights improved with the reform, the priority sector lending norms remain, which likely affect the efficiency of credit allocation.

Panel A Figure 3.8 and Columns 1-3 of Table 3.6 present the estimates on percent allocation of total credit line in a district to the agriculture sector. Average share of lending to the agriculture sector is over 40%, which is much higher than the stipulated 18% norm under the priority sector rules. However, since the districts in my sample are predominantly rural, this is likely driven by greater demand for agricultural loans relative to production loans for non-agriculture sector. As creditor rights improve after the bankruptcy reform, I note that the share of lending declines considerably in low judge capacity districts whereas it remains stable in high judge capacity districts.

Percentage share of the agriculture sector of total outstanding loan also shows a similar pattern, where the share declines in low judicial capacity district after the reform and remains stable in high capacity districts. Panel B Figure 3.8 and Columns 4-6 of Table 3.6 present these results. This suggests that improved creditor rights and enforcement capacity of local courts likely increase the implementation of the priority sector lending norms as dictated by the state policy. This may lead to credit misallocation if lending is not based on maximizing the marginal value of credit. Therefore, while an improvement in some institutions may have beneficial effects on the credit market outcomes and credit allocation within the manufacturing sector, presence of other factors could still prevent efficient allocation of credit.

3.6.3 Mechanism: Increase in Debt Litigation

An important mechanism behind the change in lending and repayment behavior faced by bank is their willingness to recognize bad loans as non-performing assets by filing debt recovery litigation in the corresponding court. Once bad loans are recognized but ordinary dispute resolution doesn't yield complete recovery, the bankruptcy reform enables the lender to initiate either liquidation or restructuring process in the bankruptcy court, which is the National Company Law Tribunal (NCLT). NCLT benches are only present in large urban districts and currently there are 15 benches across the countries. However, not all default cases end up in the bankruptcy courts and therefore, banks rely predominantly on the more accessible ordinary trial courts within their district. Well functioning trial courts through their timely resolution of case backlog encourages banks to file suits for debt recovery. This also enables timely repayment of all outstanding loans.

Panel A Figure 3.9 presents suggestive evidence indicating that banks are more likely to initiate debt related litigation in courts with better judicial capacity immediately following the reform. On the other hand, they are less likely to initiate trial proceedings in low judicial capacity districts (Panel B). Table 3.7 presents the difference in difference estimates. The results suggest that an increase in judicial capacity measured as prior period average judge occupancy increases both new filing and trial resolution post reform by 0.25-0.27 % for every one percentage point increase in judge occupancy. Alternately, this means that filing and resolution increases by 9-12 % in high judge occupancy district whereas filing decreases by 21 % and resolution by 13% in low judge occupancy districts.

One explanation for this one time spike observed in the graphs is that recognition of bad loans was given importance in the wake of the bankruptcy reform because until then, the bank officials faced a negative incentive for defaults in their portfolio. Recognizing bad loans was driven by a policy directive by the Reserve Bank of India in addressing the NPA problem requiring banks to mark loans with past due installments as NPA, which would then be addressed under the new bankruptcy law. Once loans are marked as defaults, the bank officials can initiate the recovery proceedings through both judicial and non-judicial means. The latter involves using recovery or collection agents rather than the judicial process. The results suggest that well functioning courts likely encourage banks to use judicial processes.

3.7 Conclusion

This paper provides evidence in support of the complementary role judicial institutions play in enforcing creditor rights and debt contracts on the credit allocation as well as in the functioning of local credit markets through an improvement in aggregate repayment of outstanding debts. To show this, I exploit cross-sectional variation in district judicial capacity, measured as average judge occupancy in district courts in period prior to a legal reform strengthening creditor rights, and a one-time change in bankruptcy law that put creditors above all other stakeholders in bankruptcy proceedings. Using this difference in difference research design, I find that banks reduce lending to firms known for past defaults after the reform and differentially increase lending to firms with higher MRPK in districts with better judicial capacity. Further, I note that overall repayment of outstanding loan increases with judicial capacity, driven by increased repayment of production loans by the non-agriculture sector. However, judicial capacity is not sufficient to address potential misallocation arising from other sources including legitimate policy and incentive structure.

A key mechanism through which local courts with better capacity affect the observed credit allocation and higher repayment rates is through timely enforcement of on-going trials as well as by enabling banks to file new suits pertaining to debt recovery. This shows that local courts play an important role in the functioning of markets, specifically for the financial sector, in addition to the important role played by the higher judiciary in interpreting laws and providing directions for their implementation. This is particularly important in the context of a bankruptcy framework, where local enforcement capacity leads to better credit allocation and increases repayment when the relative strength of creditor rights improve.

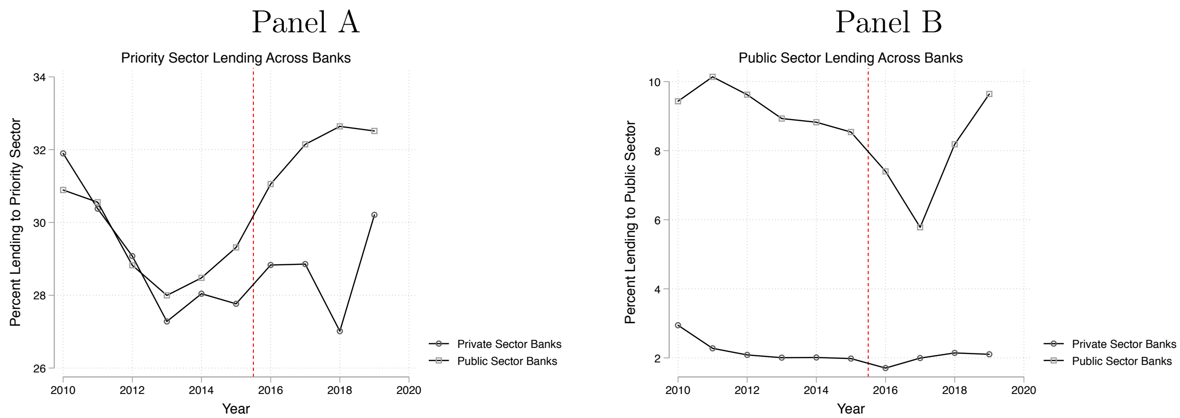
The literature examining the role of judicial institutions in the functioning of financial markets is relatively sparse, particularly empirical studies using disaggregated data to generate both cross-sectional as well as time-series variation in institutional quality. This paper thus provides micro-economic evidence on the role of courts in supporting local credit markets after an improvement in creditor rights through a reform in the bankruptcy process in India. The findings support the early cross-country literature on the importance of legal and judicial institutions for the development of financial markets and availability of credit. In addition, it shows that an improvement in rights and enforcement capacity reduces potential misallocation but does not completely eliminate it.

Given the ongoing crisis in the banking sector in India, the timing of this paper is apt. Since I use recent data and institutional reforms for the analysis, the paper presents key evidence to enable a discussion surrounding the direction of further reforms. This includes significant investment in increasing the capacities of the sub-national judiciary and encouraging debate beyond the role of higher judiciary with respect to interpretation and directions for implementing the bankruptcy law.

Since the timing of the reform is fairly recent, the paper provides short and medium run effects on credit outcomes. As the law is further amended to remove ambiguities pertaining to the rights of the different stakeholders and directions for implementation becomes clear, the long run effects maybe different. These could have ramifications on what types of firms are liquidated and what types are restructured through re-investment, and therefore left for future research as and when such data becomes available.

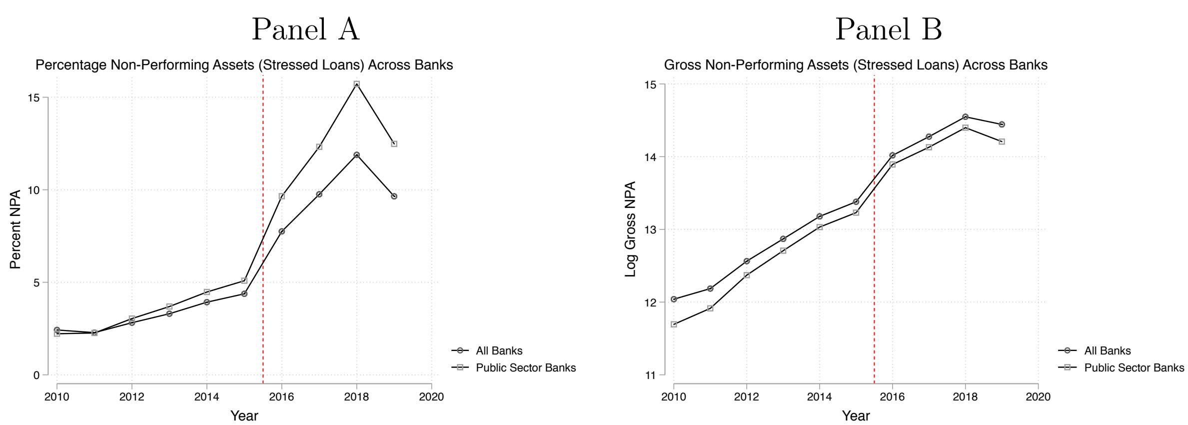
3.8 Figures

Figure 3.1: Directed Lending by Banks



Notes: The figures above plot the percentage of total lending across India towards priority section (Panel A) and towards public sector borrowing (Panel B) respectively.

Figure 3.2: NPA in Indian Banks



Notes: The figures above plot the percentage of total lending across India that turned into NPA (Panel A) and overall growth of Gross NPA (Panel B) respectively.

Figure 3.3: Timeline of Bankruptcy Reform

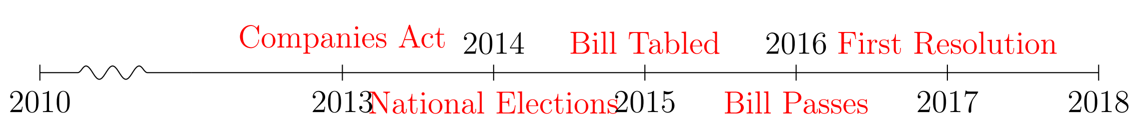
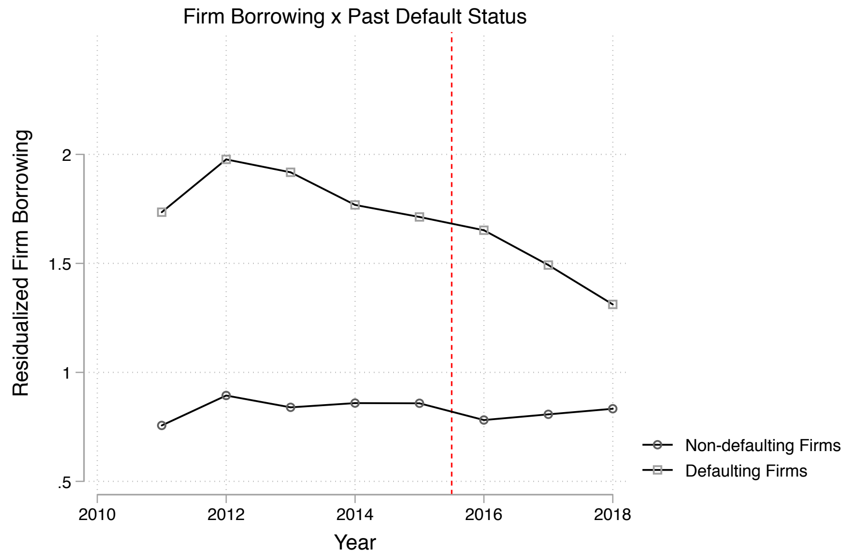
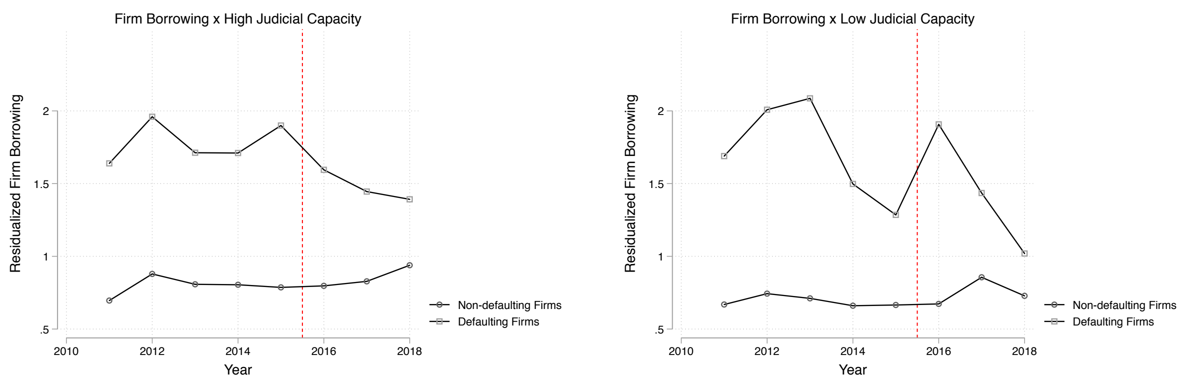


Figure 3.4: Firm Borrowing from Banks: Judge Occupancy x Bankruptcy Reform

Panel A: All Districts



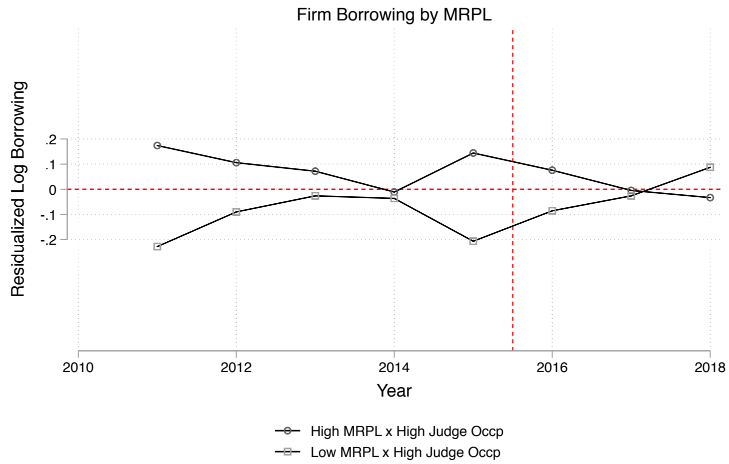
Panel B: By District Judicial Capacity



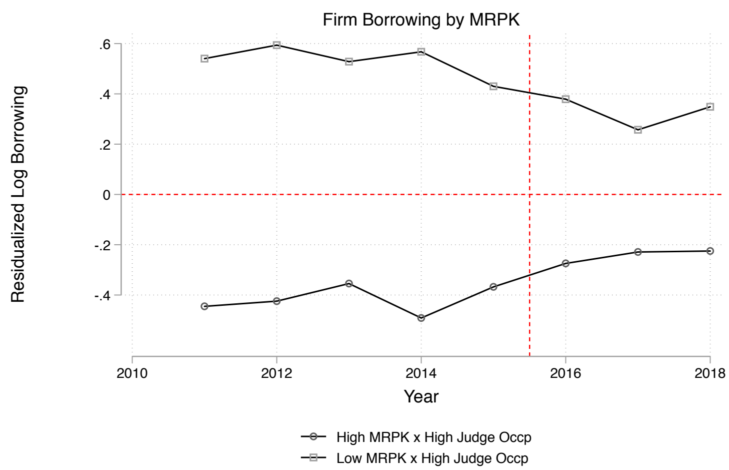
Notes: The figures above depict residualized firm borrowing by factor productivity of firms before and after bankruptcy reform (Panel A). Panel B presents the residualized means by cross-sectional differences in judicial capacities of the firms' home districts.

Figure 3.5: Firm Borrowing from Banks by MRPX : Judge Occupancy x Bankruptcy Reform

Panel A: By Firm MRPL



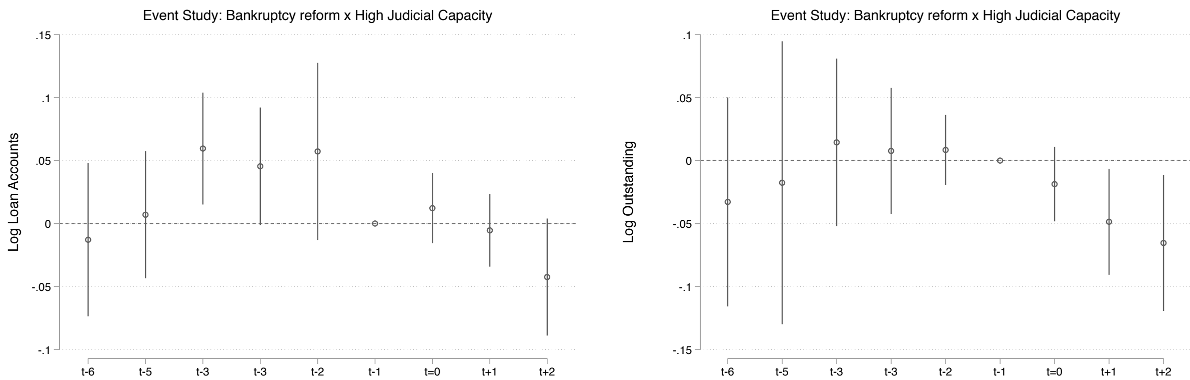
Panel B: By Firm MRPK



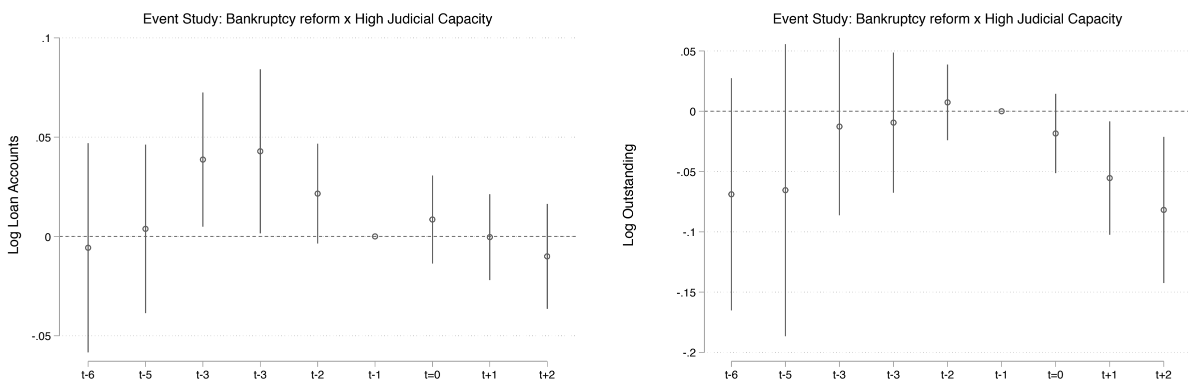
Notes: The figures above show residualized firm borrowing by default status of firms before and after bankruptcy reform. Panel A presents firm grouping by their marginal revenue product of labor. Panel B presents firm grouping by their marginal revenue product of capital.

Figure 3.6: Credit Market Outcomes: Judge Occupancy x Bankruptcy Reform

Panel A: All Banks



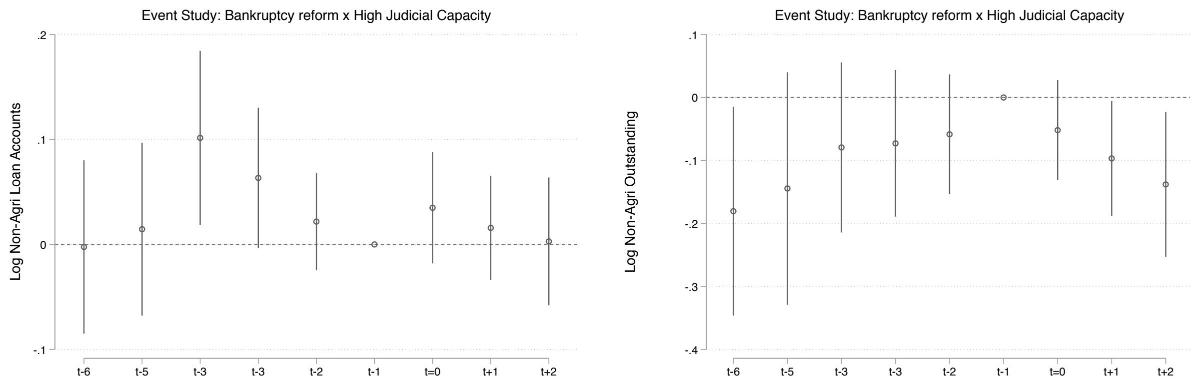
Panel B: Public Sector Banks



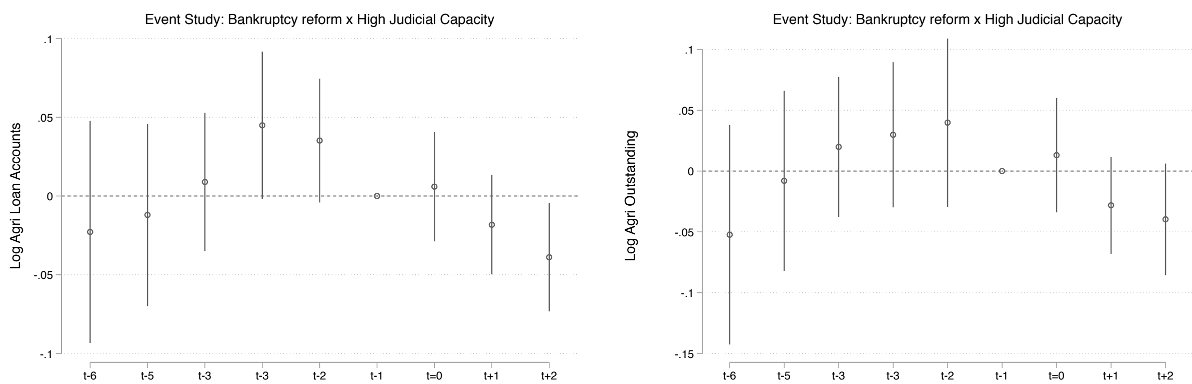
Notes: The figures present the event-study estimates of the bankruptcy reform on total lending and outstanding loans across all banks (Panel A) and by public sector banks (Panel B) in high judicial capacity districts.

Figure 3.7: Credit Market Outcomes by Sector: Judge Occupancy x Bankruptcy Reform

Panel A: Production Loans (Non-Agri)



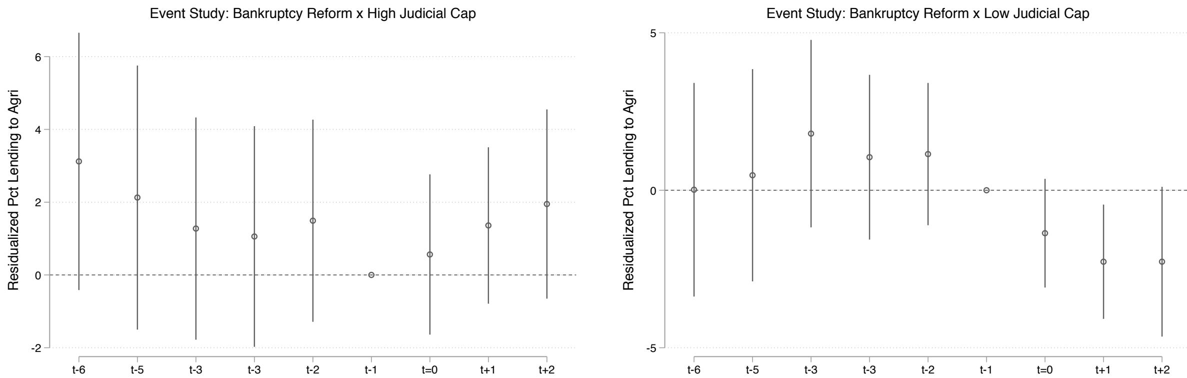
Panel B: Agriculture Sector Loans



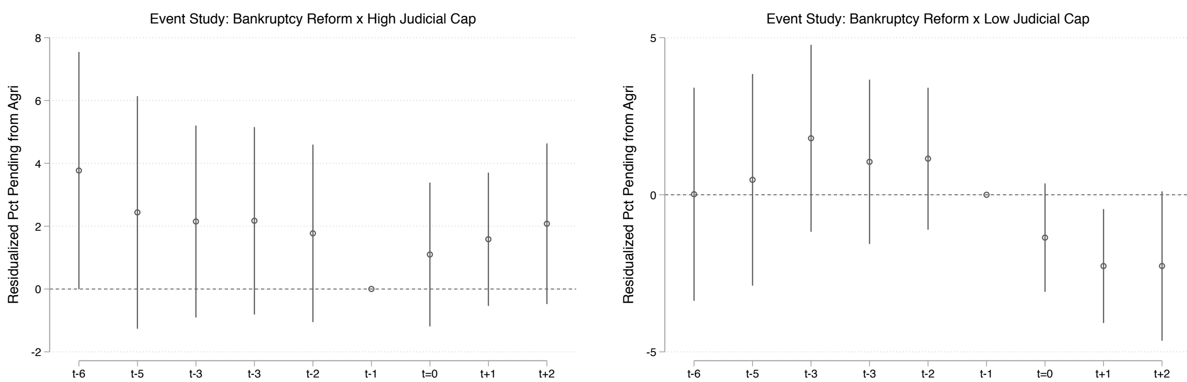
Notes: The figures present the event-study estimates of the bankruptcy reform on total lending and outstanding loans to non-agriculture sector (Panel A) and to agriculture sector (Panel B) in high judicial capacity districts.

Figure 3.8: Bank Lending to Agri Sector: Judge Occupancy x Bankruptcy Reform

Panel A: Percent Total Lending to Agri Sector



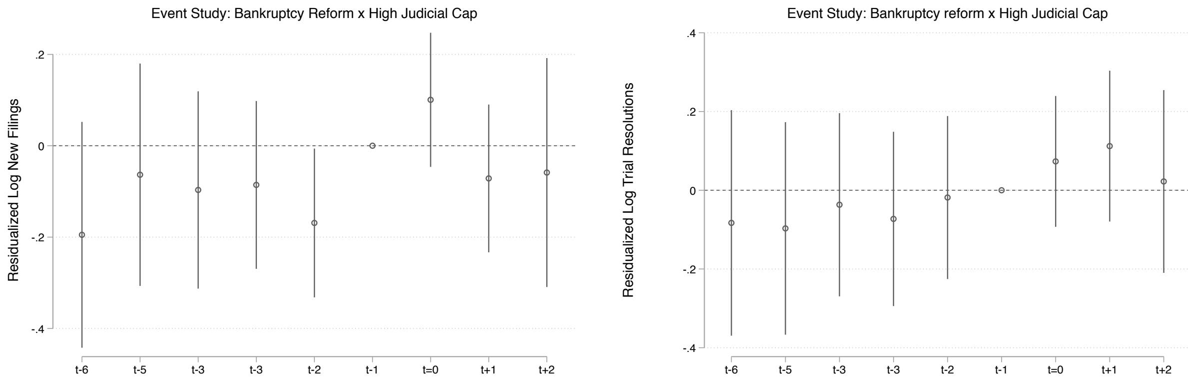
Panel B: Percent Total Outstanding From Agri Sector



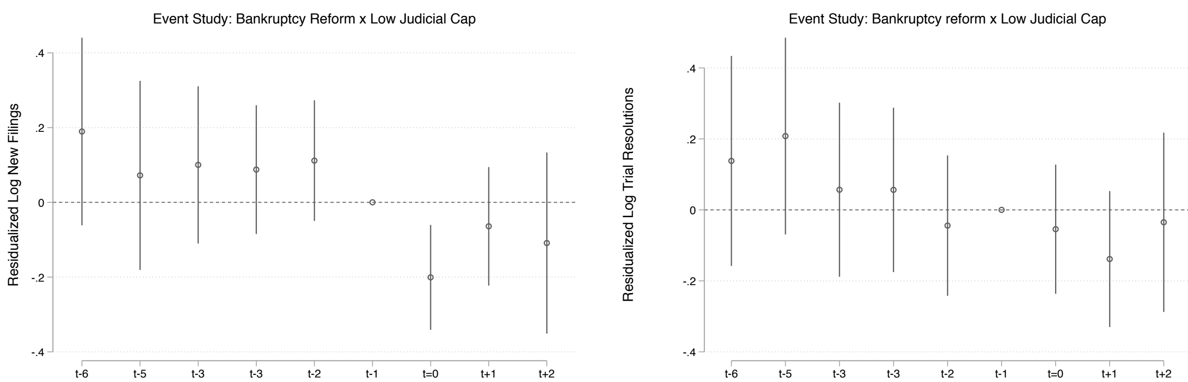
Notes: The figures present the event-study estimates of the bankruptcy reform on percentage of all lending (Panel A) and outstanding loans (Panel B) for the agriculture sector by underlying judicial capacity of the districts. Since agriculture sector is classified as a priority sector, the percentage lending represent credit allocation to the agriculture sector and percentage pending represents the percentage of all outstanding dues from the sector.

Figure 3.9: Bank Litigation: Judge Occupancy x Bankruptcy Reform

Panel A: High Judicial Capacity



Panel B: Low Judicial Capacity



Notes: The figures show the event study estimates on the number of new filing and resolution of trials pertaining to the banking sector in the corresponding district courts, grouped by their prior-period judicial capacity. High judicial capacity districts are those with over median ex-ante judge occupancy within the state whereas low judicial capacity districts are those below the median occupancy within the same state.

3.9 Tables

Table 3.1: Bankruptcy Reform: Firm Borrowing from Banks

	Dep Var: Asinh Firm Borrowing from Banks			
	(1)	(2)	(3)	(4)
	All Firms	All Firms	Firms in High Jud Cap District	Firms in Low Jud Cap District
Defaulter x Post	-0.276**	-0.341***	-0.350	-0.243
	(0.136)	(0.125)	(0.298)	(0.263)
Past Defaulter	1.042***	0	1.069***	1.118***
	(0.135)	(.)	(0.174)	(0.352)
Observations	34842	34588	10462	5546
District FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	No
State-Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Mean Dep Var	1.512	1.512	1.434	1.434
SD Dep Var	2.718	2.718	2.620	2.620
Adj R-Squared	0.100	0.600	0.100	0.110

Standard errors in parentheses

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 on bank borrowing by firm status as a past defaulter. A firm is categorized as a defaulter based on their ex-ante credit ratings, indicating default on repayments. All standard errors are clustered at the district level.

Table 3.2: Credit Allocation within Manufacturing Sector: By MRPK

	Dep Var: Asinh Firm Borrowing from Banks			
	(1)	(2)	(3)	(4)
	All Firms	All Firms	Firms in High Jud Cap District	Firms in Low Jud Cap District
High MRPK x Post	0.200**	0.146**	0.370**	-0.0284
	(0.0935)	(0.0613)	(0.154)	(0.273)
High MRPK	-0.900***	0	-1.019***	-0.823***
	(0.0754)	(.)	(0.118)	(0.213)
Observations	14076	13580	4120	2474
District FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Mean Dep Var	5.107	5.107	4.973	4.973
SD Dep Var	2.554	2.554	2.470	2.470
Adj R-Squared	0.230	0.870	0.210	0.300

Standard errors in parentheses

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 on bank borrowing by firm's marginal revenue product of capital (MRPK). Firms are classified into High and Low MRPK firms based on whether the firm is above or below median MRPK within their two digit industry in the period prior to the reforms. All standard errors are clustered at the district level.

Table 3.3: Credit Allocation within Manufacturing Sector: By MRPL

	Dep Var: Asinh Firm Borrowing from Banks			
	(1)	(2)	(3)	(4)
	All Firms	All Firms	Firms in High Jud Cap District	Firms in Low Jud Cap District
High MRPL x Post	-0.221**	-0.0431	-0.105	-0.341*
	(0.104)	(0.0550)	(0.272)	(0.172)
High MRPL	0.241***	0	0.261	0.382**
	(0.0842)	(.)	(0.159)	(0.176)
Observations	14076	13580	4120	2474
District FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Mean Dep Var	5.107	5.107	4.973	4.973
SD Dep Var	2.554	2.554	2.470	2.470
Adj R-Squared	0.210	0.870	0.180	0.280

Standard errors in parentheses

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 on bank borrowing by firm's marginal revenue product of labor (MRPL). Firms are classified into High and Low MRPL firms based on whether the firm is above or below median MRPL within their two digit industry in the period prior to the reforms. All standard errors are clustered at the district level.

Table 3.4: Bankruptcy Reform DID Estimates: Banks Lending

	(1) Log Total Accounts	(2) Log Total Accounts	(3) Log Total Accounts	(4) Log Outstanding	(5) Log Outstanding	(6) Log Outstanding
High Judge Occp x Post	-0.0386*			-0.0424		
	(0.0228)			(0.0346)		
Low Court Prod x Post		0.0283			0.0566*	
		(0.0244)			(0.0315)	
Judge Occp (pre period mean) x Post			-0.00295*			-0.00473**
			(0.00155)			(0.00223)
Observations	4772	4772	4772	4772	4772	4772
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	13.15	13.15	13.15	9.573	9.573	9.573
SD Dep Var	0.830	0.830	0.830	1.030	1.030	1.030
Adj R-Squared	0.980	0.980	0.980	0.980	0.980	0.980

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 across districts with above and below median judge occupancy on banks' lending (number of loan accounts and total outstanding). All standard errors are clustered at the district level.

Table 3.5: Bankruptcy Reform: Public Sector Banks Lending

	(1) Log Total Accounts	(2) Log Non-Agri Accounts	(3) Log Agri Accounts	(4) Log All Outstanding	(5) Log Non-Agri Outstanding	(6) Log Agri Outstanding
Judge Occp (pre period mean) x Post	-0.00136	-0.00194	-0.000923	-0.00490**	-0.00743*	-0.000884
	(0.00115)	(0.00287)	(0.00141)	(0.00237)	(0.00383)	(0.00161)
Observations	4772	4772	4772	4772	4772	4772
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	12.83	10.91	12.20	9.328	8.308	8.042
SD Dep Var	0.758	0.785	0.900	0.966	1.303	0.787
Adj R-Squared	0.990	0.950	0.980	0.980	0.960	0.970

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 by average prior period judge occupancy of the district court on public sector banks' lending and recovery outcomes. All standard errors are clustered at the district level.

Table 3.6: Bankruptcy Reform: Credit Allocation to Agriculture Sector

	(1) Percent Lending	(2) Percent Lending	(3) Percent Lending	(4) Percent Pending	(5) Percent Pending	(6) Percent Pending
High Judge Occp x Post Reform	-0.0309			-0.223		
	(1.475)			(1.362)		
Low Court Prod x Post Reform		-2.713**			-2.523**	
		(1.281)			(1.165)	
Judge Occp (pre period mean) x Post			0.183**			0.141**
			(0.0785)			(0.0691)
Observations	4772	4772	4772	4772	4772	4772
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	41.84	41.84	41.84	45.77	45.77	45.77
SD Dep Var	22.17	22.17	22.17	22.65	22.65	22.65
Adj R-Squared	0.920	0.920	0.920	0.940	0.940	0.940

Standard errors in parentheses

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 across districts with above and below median judge occupancy on banks' credit allocation to and loan recovery from the agricultural sector (considered a priority sector under directed state lending policy). All standard errors are clustered at the district level.

Table 3.7: Bankruptcy Reform: Bank Litigation

	(1) Log Filed	(2) Log Filed	(3) Log Filed	(4) Log Resolved	(5) Log Resolved	(6) Log Resolved
Judge Occp (pre period mean) x Post	0.000241			0.00275		
	(0.00605)			(0.00679)		
High Judge Occp x Post		0.0867			0.116	
		(0.0800)			(0.0801)	
Low Court Prod x Post			-0.206**			-0.127
			(0.0843)			(0.0811)
Observations	5087	5087	5087	5087	5087	5087
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Case-Type FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep Var	1.590	1.590	1.590	1.540	1.540	1.540
SD Dep Var	1.460	1.460	1.460	1.460	1.460	1.460
F-Stat	0	1.180	5.980	0.160	2.120	2.460
Adj R-Squared	0.340	0.340	0.340	0.410	0.410	0.410

Standard errors in parentheses

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

Notes: The table above reports difference in differences estimates of bankruptcy reform introduced in 2016 across districts with above and below median judge occupancy on banks' litigations in trial courts. All standard errors are clustered at the district level.

Chapter 4

Whither Justice?: Judicial Capacity Constraints Worsens Trial and Litigants' Outcomes[1]

4.1 Introduction

Disputes in economic transactions require timely resolution in which courts play a central role. Judicial capacity, measured as number of judge available in a court, has both direct effects on litigants as well as indirect effects through market-based channels. An analogy with the health-care system is apt here. The judiciary has a direct effect on litigants through the efficiency of its functioning, just like how well-equipped hospitals and health clinics are for patient outcomes. However, the judiciary also has an indirect effect on the overall economy through market-based channels similar to public health benefits of well functioning health-care institutions. Efficiency of judicial institutions and its personnel are important aspects of state capacity, which is relatively understudied compared to the functioning of bureaucrats or elected representatives. This paper draws attention to the front-line effect of judicial institutions on economic agents that actively engage the court system as litigants.

Judges are key to the functioning of the judiciary. They are public officials recruited by the state through a competitive selection process that typically requires a degree in law and minimum number of years of experience practicing law. A vast literature on the economics of crime (Rehavi and Starr 2014; Yang 2016; Dobbie, Goldin, and Yang 2018; Arnold, Dobbie, and Yang 2018; Rose and Shem-Tov 2018; Norris, Pecenco, and Weaver 2020) and bankruptcy proceedings (Müller 2020) in the context of Western democracies highlight the importance of judges' decision-making in determining the outcomes of litigants and litigant households. On the other hand, there is not much evidence on the role of judges and their effects on litigants engaged in civil disputes or in the context of developing economies where

[1] I am indebted to my advisors Aprajit Mahajan, Elisabeth Sadoulet, Frederico Finan. I acknowledge the generous funding support from International Growth Centre (IGC), State Effectiveness Initiative and UC Berkeley Library for acquiring additional datasets. All errors are my own.

state capacity is relatively weak. Kondylis and Stein (2018) highlight positive response by firms to improved pre-trial process in Senegal, requiring civil judges to complete all pre-trial proceedings within a stipulated time period. However, a big challenge in any economy is whether there are enough judges to meet the demand for judicial services. The appointments need to keep up with the demand for judiciary and ensure that periodic vacancies are addressed in a timely manner. Structural vacancies are a capacity constraint and lead to delays in the litigation process, resulting in backlogs of trials. [2]

The judge to population ratio for every million in the US is 100, in Sweden it is 213, whereas in India it is 20. Each judge presides over a courtroom within a trial court where all active trials are assigned to a specific courtroom at the time of their filing. Not only is the sanctioned judge strength small, a large fraction - close to 25% of these positions are vacant. Vacancy in any given court occurs due to retirements, transfers, resignations, or death. In this paper I examine how judge vacancy in trial courts in India affects litigant outcomes. For an ongoing trial whose life-cycle lasts multiple years, I exploit plausibly random occurrence of vacancy within the lifecycle of a trial after accounting for case characteristics, time-invariant and varying unobservables through courtroom and trial court-year fixed effects, respectively. That is, the identifying variation is driven by variation between trials that experience vacancy during their life-time and those that do not within the same courtroom in the same district court.[3]

The problem of persisting vacancies in the Indian judiciary, coupled with the system of frequent reassignment of judges to different courts that keep their tenure short, shifts the vacancies across courts over time. Further, annual assignments are announced at the same time for all courts in a state. For example, if Judge X in Court A is transferred in April (the typical month when transfers are announced), then unless there is another judge assigned to Court A at the same time, the courtroom occupied by Judge X will remain vacant at least until the next season of transfers (i.e. next year). Since the total number of judges is less than the total sanctioned judge positions or courtrooms, the vacancies sometimes last more than a year. Therefore, cases that were filed in the courtroom before Judge X is transferred will experience a vacancy shock compared to cases that were filed in the same courtroom but whose life-cycle did not straddle a vacancy. Consistent with this argument, I find no significant pre-trends in the rate of filing and trial resolutions in the years prior to the vacancy. On the other hand, trial resolutions drop significantly in the subsequent 1-2 years, adding to growing backlog. The composition of cases do not affect these patterns either. In other words, the vacancy does not coincide with any significant pre-trends in cases

[2]In the United States, appointment of judges is a highly political process. On the other hand, in India and many other former British commonwealth nations, judges are appointed by the higher judiciary, independent of the executive.

[3]Courtroom fixed effects absorbs time invariant unobserved characteristics such as available infrastructure, location, typical complexity or characteristic of cases assigned to the courtroom, etc. Trial court-year fixed effects accounts for time-varying unobservables at the level of the district court. This includes court level infrastructure upgrades, changes to court-wide administrative rules, time-varying characteristics of the court's jurisdiction including district specific population and economic growth dynamics, etc.

pertaining to specific types of litigants and the drop in resolution subsequent to vacancy occurs consistently across litigant types.

The first set of outcomes that I examine pertain to that of the trials, including overall case duration, number of hearings, whether uncontested by defendant, and whether dismissed by the judge. While case duration and number of hearings help measure the trial process, rate of contestation and dismissals provide measures of trial outcome. These latter two variables capture the choice made by either the defendant in pursuing the case or the judge in admitting the case for full trial, respectively, therefore, providing information on trial outcomes. Vacancy increases case duration by 0.3 SD or 168 days. They are 15.3 percentage points more likely to be uncontested by defendants, and 7.4 percentage points more likely to be dismissed by the subsequent judges without completing the full trial process. On the other hand, there is no meaningful difference in the total number of hearings. Since I am interested in identifying the welfare effects of vacancy on litigants, I restrict the trial sample to the subset of trials where I matched litigants to a sample of formal sector firms. The average treatment effects are similar - the case duration increases by similar magnitude (147 days extension), likelihood that the trial is uncontested remains stable around 16 percentage points, however the probability of dismissal without full trial doubles to 15 percentage points. Statistically, the total number of hearings reduces but the effect size is less than 0.05 SD, which is very small. However, whether the litigating firm appears as a plaintiff or as a defendant matters whether the case is likely to be dismissed. Judge vacancy increases the rate of dismissals for plaintiff firms by 22.5 percentage points whereas it does not affect trials where firms appear as a defendant. The remaining trial outcomes do not differentially vary by the litigant status of the matched firms. If the nature of trials are likely to be similar whether or not firms appear as a plaintiff or as a defendant, then we shouldn't see a differential dismissal rate. Indeed, I do not see any differential effects on other case outcomes including duration even after accounting for the nature of the trial through case-type fixed effect. The differential dismissal implies that the plaintiff firm may need to re-file the suit or seek alternate means of dispute resolution. This could have particular equity concerns if plaintiff firms are more likely to be smaller and have fewer assets than defendant firms.

To examine the effect on litigant firm outcomes, I employ the panel nature of the firms' balance sheet data. Owing to the fact that the firms can be engaged in litigation across multiple courts as well as in multiple litigations within the same court, I redefine the shock from judicial incapacity as a dummy variable that takes value 1 if any of the ongoing trials involving the firm experiences judge vacancy. Identifying the effects of judicial incapacity on litigant outcome is hard because it is hard to pin down the location of the relevant court. I overcome this by using detailed trial data matched with firm data, which enables me to identify the set of relevant courts where the firm has an ongoing litigation and address the causal effect of judge vacancy. I find that judge vacancy decreases legal expenditure, wage bill, and asset value of plaintiff firms by 7.5, 10, and 12 percent respectively. On the other hand, the effects are substantially lower for defendant firms. The stronger negative effects experienced by plaintiff firms also coincide with the fact that such firms are more likely to have their trials dismissed. Since smaller firms are more likely to initiate litigation as a plaintiff in these trial courts, the results likely imply equity consequences of judicial incapacity. Although I cannot disentangle whether observed dismissals arise from judge incentives or litigants' incentives, not completing the full trial process is likely a negative outcome for the plaintiff. It is likely that trials get backed up when there is a vacancy and the subsequent judge has to deal with a larger docket that may alter their incentives and therefore, their decisions. For example, a larger docket of backlogged trials may motivate judges to dismiss more cases than they would have in a counterfactual scenario.

This paper contributes to the literature on the organizational economics of public sector and governance institutions on the quality of "service" delivery. Chaudhury et al. (2006) highlight the problem of absenteeism among front-line public service providers that ranges between 19 percent among public school teachers and 35 percent among healthcare workers. Banerjee, Deaton, and Duflo (2004) show that high rates of absence among public healthcare workers is associated with higher expenditure incurred by local population on healthcare, including costs of multiple trips and increased visits to traditional, untrained, unregulated healers. Finan, Olken, and Pande (2015) summarize the personnel economics of public sector employees, exploring the role of selection, incentives, and monitoring behind the quality of service delivery. While a majority of the literature in this area focus on absenteeism as a measure of state capacity, this paper provides the first evidence on the organizational capacity of the front-line judicial sector measured as judge vacancy in trial courts. Frequent vacancies in courts increase the trial duration and worsen other trial related outcomes. These have negative consequences, specifically for smaller firms that rely on courts to adjudicate transactional and contractual disputes.

A large literature on legal studies in the context of United States and other western democracies examine dispute resolution in relation to corporate finance (e.g. bankruptcy reforms). However, we do not know much about how courts function in these contexts let alone in the context of developing economies. For example, is congestion of ongoing trials in courts a big barrier in the functioning of financial markets in the United States? If so, what are the drivers of congested courts? Müller (2020) shows that a reform to 2005 bankruptcy law in the United States substantially reduced the backlog of cases in bankruptcy courts, which subsequently improved the functioning of credit markets through increased recovery and leverage. Visaria (2009) and Ponticelli and Alencar (2016) show the effects of lowering congestion in courts through bankruptcy reforms in India and Brazil respectively and their subsequent impact on credit markets. All these paper use shocks to the filing of trials that subsequently reduce the backlog in courts or take the existing distribution of backlog as given. This paper complements this literature by emphasizing the role of organizational capacity - excessive vacancies in judge positions leading to negative consequences on the quality of judicial service. I show that this is specifically important for the growth of the corporate sector (formal sector firms) in developing economies and potentially for other types of litigants, that should be examined in future research.

The rest of the paper is structured as follows. Section 2 describes the institutional context of trial processing in trial courts in India. Section 3 describes the datasets and summarizes key variables used in the analyses. I present the empirical strategy in section 4 and present the results in section 5. Section 6 concludes.

4.2 Context

The court of interest is the District and Sessions Court, which is the principal court within the district trial court system in India. Each courtroom is headed by one judge, who is frequently rotated to a new district court at the end of their relatively short tenure. A large share - roughly 23 % - of these courtrooms are vacant. Due to frequent rotation of judges, the vacancy occurs during different years even within the same courtroom in a district court.

The workflow of a trial in a court is as follows. Cases are filed with the registrar by the plaintiff or their lawyer. Many courts have dedicated filing counters and the process involves filling up an application with the details of the suit and paying the registration fee. Once a case is successfully registered, the court administration system assigns the case to a courtroom. The system of assignment is not randomized and depends on the discretion of the administrative judge for the court. Once it is assigned, the judge and clerks associated with the relevant courtroom set the first hearing date and the trial subsequently begins.

A trial must complete various stages before the final judgement. These begin with issuing summons to the defendant. If the defendant does not appear after the summons, the trial proceeds ex-parte, i.e. the judgement is based on the arguments and evidence provided by the plaintiff alone. If the defendant responds, then the defending party provides written statement of objections or contentions and the trial proceeds by framing of issues, examining evidence and arguments put forth by both sides before judgement is pronounced. However, the trial may be dismissed at any of these stages if the complaint is not valid as per applicable laws or if either of the parties fail on their part in providing evidence or appearing during hearings.

Within this system of trial litigation through district courts in India, there is no pre-trial hearings or intervention before a case is official filed in a court. The judge themselves determine whether the suit warrants a full trial after issuing summons to the defendants, studying the formal written responses and framed issues. Subsequently, once the trial begins, the case may be dismissed on different accounts or can complete the full trial as per the judge's decision. A dismissal after multiple hearings is potentially a welfare loss for the litigants as they don't get full redressal in the form of a formal decree that can be executed. The loss is likely worse for the plaintiff, who may have no other means of dispute resolution. For example, small firms often do not have a separate legal team or have access to a complex system of arbitration that can be held outside the courts. Such firms may have to appeal or re-file the case after addressing the reasons for dismissal, often costing them more.

Trial courts are additionally important because they provide execution orders to promulgate decisions from any other quasi-judicial body or arbitration proceedings. So, even if trial resolution is done outside the court system, a judge is required to hear the petition for executing the orders, known as execution petition. Delays in addressing execution petition is problematic because it delays obtaining legal status to a dispute resolution order that has already been concluded. Firms are also more likely to engage in execution petitions on orders from arbitration proceedings and other quasi-judicial bodies.

The role of judicial capacity is therefore to provide both timely as well as fair judgement following due process. In this paper, I focus on the timeliness aspect whereas it is likely that the two interact. While I do not have data to be able to classify the fairness in judgements, I use outcomes of litigation such as whether they remain uncontested or dismissed without full trial as complementary measures of quality to shed light on the front-line effects of judicial capacity on litigant welfare.

4.3 Data

In this section, I describe the datasets I use for analyses. There are two key datasets - one covering the universe of trials in a sample of district courts and another containing annual balance sheet data of a sample of formal sector firms.

4.3.1 Trial Data

To study the effect of judicial capacity on trial and litigant outcome, I exploit the universe of ongoing trials between 2010 and 2018 across 1967 court-halls in 195 district courts in India that I assembled from case meta data from the e-courts database. I observe ongoing trials filed before 2010, trials filed during the period, as well as trials resolved in each of the years in the sample, which add up to 6.96 million unique trials. 5.25 million trials are filed in or after 2010 with full set of available fields. The meta data also includes the trial characteristics including dispute type, assigned courtroom, litigant identity and outcomes constructed out of time-stamps including case duration in days, total number of hearings, and case outcome. The data does not include the details of the ruling or judgement order, which is available as a text file attachment for the set of trials that undergo full trial.

4.3.2 Firms Data

I use annual firm-level panel data comprising a sample of formal sector firms in India known as the Prowess dataset curated by Center for Monitoring Indian Economy (CMIE). The dataset contains many variables of firm performance including balance sheet information, required under public disclosure laws. In addition, the dataset contains detailed characteristics of the firm including industry, sector, and ownership details. For the purposes of analyses in this paper, I focus on five key variables from this dataset determined ex-ante. These include legal expenditure, wage bill, asset value, sales revenue, and accounting profit. The variables are transformed using inverse hyperbolic sine transformation as is standard in the literature. This also enables interpreting the effect in terms of percentage change in the outcomes of interest.

The sampling frame of firms to examine the effect of judicial capacity includes all non-banking firms with at least one ongoing case in the court sample. Whereas banks intensively use courts for debt recovery related contractual disputes that I explore in detail in an accompanying paper, this paper focuses on the effect of courts on manufacturing and service sector firms' production outcomes, including legal expenditure, wage bill, asset value, sales revenue, and accounting profit.

4.3.3 Matching Trials with Firms

The trial data provides identifying information on the litigants, which I use as a key to fuzzy-match with the firms panel data. The matching algorithm uses a combination of regular expressions allowing spelling errors, spaces and special characters, and manual verification of the resulting matches across all 5351 matched firms. 5236 of these firms are non-banking firms, which form the sample of interest.

The matched firms have an average of 91 trials and a median of 2 trials. These are filed in different courts, including those other than the location of the firms' registered office. The location of the trial is determined by the relevant jurisdiction depending on the dispute. Typically, an aggrieved firm would file a plaint against the defendant in the court corresponding to the defendant location or the location of the damage. As a result, a litigating firm has multiple trials across different district courts and therefore, affected by the judicial capacity of not only their home district court but also other district courts. In the sample, about 19 % of the matched non-banking firms have ongoing litigation in the same district court as their registered office location. Therefore, judge vacancies occurring in any district court with an ongoing trial concerning the firm will likely affect the firms' production outcomes.

4.3.4 Judge Shock

For the trial sample, I create judge shock as a dummy variable if an ongoing trial experiences judge vacancy during it's life cycle, i.e. between the date of filing and the date of resolution. For the matched firm sample to estimate the effect on production outcomes, I define the judge shock as a dummy variable if at least one on-going trial involving the firm in any district court experiences judge vacancy in a given calendar year.

4.3.5 Summary Statistics

Table 4.1 and Table 4.2 present the summary statistics of trials in the trial sample, grouped by whether or not a trial experiences a judge vacancy during its lifecycle. About 27,000 trials experience at least one vacancy during their life-time. Simple mean differences between the two groups indicate that the duration of trials experiencing judge vacancy as nearly twice as many days as trials that do not. Other trial outcomes are also poor relative to the group that don't experience any vacancy. Time to first hearing since the filing of the case is 123 days on average whereas it is only 69 days when there is no vacancy. Trials are also more likely to be uncontested and dismissed when they encounter vacancy. These are likely to have causal implication on the welfare outcomes of the litigants which I explore in the rest of the paper.

The causal effects of judge vacancy are likely to be heterogeneous depending on whether the litigant is the aggrieved (i.e. a plaintiff) or a defendant. Figure 4.1 shows that the smaller firms, based on their asset sizes, are more likely to be plaintiff rather than a defendant. On the other hand, defendant firms are more likely to be larger firms. In the next section, I present the empirical strategy for estimating the causal effects of judge vacancy on trial outcomes and subsequently on litigant welfare.

4.4 Empirical Specification

4.4.1 Trial Outcomes

I exploit the fact that the district courts in India do not have enough number of judges to fill the available courtrooms (judge seats). Vacancy generated by this structural problem in a given court in any year is plausible random due to the fact that the existing judges get frequently relocated to a new district court at the end of their predetermined tenure. The system of judge assignment is based on specific rules and is managed by a centralized authority, such that the timing when an ongoing trial experiences a vacancy is as good as a random shock. As a result, vacancy lasts until a new judge is appointed to the vacant courtroom. Given the fact that there are simply not enough judges, the vacancy lasts a long time. Therefore, the identification strategy compares the trial outcomes for cases that experience a random judge vacancy shock with cases that don't experience such a shock in the same courtroom within a district court, after flexibly accounting for the court specific time trend.

Using the universe of ongoing trial data between 2010 and 2018, I observe whether a courtroom within a district court experiences judge vacancy in any given year during this period. Since all cases filed in a district court are assigned a courtroom at the time of filing, I encode judge vacancy as a dummy variable taking on value 1 if the courtroom experiences judge vacancy in a given calendar year. Restricting the set of trials to only ongoing trials at the time of vacancy, the encoding accounts for potential endogenous response in the form of new filing. The first set of outcomes I examine pertain to the outcomes of the trial including case duration and case outcomes that indicate whether or not the case is uncontested by the defendant, and whether or not the case is dismissed by the judge. To account for unobserved factors affecting the timing of vacancy and case outcomes, I include two-way fixed effects in terms of district court-year fixed effects to account for time-varying unobservables at the level of the district court and courtroom fixed effects to control time-invariant unobservable characteristics of the courtroom. Additionally, I include case-type fixed effects to address any procedural differences in the litigation process across litigation by the type of dispute. The regression specification used is as below:

$$y_{ihcdt} = \delta_h + \delta_{dt} + \delta_c + \beta shock_{ihcdt} + \epsilon_{ihcdt} \tag{4.1}$$

The unit of analysis is a case or trial i, filed in courtroom h within a district court d in year t - which represents the year of filing. y_{ihcdt} is the outcome of case, which experiences a shock $shock_{ihcdt} = 1$ if there is a judge vacancy between the year the case was filed and the year of its resolution or the end of the study period. The specification also accounts for fixed effects as discussed above. I cluster the standard-errors by courtroom, which is the level of quasi-random variation.

Causal identification requires that the set of cases that experience the judge shock are similar in expectation to cases that do not. To demonstrate this, I present event-study results of the entire work-flow (trial filing and resolutions) of the courtroom at the time of judge vacancy. Since vacancy in a given year affects all ongoing trials within a courtroom, I test whether the timing of the shock is correlated with any past trends in the work-flow. An absence of any significant and meaningful trend suggests that the timing of the shock is as good as random.

4.4.2 Trial Outcomes for Matched Firms

I run regression specified by equation (1) on the subset of trials involving formal sector firms in Prowess dataset. I match firms in the trial dataset with those in Prowess by their name, using a combination of regular expressions and manual verification of the match quality as discussed above. This generates the set of firms that use courts intensively and for whom, I can track their production and economic outcomes. I examine the subsequent welfare effect on these litigating firms using the empirical strategy detailed in the next subsection.

To examine any heterogeneous effects depending on whether the litigating firm appears as a plaintiff or as a defendant, I interact the judge shock with a dummy variable highlighting the litigant status of the firm. Examining this heterogeneity is important and useful to understand the equity implications of weak judicial capacity. If there is no differential effect of judge vacancy when a firm is involved as a plaintiff, we fail to reject the claim that the judicial system is equitable. Presence of a differential effect is likely indicative that judge vacancy has further negative consequences to the initiator of the trial (the plaintiff).

$$\begin{aligned} y_{ifhcdt} &= \phi_h + \phi_{dt} + \phi_c + \kappa_1 shock_{ifhcdt} \text{ x Plaintiff}_{ifhcdt} \\ &\quad + \kappa_2 shock_{ifhcdt} + \kappa_3 \text{Plaintiff}_{ifhcdt} + \xi_{ifhcdt} \end{aligned} \tag{4.2}$$

f represents firm f in Prowess sample matched to the trial sample. The firm can appear either as a plaintiff, $\text{Plaintiff}_{ifhcdt} = 1$, or as a respondent within a trial i. The remaining variables and index symbols are the same as in equation (1).

4.4.3 Matched Firms' Production Outcomes

To measure the effect of judicial incapacity on the outcomes of the litigants, I examine the reduced form effects of judge vacancy on the annual production outcomes of the litigant. As mentioned earlier, I restrict the set of litigants to formal sector firms in the non-banking sector. A large share of such firms are from the manufacturing sector and therefore, this analysis helps shed light on the importance of well functioning courts for economic production.[4]

Given that I observe the outcome at the level of a firm, which may have many ongoing trials across different courts in my sample, I define the judge shock slightly differently and use a regression specification that uses firm-level annual panel data on production outcomes. I define the judge shock treatment variable as a dummy variable if a firm encounters judge vacancy in any of the courts in the sample where it has an ongoing trial in a given year. For causal identification, I use an event-study specification where I examine the effect of judge vacancy on the current and post-period outcomes, conditional on two-way fixed effects incorporating firm and year fixed effects. The regression specification is as follows:

$$y_{ft} = \gamma_f + \gamma_t + \gamma shock_{ft} + \zeta_{ft} \tag{4.3}$$

y_{ft} is the outcome of the firm in year t, which primarily includes legal expenditure, wage bill, asset value, sales, and accounting profit. $shock_{ft}$ is encoded as a dummy variable, taking on value 1 when a firm encounters a judge vacancy in any of the courts with their active ongoing trial(s). The above specification accounts for firm fixed effects γ_f and year fixed effects γ_t to account for all time invariant unobserved factors by firm and secular non-parametric time trend. I cluster the standard errors by firm to account for serial correlation between yearly firm outcome measures.

As in event-studies, the identifying assumption is that the trend will continue in the absence of the judge shock. Any deviation in the trend relative to the counterfactual can be attributed as the causal effect of judicial capacity. Since the counterfactual trend is fundamentally unobservable, I test for any pre-trends in the outcome variables.

4.5 Results

4.5.1 Tests for Identification

The empirical specification compares ongoing trials within the same courtroom in a district court that encounter a judge vacancy with those that don't. The identifying assumption for studying the implication of judge vacancy on trial and litigant economic outcomes requires that the characteristics and the potential outcomes of the trials experiencing the shock are similar in expectation to trials that don't. Since I condition on many of the observed trial

[4] I examine the effects on the credit market and the banking sector in a separate paper here.

characteristics, I rely on the absence of any significant trend in the work-flow in the prior-period of the courtroom experiencing vacancy to support the identifying assumptions. First, I show that the work-flow is not correlated with the timing of the shock by examining the flow of new trials and resolutions in a courtroom using an event-study specification. Additionally, I also examine the composition of the work-flow by the litigant type involved (i.e. set of trials involving firms or government agents).

Figure 4.2 shows the work-flow before and after the first judge shock in a courtroom. The y axis plots residualized number of case filing and resolutions, after conditioning for courtroom fixed effects and district court-year fixed effects. Panel A depicts number of filings and resolutions respectively across all trials filed within the courtroom. Panel B and C present the composition of the trials filed and resolved by categorizing whether the trials involved firm or government agents as either of the litigating parties, respectively.

The figures suggest that the number of filings remain relatively stable 2 years before and after the shock, which typically includes the tenure of a judge in a district court. On the other hand, the number of resolutions drop in the succeeding years suggesting that vacancy is likely sticky and adds to the backlog of cases. However, there is no evidence of a significant pre-trend that could likely affect the timing of the vacancy. This suggests that the effect of judge vacancy shock on trial and litigant outcomes can be interpreted as plausibly causal subject to the assumption that the trend would have continued had there been no shock.

4.5.2 Trial Outcomes

All Trials Table 4.3 presents the effect of judge vacancy on trial outcomes using the sample of all trials in the sample. The key outcomes examined are case duration, number of hearings, whether trial is uncontested, and whether the trial is dismissed. Experiencing judge vacancy during the life cycle of a trial increases the duration of the trial by 168 days, which represents an effect size of 0.3 SD. On the other hand, the total number of hearings remain unaltered. What this suggests is that judge vacancy leads to a postponement of hearings rather than increase or decrease the total number of hearings relative to the counterfactual. Vacancy also increases the likelihood that the trial goes uncontested by the defendant by 15.3 percentage points or by 0.36 SD as well as increases the likelihood that the trial is dismissed by the next judge by 7.4 percentage points (0.2 SD).

Trials of Matched Firms Restricting the trial sample to those matched with the firm data, which is roughly about 10% of the universe of trials, I find similar effects on case duration and the rate a trial goes uncontested. Table 4.4 presents these outcomes. Case duration increases by 147 days, representing an effect size of 0.23 SD. The likelihood of being uncontested increases by 16.0 percentage points or by 0.33 SD. These are similar to the whole sample. However, the number of hearings reduces by a fraction 0.16, which while being statistically significant presents an effect size of less than 0.05 SD. Finally, the rate of dismissals increases by 15 percentage points (0.38 SD).

Examining the heterogeneous effects by whether the firm appears as a plaintiff or as a defendant, Table 4.5 shows that judge vacancy affects the trial outcomes similarly when examining case duration, number of hearing, or the rate of uncontested trials. However, the rate of trial dismissals substantially increases on trials involving matched firms as a plaintiff. This likely implies that firms are less likely to benefit from trial resolution through the courts in the presence of judge vacancy when they initiate litigation as plaintiff. This is because dismissal implies that there is no verdict passed through the judicial proceedings and the plaint is not resolved by the court.

4.5.3 Matched Firms' Production Outcomes

To examine the subsequent effects on the production outcomes of firms engaged in litigation across courts in the trial sample, I estimate equation (3) on subsamples of trials involving the matched firms as a plaintiff and subsamples involving firms as defendant. Table 4.6 presents the results on plaintiff firms' legal expenditure, wage bill, asset value, sales revenue, and accounting profit. Firm experiencing judge vacancy in any of the sample courts in a given calendar year when they have an ongoing trial in the courts decreases legal expenditure, wage bill, and asset value by 7.5, 10, and 12 percent respectively. Since plaintiff firms are more likely to experience dismissal of their trial as a result of judge vacancy, they also experience a contraction in production. Sales revenue also decreases by 1.1 percent but is statistically insignificant. On the other hand, accounting profit (total income net of total expense) increases but is not significant.

The effects of judicial incapacity has a similar but muted effects when firms appear as defendant (Table 4.7). The point estimates have the same sign but the magnitude is half the point estimates when the firm appears as a plaintiff. Additionally, none of the coefficients are statistically significant.

4.5.4 Discussion

I show that judge vacancy occurring as good as randomly increases the trial duration of an ongoing case. This does not have an effect on the total number of hearings between trials experiencing vacancy relative to those that don't. However, such trials are more likely to go uncontested by the defendants and more likely to be dismissed by the subsequent judge. These patterns hold for the subset of cases involving formal sector firms matched with a firm-level panel data.

Distributional Consequences The differential effects of judicial capacity on whether the litigant firm is one among the plaintiff or the defendant points towards equity consequences of poor judicial capacity. Plaintiff firm experiences an increase in costs not only from longer case duration that similarly affects the defendant firms, but additionally experiences a higher likelihood of their trial being dismissed. This negatively affects their production outcomes, lowering wage bill and asset value. On the other hand, they spend less on legal expenditure category, plausibly because payments to lawyers are tied to number of hearings attended rather than case duration. Longer trial duration likely stretches legal expenditure such that average annual expenditure is lower than the counterfactual situation. However, increase in trial duration and increased likelihood of dismissal of their plaint may cause firms to contract production by reducing wage bill and assets losing their value. This leads to concerns on equity since smaller firms are also more likely to use the courts system to initiate litigation to resolve transactional or other types of disputes.

4.6 Conclusion

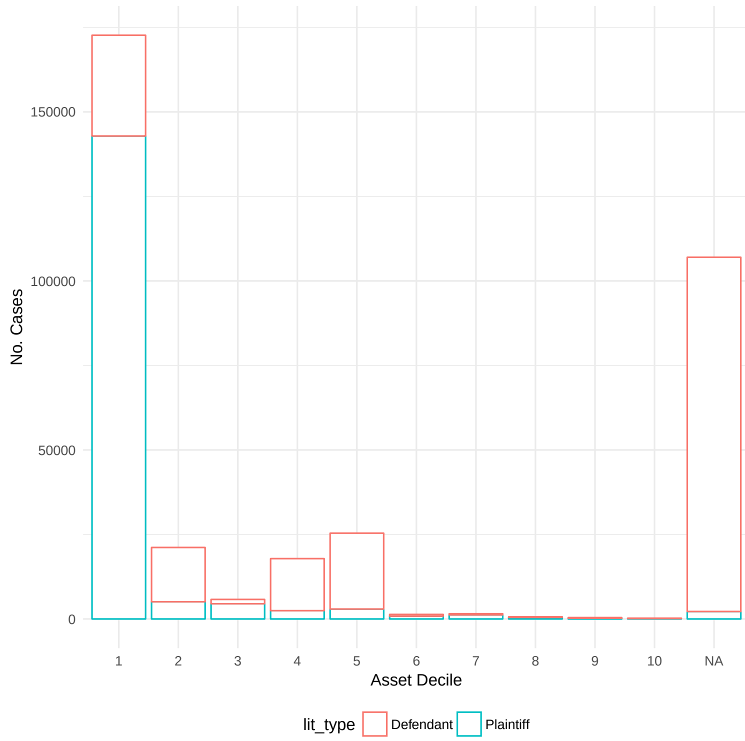
To conclude, this paper demonstrates that judicial capacity constraints measured in terms of judge vacancy negatively affects trial outcomes and leads to welfare loss for litigants. By exploiting plausibly random occurrence of vacancy within the lifetime of an ongoing trial, I show that trials encountering vacancy face delays in trial conclusion. This increases the backlog of trials on the docket of the incoming judge who later fills the vacant position. Subsequent outcomes of the trials, including the rate at which the trial is uncontested and the rate of dismissal increase whereas the total number of hearings is not affected by the vacancy. The trial outcomes are similar for the subset of trials with matched firms as litigants. Further, litigating firms appearing as plaintiff in trials facing vacancy experience lowering of their legal expenditure, wage bill, and asset values, indicating a potential welfare consequence of judicial incapacity.

What remains to be addressed is how the capacity issue affects the performance incentives of existing judges that inherit backlog of trials due to preceding vacancy. Further, disentangling trial outcomes resulting from judge behavior from that of litigant behavior is important to design the appropriate policy response.

The role of judiciary in building state capacity and promoting economic development is relatively understudied but nonetheless important. More research is needed to fully understand how these institutions function and how they interact with other government and market institutions in the economy. As detailed administrative data and experimental evidence addressing these open questions become more common, we will be able to shed light on appropriate policy action and design of institutions.

4.7 Figures

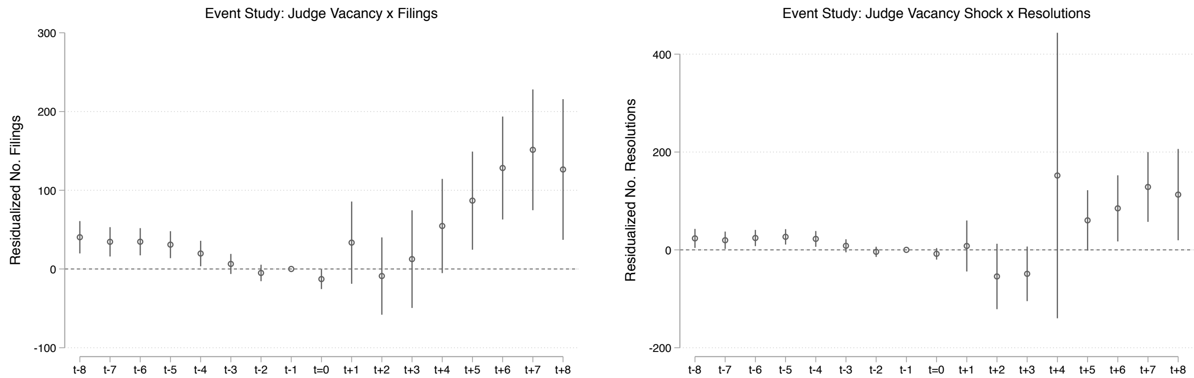
Figure 4.1: Number of Cases by Litigant Firm: Plaintiff vs. Defendant



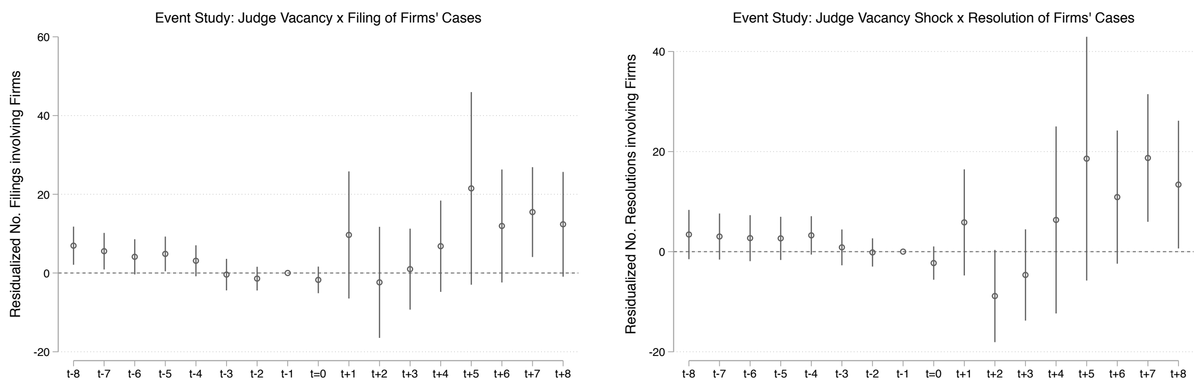
Notes: Above figure presents number of trials with matched firms grouped by whether the firm appears as a plaintiff or defendant across asset deciles.

Figure 4.2: Judge Vacancy: Event-Study on Court Hall Work-Flow

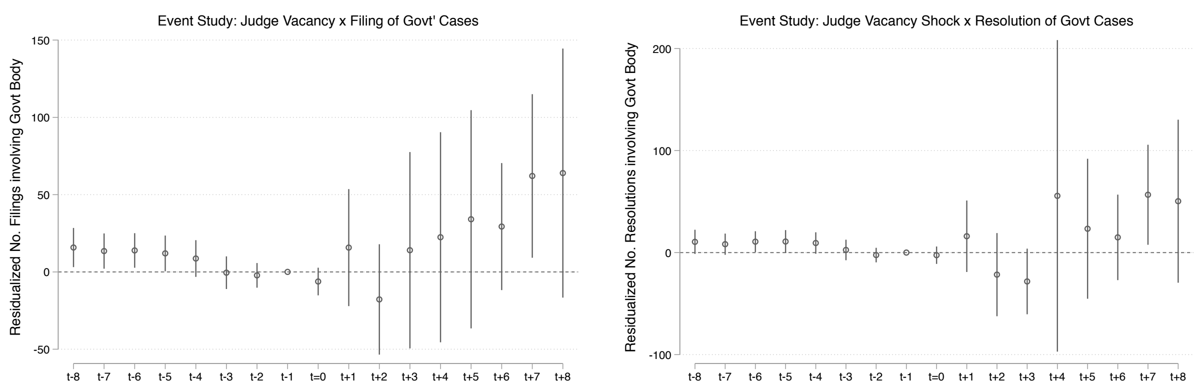
Panel A: All Trials Assigned to a Court-Hall



Panel B: Firm-Specific Trials Resolved in a Court-Hall



Panel C: Govt Trials Resolved in a Court-Hall



Notes: Figures present event study results of first judge vacancy shock on filings and resolutions overall (Panel A) and by whether either of the litigants involve a firm (Panel B) or a government entity (Panel C). The dependent variables - incoming cases and resolutions - are residualized of courtroom and district court-year fixed effects.

4.8 Tables

Table 4.1: Summary Statistics - Trials without Vacancy

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Case Duration (days)	5,042,069	428.023	576.898	0.000	16.000	625.000	4,022.000
Time to first hearing (days)	4,943,111	69.482	208.241	0.000	1.000	42.000	3,740.000
Number Hearings	4,520,278	2.760	6.137	1.000	1.000	3.000	788.000
Fraction Uncontested	5,099,871	0.227	0.419	0	0	0	1
Fraction Dismissed	5,099,871	0.162	0.368	0	0	0	1

Notes: Above table presents the summary of trial outcomes for cases that do not experience a judge vacancy over their lifetime.

Table 4.2: Summary Statistics - Trails with Vacancy

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Case Duration (days)	27,048	868.029	648.445	3.000	352.000	1,213.000	3,206.000
Time to first hearing (days)	25,941	122.623	267.338	0.000	1.000	92.000	2,857.000
Number Hearings	23,841	2.510	4.151	1.000	1.000	3.000	62.000
Fraction Uncontested	27,051	0.429	0.495	0	0	1	1
Fraction Dismissed	27,051	0.223	0.416	0	0	0	1

Notes: Above table presents the summary of trial outcomes for cases that experience a judge vacancy over their lifetime.

Table 4.3: Effect of Judge Vacancy on Trials

	Dependent variable:			
	Case Duration (days)	No. Hearings	If uncontested	If dismissed
	(1)	(2)	(3)	(4)
Judge Vacancy	168.408^***	-0.085	0.153^***	0.074^***
	(42.371)	(0.295)	(0.020)	(0.017)
Control Mean	428.02	2.76	0.23	0.16
Control SD	576.9	6.14	0.42	0.37
Court-Hall FE	Yes	Yes	Yes	Yes
Court-Year FE	Yes	Yes	Yes	Yes
Case-type FE	Yes	Yes	Yes	Yes
Observations	5,069,117	4,544,119	5,126,922	5,126,922
Adjusted R^2	0.516	0.448	0.250	0.208
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Above table presents the reduced form effects of judge vacancy on trial outcomes. Standard errors are clustered by courtroom that experiences vacancy over time.

Table 4.4: Effect of Judge Vacancy on Firms' Trial Outcomes

	Dependent variable:			
	Case Duration (days)	No. Hearings	If uncontested	If dismissed
	(1)	(2)	(3)	(4)
Judge Vacancy	146.867^***	-0.164^***	0.160^***	0.151^***
	(40.280)	(0.044)	(0.034)	(0.034)
Control Mean	559.23	2.18	0.38	0.2
Control SD	647.24	3.4	0.49	0.4
Court-Hall FE	Yes	Yes	Yes	Yes
Court-Year FE	Yes	Yes	Yes	Yes
Case-type FE	Yes	Yes	Yes	Yes
Observations	558,300	448,494	570,661	570,661
Adjusted R^2	0.479	0.743	0.374	0.391
Note:				*p<0.1; **p<0.05; ***p<0.01

Notes: Above table presents the reduced form effects of judge vacancy on trial outcomes for the subset of trials involving firms matched with Prowess. Standard errors are clustered by courtroom that experiences vacancy over time.

Table 4.5: Effect of Judge Vacancy by Firm's Litigant Status

	Dependent variable:			
	Case Duration (days)	No. Hearings	If uncontested	If dismissed
	(1)	(2)	(3)	(4)
Judge Vacancy x Plaintiff	13.448	0.005	0.036	0.225^***
	(79.816)	(0.073)	(0.063)	(0.056)
Judge Vacancy	139.214^*	-0.167^***	0.139^***	0.021
	(80.099)	(0.058)	(0.042)	(0.024)
Plaintiff	24.782	-0.048	0.001	0.001
	(18.124)	(0.031)	(0.011)	(0.013)
Control Mean	559.23	2.18	0.38	0.2
Control SD	647.24	3.4	0.49	0.4
Court-Hall FE	Yes	Yes	Yes	Yes
Court-Year FE	Yes	Yes	Yes	Yes
Case-type FE	Yes	Yes	Yes	Yes
Observations	558,300	448,494	570,661	570,661
Adjusted R^2	0.479	0.743	0.374	0.392
Note:				$^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: Above table presents the heterogeneous effects of judge vacancy by litigant status on trial outcomes for the subset of trials involving firms matched with Prowess. Standard errors are clustered by courtroom that experiences vacancy over time.

Table 4.6: Effect of Judge Vacancy on Plaintiffs' Outcomes

	Dependent variable:				
	Asinh Legal Exp	Asinh Wage Bill	Asinh Assets	Asinh Sales Rev	Asinh Profit
	(1)	(2)	(3)	(4)	(5)
Judge Vacancy	-0.075^**	-0.100^***	-0.120^***	-0.011	0.150
	(0.044)	(0.031)	(0.032)	(0.038)	(0.225)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8,866	12,549	13,348	11,238	13,029
Adjusted R^2	0.903	0.950	0.953	0.945	0.476
Note:					*p<0.1; **p<0.05; ***p<0.01

Notes: Above table presents the reduced form effects of judge vacancy on plaintiff firm outcomes for litigating firms matched with Prowess. Standard errors are clustered by the litigating firm that experiences vacancy over time.

Table 4.7: Effect of Judge Vacancy on Defendants' Outcomes

	Dependent variable:				
	Asinh Legal Exp	Asinh Wage Bill	Asinh Assets	Asinh Sales Rev	Asinh Profit
	(1)	(2)	(3)	(4)	(5)
Judge Vacancy	-0.047	-0.033	-0.052	-0.003	0.107
	(0.036)	(0.030)	(0.033)	(0.043)	(0.227)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,352	14,593	15,670	13,512	15,255
Adjusted R^2	0.899	0.944	0.945	0.934	0.480
Note:					*p<0.1; **p<0.05; ***p<0.01

Notes: Above table presents the reduced form effects of judge vacancy on defendant firm outcomes for litigating firms matched with Prowess. Standard errors are clustered by the litigating firm that experiences vacancy over time.

Table 4.8: Robustness of Plaintiffs' Outcomes: Without Frequent Litigators

	Dependent variable:				
	Asinh Legal Exp	Asinh Wage Bill	Asinh Assets	Asinh Sales Rev	Asinh Profit
	(1)	(2)	(3)	(4)	(5)
Judge Vacancy	-0.067	-0.088^***	-0.097^***	-0.014	0.230
	(0.047)	(0.033)	(0.034)	(0.041)	(0.233)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	8,341	11,740	12,517	10,629	12,201
Adjusted R^2	0.899	0.947	0.953	0.939	0.470
Note:					*p$<$0.1; **p$<$0.05; ***p$<$0.01

Notes: The table presents robustness of judge vacancy effect on plaintiff firms when removing highly litigating firms - over 99 percentile of number trials - from the sample. Standard errors are clustered by the litigating firm that experiences vacancy over time.

Table 4.9: Robustness of Defendants' Outcomes: Without Frequent Litigators

	Dependent variable:				
	Asinh Legal Exp	Asinh Wage Bill	Asinh Assets	Asinh Sales Rev	Asinh Profit
	(1)	(2)	(3)	(4)	(5)
Judge Vacancy	-0.035	-0.027	-0.040	0.008	0.073
	(0.039)	(0.033)	(0.036)	(0.047)	(0.233)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,731	13,735	14,788	12,777	14,377
Adjusted R^2	0.895	0.940	0.942	0.929	0.477
Note:					*p$<$0.1; **p$<$0.05; ***p$<$0.01

Notes: The table presents robustness of judge vacancy effect on defendant firms when removing highly litigating firms - over 99 percentile of number trials - from the sample. Standard errors are clustered by the litigating firm that experiences vacancy over time.

Chapter 5

Conclusion

This dissertation contributes to the limited evidence on the importance of trial courts and judicial institutions for economic development. I exploit disaggregated and detailed administrative data on trial records of all ongoing trials in a sample of 195 district courts in India that enable me to identify both direct as well as indirect effects of courts on litigants and the overall economy. I use contextual knowledge of personnel management within the judicial system, which is also applicable to contexts outside India and beyond judiciary, to isolate exogenous factors affecting the performance of trial courts to enable causal inference.

Specifically, I find that reducing judge vacancy by one judge reduces trial backlog by 6%. This increases lending by banks for manufacturing and consumption uses, which subsequently expands production by formal sector firms and improves their profits. Public revenue earned through increased economic production implies an 8:1 benefit-cost ratio of addressing judge vacancy in district courts. Further, I show that well functioning courts are complementary to strengthening creditor rights in increasing the efficiency of bank lending operations. Banks reduce lending to unproductive uses such as to defaulting firms and increase lending to firms with higher marginal revenue product of capital. I show that a plausible mechanism behind this complementarity is that courts with high judicial capacity enable banks to file debt recovery related litigation in a context with better creditor rights. Correspondingly, banks are less likely to file fresh suits in courts with high vacancies. In the final chapter, I show that vacancies in the judiciary delay trial resolution and affect the asset value and production decisions of litigating firms.

This sets a rich research agenda to examine additional channels of influence of the judiciary on a number of other markets including land property markets. Further, it underlines the need to examine the labor market constraints leading to high judge vacancies and how these influence the incentives facing existing judges in their decision-making and the decisions to choose litigation as a mechanism for dispute resolution by a large number of economic agents beyond formal sector firms.

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Appendix A

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

A.1 Describing Outcome Variables

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

1. Bank Lending: Bank lending variables are obtained from RBI data on district wise number of loan accounts and total outstanding loan amount (in INR Crore) annually aggregated across 27 scheduled commercial banks (national level banks).

2. Bank Deposits: Details on saving and term deposits also from RBI data on district wise number of deposit accounts (in thousands) and total deposited amount (in INR Million) annually aggregated across the national level banks.

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

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

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

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

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

1. Annual revenue from sales: This variable captures income earned from the sales of goods and non-financial services, inclusive of taxes, but does not include income from financial instruments/services rendered. This reflects the main income for non-financial companies.

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

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

4. Total wage bill: This captures total payments made by the firm to all its employees, either in cash or kind. This includes salaries/wages, social security contributions, bonuses, pension, and other parts of the contract with employees.

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

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

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

A.2 Matching Firms with Case Data

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

1. Identify the set of cases involving firms on either sides of the litigation (i.e. either as a petitioner, or as a respondent, or as both) using specific naming conventions followed by firms. Common patterns include firm names starting with variants of "M/S", ending with variants if "Ltd", and so on. This produces about 1.2 million cases, or 20% of the universe of cases that involve a firm.

2. Create a set of unique firms appearing in above subset of case data. I note that same firm appears as a litigator in more than one district, both as a petitioner or as a respondent. This is because the procedural laws pertaining to civil and criminal procedures determine where a specific litigation can be filed based on the issue under litigation.

3. Map firm names as they appear in the case data in step 2 with firm names as they appear in Prowess dataset using common patterns with the aid of regular expressions. This takes care of extra spaces, punctuation marks, as well as common spelling errors such as interchanging of vowels. Further, I also account for abbreviations. For example, "State Bank of India" appears in the case dataset as "State Bank of India", "SBI", S.B.I", and similar variants. I map all these different spellings to the same entity "State Bank of India".

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

5. Create primary key as the standardized name, from step 3 to match with both case as well as firm datasets.

6. When more than one firm match with a case, that is when there are multiple entities involved as either petitioners or respondents, I select one matched firm at random. These many-to-one matches are about 5% of the matches. In future, I plan to modify my algorithm to allow these types of scenarios.

A.3 Model Proofs

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

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

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

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

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

Constrained Optimization:

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

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

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

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

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

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

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

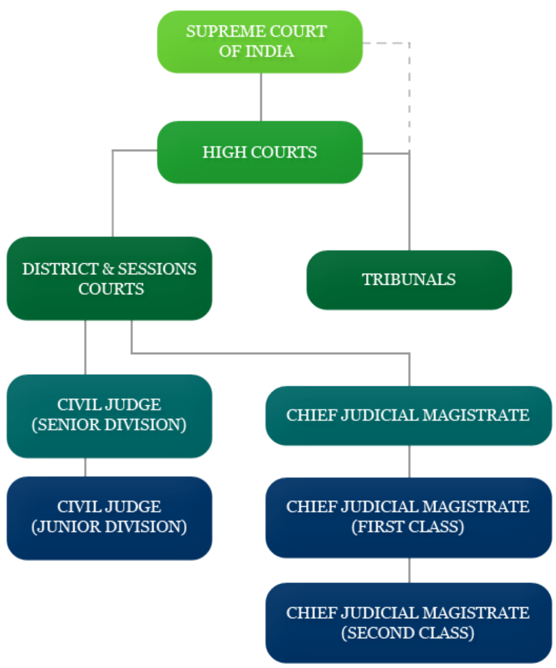
3. For inframarginal small firms, $i = S$ and $W << W^*$, neither their optimal inputs nor their profits change under improved institutional quality since $(\underbrace{\frac{\partial K_S}{\partial \gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial \gamma}}_{\approx 0}) \approx 0$.

A.4 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 A.11 presents the results on borrowing-lending outcomes and Table A.12 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.

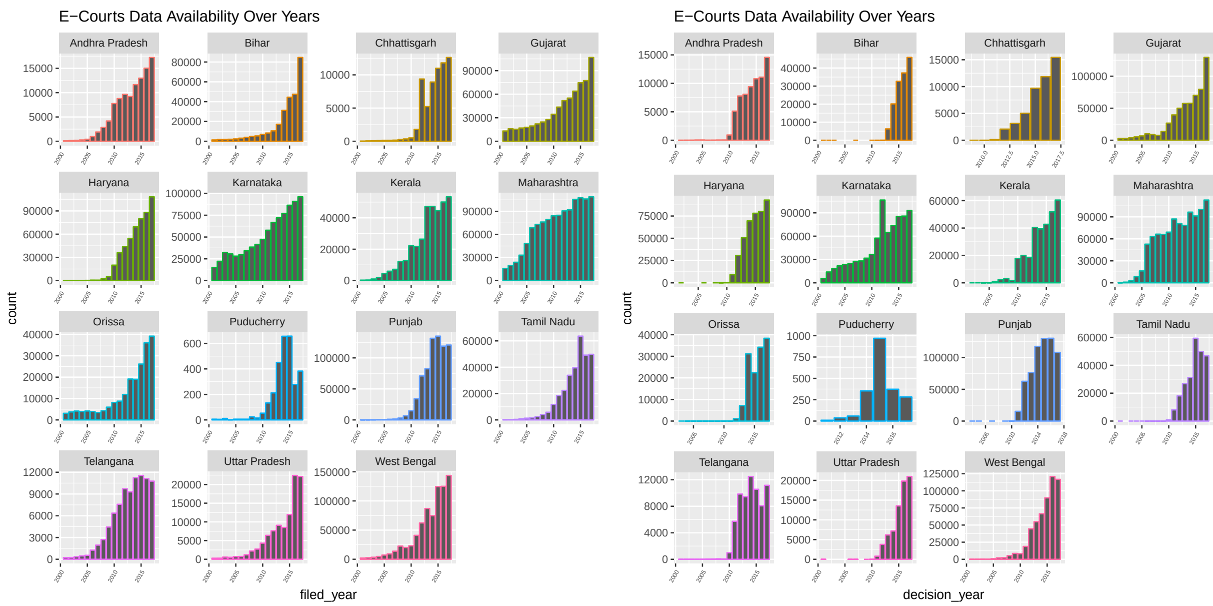
A.5 Appendix: Figures

Figure A.1: The Indian Judiciary Org-Chart



Source: Daksh, India.

Figure A.2: Data Availability



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

Figure A.3: Court Variables: Sample Case Page on E-Courts

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

Back

City Civil Court, Mumbai

Case Details

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

Case Status

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

Petitioner and Advocate

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

Respondent and Advocate

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

Acts

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

Sub Matters

Case Number :	/102240/2017

History of Case Hearing

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

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

Figure A.4: Construction of Firm Sample

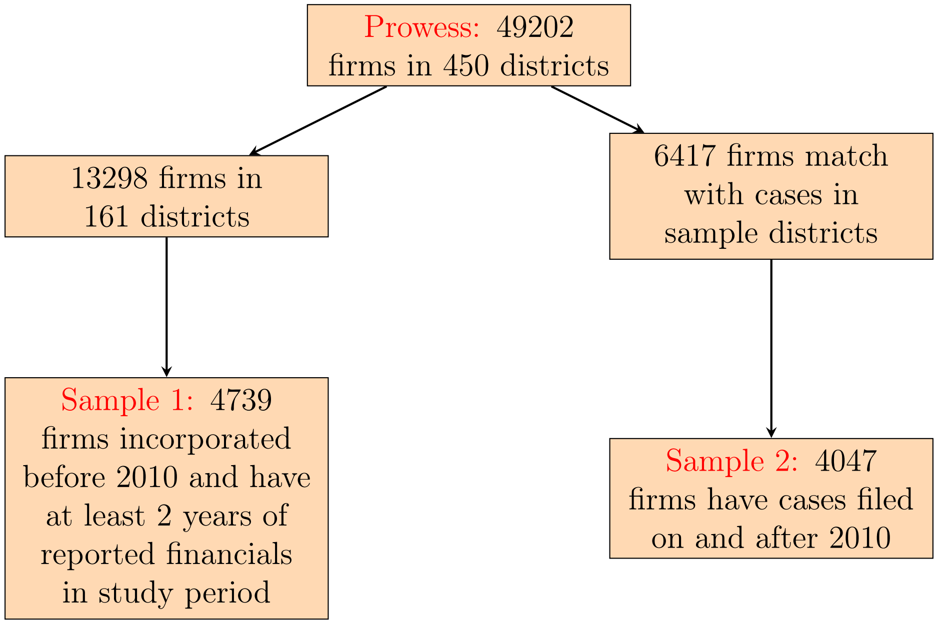


Figure A.5: Correlation Between Judge Occupancy and District Population Change

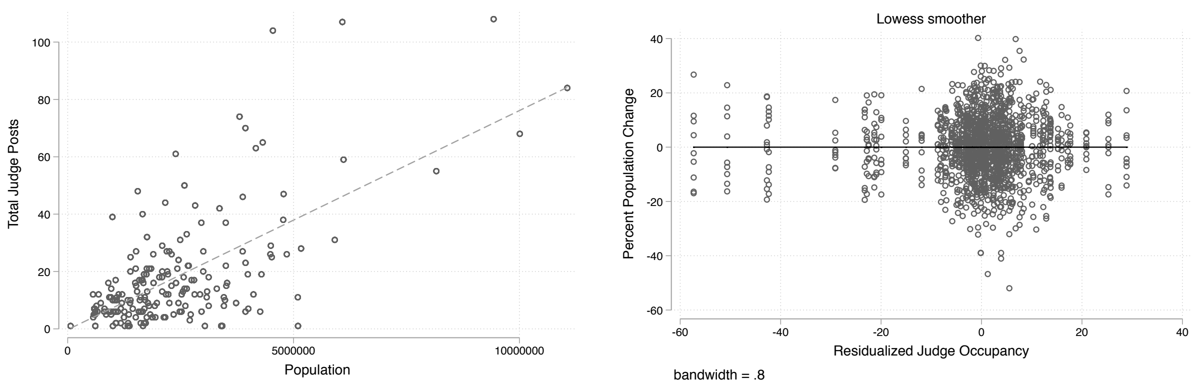
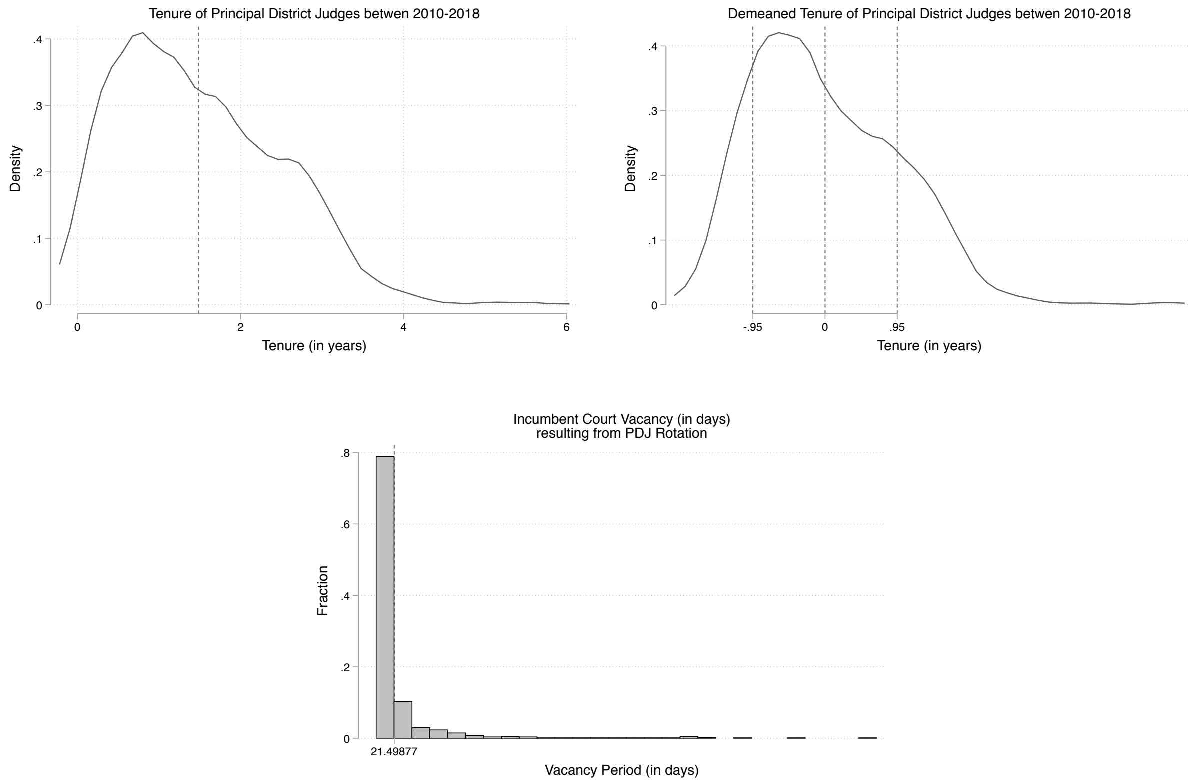
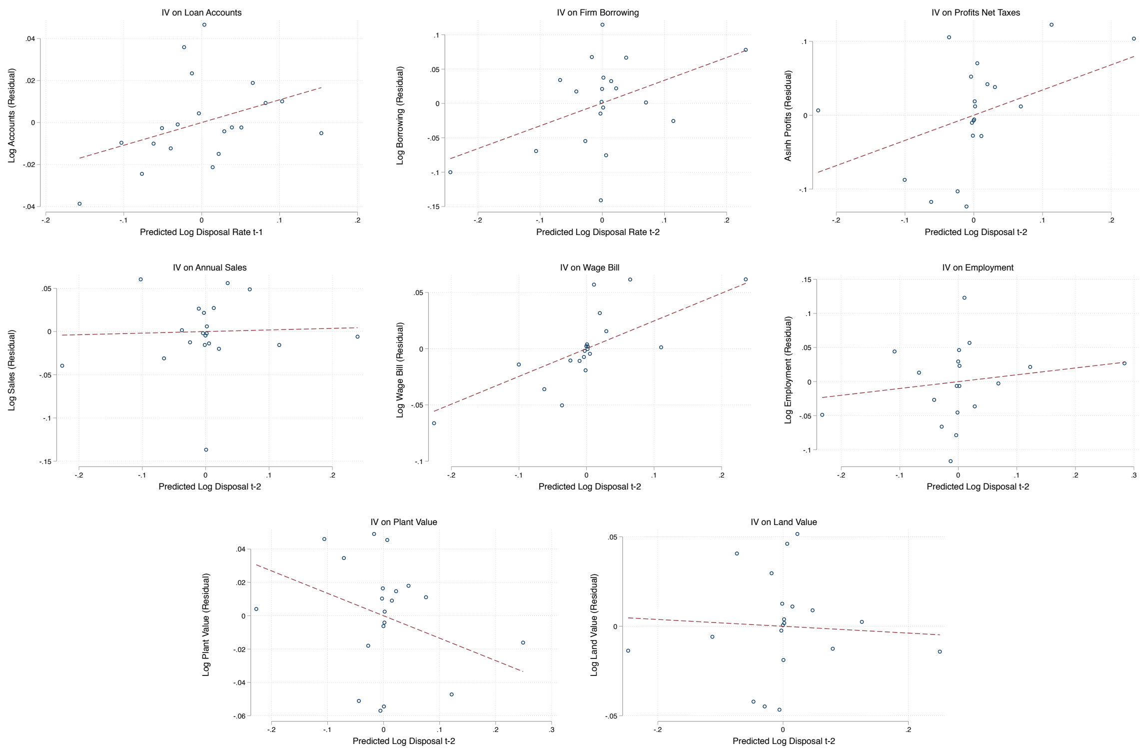


Figure A.6: Judge Tenure: An Example of Principal District Judge



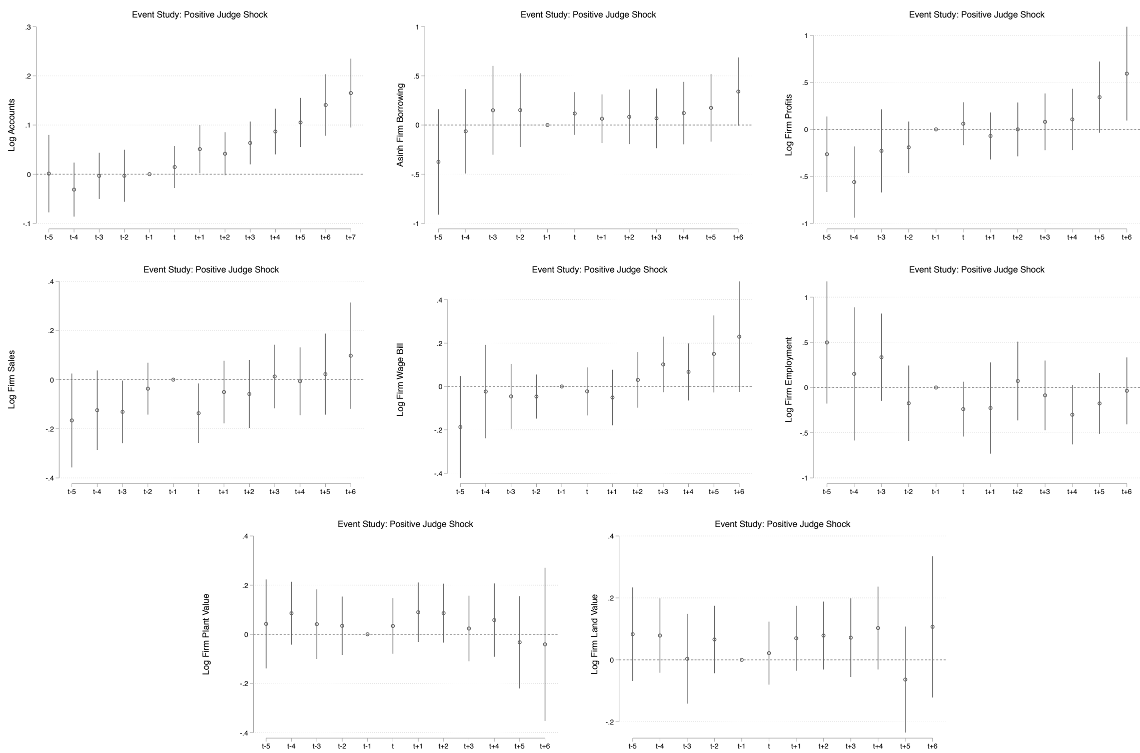
Notes: Above graphs show the distribution of turn-around and tenure of the highest position in the District and Session Court - the Principal District Judge.

Figure A.7: Visual IV Results



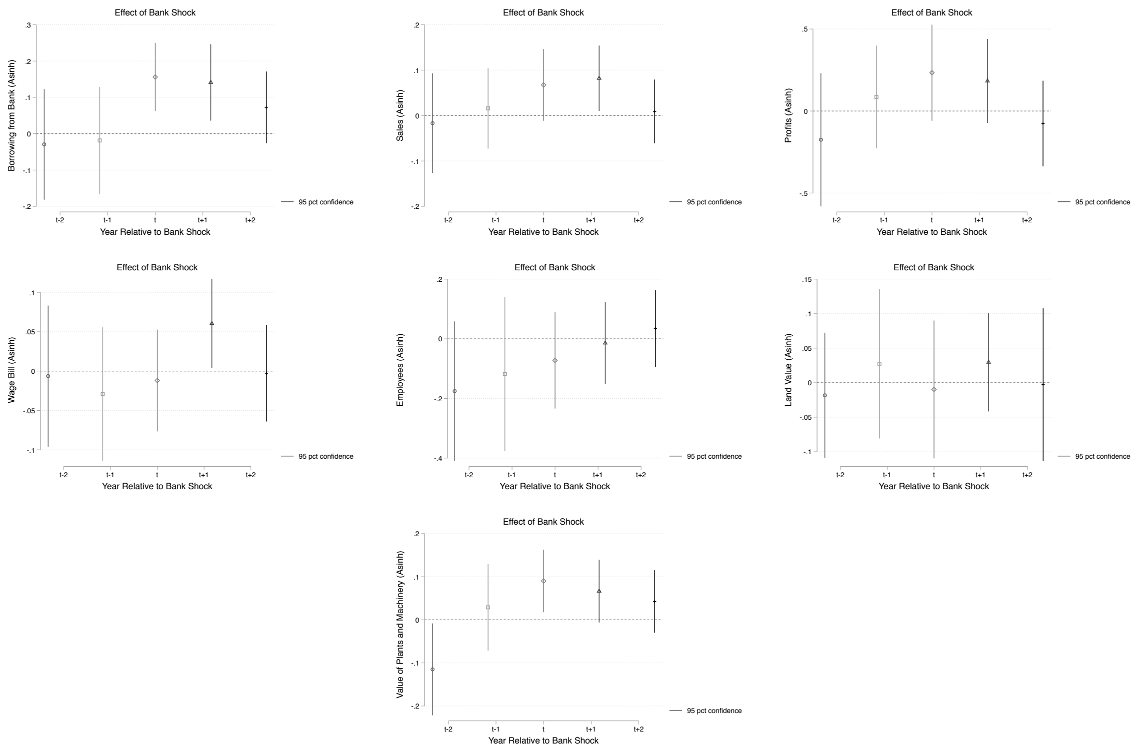
Notes: Above are binned scatters-plots depicting the relationship between various outcomes of interest and predicted log disposal rate.

Figure A.8: 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 A.9: 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.

A.6 Appendix: Tables

Table A.1: Study E-Courts Sample District Coverage

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

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

Table A.2: Description of Firms Registered in Sample Court Districts

	(1)				
	Sample Mean	Sample SD	Not in Sample Mean	Not in Sample SD	Difference (p-val)
Number of firms per district	1854.135	1946.777	1447.903	1121.478	0.000
Firm Age (yrs)	27.996	18.818	24.777	14.894	0.000
Entity Type:					
Private Ltd	0.353	0.478	0.352	0.478	0.893
Public Ltd	0.641	0.480	0.642	0.479	0.848
Govt Enterprise	0.000	0.017	0.001	0.033	0.016
Foreign Enterprise	0.000	0.012	0.000	0.008	0.493
Other Entity	0.006	0.076	0.005	0.069	0.243
Ownership Type:					
Privately Owned Indian Co	0.750	0.433	0.717	0.450	0.000
Privately Owned Foreign Co	0.025	0.157	0.026	0.160	0.623
State Govt Owned Co	0.015	0.122	0.019	0.136	0.017
Central Govt Owned Co	0.008	0.091	0.012	0.108	0.003
Business Group Owned Co	0.201	0.401	0.226	0.418	0.000
Finance vs. Non-Finance:					
Non Finance Co	0.789	0.408	0.831	0.375	0.000
Non Banking Finance Co	0.208	0.406	0.166	0.372	0.000
Banking Co	0.003	0.053	0.003	0.050	0.675
Broad Industry:					
Trade, Transport, and Logistics	0.150	0.357	0.139	0.346	0.011
Construction Industry	0.054	0.226	0.086	0.280	0.000
Business Services	0.300	0.458	0.282	0.450	0.001
Commercial Agriculture	0.031	0.173	0.025	0.157	0.006
Mining	0.033	0.179	0.028	0.165	0.014
Manufacturing	0.432	0.495	0.439	0.496	0.194
Companies in Study Sample	13298				
Companies Not in Study Sample	15042				
Districts without Companies in Prowess	34				

Notes: "Not in Sample" excludes Delhi and Mumbai, which are the two largest cities in India also appearing among top global cities. For better comparison, firms in my study sample need to be compared with those registered in similar districts not in my sample. Finally, all firms considered for analysis are those incorporated before 2010.

Table A.3: Description of Firms by Litigant Type

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

Notes: All firms in the table above are those registered in any of the sample court districts. Firms can be involved in cases either in its home district or in any other district based on the case jurisdiction. A firm is coded as petitioner only if the firm appears only as a petitioner in the sample court data. Similarly for respondent only. Firms that appear as petitioner as well as respondent are coded as “Both".

Table A.4: Correlations Between the Measures of Overall Court Output

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

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

Notes: All measures except duration are highly correlated with the disposal rate measure.

A.6.1 Appendix: Tables Testing Tenure Independence

Table A.5: District Time-Varying Outcomes and Judge Tenure

	(1) Log Pop Density	(2) Log % Sown Area (t-1)	(3) Log % Sown>1(t-1)	(4) Log Crime per cap (t-1)	(5) 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 A.6: Independence: Past Firm Outcomes and Judge Tenure

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

Standard errors in parentheses
* $p < 0.1$, ** $p < .05$, *** $p < 0.01$
Note: All standard errors are clustered at the district-year level.

Table A.7: 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 A.8: 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 A.9: Robustness Check Firm Outcomes: Clustering by State-Year

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

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

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

Table A.10: Robustness Check Firm Outcomes: Clustering by District

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

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

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

A.6.2 Tables: Firm Fixed Effects

Table A.11: Court Congestion and All Firm Intermediate Outcomes: Firm Fixed Effects

	(1)	(2)
	Asinh Long Term Borrowing	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 A.12: 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.