Front-line Courts As State Capacity: Evidence From India

Manaswini Rao*

November 30, 2022

Well-functioning frontline courts facilitate dispute resolution, making them a core aspect of state capacity. Using rich data from India and an event study research design around the timing of judge staffing changes, I show that these have a persistent effect on judge headcount and vacancy rates in the corresponding district court. Removal of vacancy substantially improves local judicial capacity, where each additional judge improves the rate of backlog resolution by 10 percent. In a context with high levels of congestion in local courts, this capacity improvement enables credit circulation, and increases the productivity of local formal sector firms, generating a benefit-cost ratio exceeding 3. Creation of vacancy has a negative effect on the local firms. The effects of reduced judicial capacity is likely manifested through the ability of law enforcement agencies to contain less serious crimes that require court orders prior to investigation.(*JEL* O16, O43, K41, G21)

A state that facilitates timely enforcement of contracts and the law supports the development of formal financial sector, investment in the production of goods and services, and ultimately, long-run economic growth (La Porta et al. 1998; Djankov et

*Contact: Post-Doctoral Scholar, Dept. of Economics, UC San Diego; manaswini.rao@gmail.com.
Special thanks to Aprajit Mahajan, Elisabeth Sadoulet, Frederico Finan, Emily Breza, Arun Chandrasekhar, and Karthik Muralidharan for their support and guidance. I thank Abhay Aneja, Sam Asher, Samuel Bazzi, Prashant Bharadwaj, Johannes Boehm, Benjamin Bushong, Decio Coviello, Daniel Chen, Matthieu Chemin, Julie Cullen, Alain de Janvry, Gordon Dahl, Ernesto Dal Bo, Giacomo De Giorgi, Marco Gonzalez-Navarro, Rema Hanna, Sean Higgins, Supreet Kaur, Erin Kelley, Ben Krause, Ethan Ligon, John Loeser, Frances Lu, Jeremy Magruder, Craig McIntosh, Ted Miguel, Paul Niehaus, Yusuf Neggers, Matthew Pecenco, Jeffery Perloff, Nicola Persico, Gerard Roland, Vaishnavi Surendra, Tom Vogl, and all participants at seminars and workshops at UC San Diego, UC Riverside, UC Berkeley, NEUDC, Pacdev, SIOE, NBER (Dev) Fall 2020, Barcelona GSE, and the World Bank ABCDE 2022. Importantly, thanks to Kishore Mandyam, Harish Narasappa, and Surya Prakash at DAKSH Society, and members of the Indian judiciary for help with court data extraction and insightful discussions. Special thanks to S.K. Devanath, Suhrid Karthik, and Vinay Venkateswaran for thoughtful discussions. I acknowledge the generous funding support from the International Growth Centre (IGC) State Effectiveness Initiative, and UC Berkeley Library. This paper was previously circulated as "Judges, Lenders and the Bottom Line: Court-ing Firm Growth in India", "Judicial Capacity Increases Firm Growth Through Credit Access: Evidence from Clogged Courts of India", "Courts Redux: Micro-Evidence from India", and "Front-line Courts As State Capacity: Micro Evidence from India". All errors are my own.

al. 2003). Contract enforcement by courts is an important type of dispute resolution that has a formal state mandate. Delays in dispute resolution due to congested courts can increase uncertainty and transaction costs that impede effective contracting and weaken *de facto* rights (North 1986; Johnson et al. 2002; Nunn 2007). In addition and perhaps more immediately, effective courts enable recirculation of assets under dispute into productive uses through timely resolution of litigation.

While the literature has extensively focused on the long-run variation in the capacities of legal and judicial institutions, it has often overlooked the more immediate and important medium-term transactional nature of courts in providing legal services. These include issuing court orders in the recovery of unpaid debt from defaulters and warrants to initiate criminal investigative processes by the law enforcement agencies. This role is primarily played by front-line courts such as the district or county courts, which are typically the courts of first instance.

Availability of adequate number of judges is a key constraint in enabling such courts to deliver legal services in a timely manner. However, staff vacancies and its sporadic redressal is a fundamental problem in bureaucratic organizations. This situation is not only exclusive to India and other developing economies but also common among the judiciary in many OECD countries (Coviello et al. 2015; Yang 2016). District courts in India have over 10 million trials pending for more than 3 years, implying 10 times more backlog per capita relative to similar courts in the United States. There are fewer than 20 judge posts per million in India in contrast to 70 per million recommended by the United Nations. This ratio worsens after taking into account the extent of vacancies.[1]

In this paper, I exploit the timing of judge staffing changes that generate sharp and persistent discontinuities in the number of judges and vacancy rates in district courts. I combine this variation with the universe of legal case-level data (6 million) between 2010 and 2018 from a 195 sub-national (district) courts in India to examine the effect of judicial capacity constraints on local development outcomes. I use a stacked event study design that accounts for treatment effect heterogeneity across districts and over

[1]Pending case data as of 2019 from both India and US district courts. District courts in India have jurisdiction over disputes arising in the corresponding administrative district. These are similar to the county seats of state and federal trial courts in the United States. They are the first interface of the judicial system to resolve disputes through civil and criminal litigation. Therefore, these courts have the highest level of trial workload, many of which are resolved without going through appeals at higher courts. Districts in India also correspond to local economies and is the smallest geographic aggregation for studying policy implications.

time (Sant'Anna and Zhao 2020, Sun and Abraham 2021) given the multiplicity and opposing direction of staffing changes over time.[2] Using the timestamps in the micro-data, I construct a more reliable administrative dataset of annual court-level capacity (number of judges) and performance variables (number of cases filed and resolved, and the rate of backlog resolution) relative to bureaucrat-reported aggregate data on courts (Singh 2020).[3] I merge this court-level dataset with firm and district-level development outcomes including productivity of local formal sector firms, the extent of credit circulation within a district, local reported crime, and annual average night lights data.

On the firms side, I match a balanced panel of non-financial sector firms' annual production and financial variables using their registered office location. A majority of such firms in India are single plant firms (Hsieh and Olken 2014); therefore, the location of registered office is also the location of production. Further, firms rely on local institutions to meet their production needs including financing from local branches of banks and protection from crime. Therefore, the ability of the corresponding court in debt recovery and supporting criminal investigation is critical for liquidity, credit recirculation and firms' access to credit,[4] and protection from crime. Importantly, these mechanisms highlight the role of the judiciary in providing essential legal services to aid the economic development process.

There are three main results. First, I find a significant impact on court-level rate of disposal of pending legal cases when vacancy is reduced by adding more judges. A positive staffing change has a persistent effect on reducing vacancy, increases the number of resolutions by 200 cases per judge added, and increases the disposal rate by 20 percent (2-3 percentage points) each year over the next few years. On the other

[2]The timing of these changes are exogenous to development outcomes and I verify this both empirically and by discussing the context. Importantly, I find that there are no significant trends in the prior period as a support for the parallel trends assumption. I examine the robustness of the reduced form results through an alternate approach using the number of judges as a continuous-valued policy variable in a generalized event study design.

[3]Given the granularity of legal case-level data and the requirement for electronically updating case files in real time, this approach likely generates a reliable administrative data on judge staffing than attendance records at courts, where the latter could be more easily doctored. I discuss data construction in detail in Section 2.

[4]While bank branches can be a part of large public or private-sector banks spanning national or international markets, the amount of credit for circulation is typically determined based on quotas with targets set for each branch. Therefore, recovered capital from debt-recovery litigations serve as additional liquidity available for recirculation locally. I discuss the context of banking in India in detail in Section 2B.

hand, a negative staffing change that introduces vacancy has negligible effect on the rate of backlog resolution but has other potential negative effects on the quality of case resolution measured as the composition of legal cases that are appeals from lower courts. This non-symmetric effect of court-level performance is consistent with the fact that existing judges are given additional charge of ongoing cases in courtrooms experiencing judge vacancy.

Second, profits, input expenditures, and sales revenue of local firms increase following positive changes in judge staffing and decrease following negative changes. When vacancy is reduced, I find that the average wage bill and the average profit increase by around 5% and 40%, respectively. On the other hand, an increase in judge vacancy has a negative effect on firms' production and financial outcomes but is lower in magnitude relative to a reduction in vacancy. Wage bill and profits contract by around 2 and 20% respectively. I perform a number of robustness checks to confirm these results. Importantly, I find no strong evidence for bias in the estimates due to the composition of firms in the district not included in the sample.[5]

Third, I find evidence in support of the transactional role played by courts in economic production through facilitating local markets. Importantly, I note an immediate increase in local firms' working capital, reduction in interest rates, and an increase in district-level aggregate lending by banks to industrial borrowers in the years following vacancy reduction. Local reported crime rates also drop following judge vacancy reduction. On the other hand, vacancy creation does not lead to a symmetric decline in firms' access to capital or bank lending behavior but is associated with an increase in lower order recorded crimes. Decomposing the long-run reduced form effect of vacancy reduction on firm profits, I find that the increase in working capital and the reduction in interest expenditure together explain over 80% of the increase in profits and reduction in lower order crime explains about 8%. Increase such crimes following vacancy creation explains over 17% of the reduction in firms' profits.

[5] First, I show that these effects are also seen among a subset of firms with no legal case in the corresponding district court to support the fact that these effects are not mechanical due to awards from courts to firms that are involved in legal cases, suggesting a broad-based impact. Second, I note that these effects are only observed among local firms and not among firms in the neighboring districts where the sample court has no jurisdiction, suggesting the local nature of the effects of frontline court capacity. Lastly, I also test whether the observed effects are driven by negative selection of other firms in the district not included in the sample due to missing data, leading to an overstating of the results. In fact, contrary to this, firms are more likely to report their annual statements in years following vacancy removal and less likely following vacancy creation, suggesting that the estimates from the firms' sample is at least a lower bound.

To elucidate the economic role of well-functioning local courts, I develop a conceptual framework that builds on standard lending models by introducing variation in the quality of contract enforcement by such courts. Lenders respond to an improvement in enforcement capacity by expanding access to cheaper credit to all firms and particularly to smaller firms. I find support for these propositions in my data, observing access to cheaper credit across all sample firms, and specifically among smaller firms with low ex-ante leverage. This suggests that an expansion of cheaper credit is important for firms' working capital to support the scale of their operations, especially in developing economies like India where firms are both credit constrained and credit rationed (Banerjee and Duflo 2014). Conversely, increasing vacancy may not have an immediate effect on credit outcomes, especially if banks take time in recognizing a "bad loan" and/or in filing an official debt recovery case (Ashraf et al. 2020) .[6]

These findings highlight a substantial economic role played by the frontline judiciary in India, including the large costs incurred by failing to reduce judge vacancies in such courts. A back of the envelope calculation of the benefit-cost ratio of reducing vacancy shows large returns. Using the causal estimates of vacancy reduction, I compute the benefit-cost ratio both from the perspective of public finance as well as social return. I measure social return only accruing to sample firms (through corporate profit) and their employees (through wages), which is likely to be an underestimate considering that an improvement in judicial capacity could generate many other benefits not examined by this paper. The calculation suggests that investing in judicial staffing generates over 3 times tax revenue relative to its cost considering even the most conservative estimate (the average indicates over 5 times return on investment). The social return is orders of magnitude higher.

This paper contributes to three strands of the literature. First, this shows that subnational judiciary is important for local economic development through an expansion of formal sector economic activity. In this regard, this paper builds on the works by Djankov et al. 2003; Chemin 2009; Visaria 2009; Chemin 2012; Ponticelli and Alencar 2016; Amirapu 2017; Kondylis and Stein 2018; Boehm and Oberfield 2020. The literature hitherto has either taken an aggregate approach - exploiting cross-sectional variations in court efficiency measures, or focused narrowly on a small number of

[6]Based on conversations with bankers in India, the general debt recovery strategy includes going to the court as the last stage in the recovery process. The bank managers try other methods for recovery first, such as sending notices, collection agents, etc., before filing a case in court, naturally introducing delays between occurring of a loan default and filing a case in the court.

courts, reflecting a lack of micro-data at scale.[7] Using large-scale disaggregated data, I am able to construct a district-level panel data on local judicial capacity. I show that courts experience varying degrees of staffing shortages over time that affect their capacity to resolve ongoing litigation, generating a substantial consequence on social welfare. These estimates are likely a lower bound since I do not consider longer-term efficiency gains through channels such as: firm entry and exit, spillovers on the informal sector, and effects on household consumption.

Second, the results in this paper underscore the importance of personnel policies in public institutions, including staffing, in order to enhance state capacity in low and middle income countries (Dal Bó et al. 2013). A growing body of literature has noted a significant relationship between reducing staffing constraints and improving public service delivery in sectors ranging from education (Muralidharan and Sundararaman 2013), public programs (Bandiera et al. 2009; Dasgupta and Kapur 2020; Bandiera et al. 2021; Fenizia 2022), and early childhood development (Ganimian et al. 2021).[8] This also complements literature that examines the economic costs of staff absence in the public sector (Duflo et al. 2012; Dhaliwal and Hanna 2017). By focusing on the bureaucracy of a much understudied sector - the sub-national judiciary, this paper estimates the marginal value of public fund (Hendren and Sprung-Keyser 2020) of at least 3 from reducing judge vacancies.

Finally, this paper highlights the importance of well-functioning courts as providing essential legal services to local firms. A large literature has documented the significance of external finance for firm and economic growth (Rajan and Zingales 1998; Burgess and Pande 2005; Banerjee and Duflo 2014) and many institutional barriers against efficient allocation of credit (Khwaja and Mian 2005; von Lilienfeld-Toal et al. 2012; Giné and Kanz 2017). This paper shows that courts help unlock capital tied-up in litigations when judge vacancy is resolved. While vacancy creation does not generate a symmetric reduction in credit access, local firms' productivity suffers through worsening law and order.

[7] In contrast, rich data from advanced economies has enabled studying the effect of incarceration on recidivism and future employment outcomes by exploiting variation in judge leniency and quasi-random assignment of judges to trials as in Dobbie et al. (2018); Bhuller et al. (2019); Norris et al. (2020).

[8] Among this literature, Ganimian et al. (2021) compute a benefit-cost ratio, albeit using strong assumptions linking childhood learning and health outcomes to lifetime increase in wages among treated pre-school children. This paper estimates an immediate and large return on investment in local judicial capacity using direct measures of economic outcomes.

The rest of the paper is organized as follows. Section 1 discusses the context generating the identifying variation. Section 2 documents the data sources, and discusses the construction of court and economic outcome variables. Section 3 details the empirical strategy for causal identification, with the main results summarized in Section 4. Section 5 discusses potential mechanisms situated within an economic framework on access to credit. I discuss an alternate empirical approach in Section 6 and argue about the broader implication of this analysis in Section 7. Section 8 concludes.

1 Context

World Justice Project Rule of Law Index ranks India in the bottom half of 128 countries in civil and criminal justice (ranks 98 and 78, respectively, as per World Justice Project 2021). More generally, countries in the bottom half of the ranking are mainly low and middle income countries suggesting a strong correlation between rule of law and economic development. There are likely multiple reasons behind the lack of an effective judicial system. These could include antiquated laws, difficult legal procedures, as well as severe staffing constraints (for e.g., judge vacancies) affecting judicial capacity.

The judiciary in India is a three tier unitary system in contrast to the federal structure of the executive and the legislature. In this paper, I examine the functioning of courts at the district-level, which are often the first interface of the judicial system. Specifically, I study the District and Sessions Court (hereinafter called district court), which is typically the court of first instance for disputes involving contracts and firms. There is one district court per administrative district, which also serves as the court of appeal for judgements from sub-district courts within its jurisdiction.[9]

Due to separation of powers, the judiciary in India is responsible for setting policies for its functioning including recruitment of judges and management of courts whereas the budgetary power rests with the state-level executive. Coordination failures underpin many of the constraints in expanding judicial capacity in India as in other developing countries. One such key constraint that I examine in this paper is judge vacancy that the judiciary alone is unable to address. I describe the judicial staffing constraints in detail in this section.

[9]The Supreme Court of India and state-level High Courts serve mostly appellate functions with original jurisdiction over constitutional matters or conflicts involving the organs of state. The district courts system is the main institution responsible for administering justice, has original jurisdiction over a large number of matters arising from both national and state-level legislations, and enforces rule of law for day-to-day economic and social matters.

1A Judicial Capacity Constraints

The number of judges relative to the country's population is perhaps one of the most critical constraints. On average, there are 20 authorized judge posts per million. In contrast, there are close to 100 judges per million in the United States and close to 200 per million in the European Union as per official statistics. This ratio is further reduced when we account for the extent of vacancies in these posts.

The total number of judge posts and judge recruitment drives in a district are determined jointly by the respective state high court and the state-level executive (through budget allocation), whereas personnel policies such as judge tenure and assignment are under the purview of the high courts alone. There is no clear rule on how the number of judge posts are revised over time, and periodic reports by the Law Commission of India, an executive body under the central government Ministry of Law and Justice (particularly, The Law Commission of India 2014 report No.245) point out that this is relatively ad hoc without any specific calculus. Typically, the numbers are determined at the time of setting up a court's physical infrastructure, which happens once every few decades (mainly at the time of district formation) rather than vary at a shorter time scale. Figure A.2 (Top Panel) shows a strong, albeit imperfect correlation between district population and the number of judge posts.

In addition to low judge post-population ratio, the district judiciary also faces persistent vacancies. About a quarter of judge posts in district courts are vacant, which have continued or worsened over the years (see Bottom Panel Figure A.2). Though vacancies are natural as judges reach retirement age, they become a constraint if recruitment does not catch up with the extent of turnover. Addressing vacancies in district courts requires close coordination between the judiciary and the state-level executive, particularly to organize and implement recruitment drives. The Law Commission of India (2014) Report No. 245 expresses concern about the high number of district judge vacancies and recommends an algorithm to determine the required number of judges to reduce backlogs but these recommendations are not followed in practice.[10] Further, the recruitment drives occur sporadically to address vacancies,

[10]The algorithm recommends ideal number of judges for a court based on past annual case filing and average judge productivity (resolution rate). However, this algorithm is problematic because the ideal judge strength would be correlated with past judge strength since average judge productivity includes historical number of judges, thereby introducing serial correlation in these measures. Moreover, applying this rule to the data shows that this recommendation is rarely followed (Bottom Panel, Figure A.3)

based on budgetary approvals by the respective state government (executive body).

District judges are senior law officials, who are promoted from sub-district courts after reaching seniority. A few are directly hired from the state bar council, and a few through competitive exams. They typically serve 10-15 years before retiring, unless promoted to the state high court, if at all. These judges serve a short tenure in any given court - 2-3 years (see Top Panel, Figure A.3), and are either rotated out or retire at the end of their tenure in a given court. The state high courts determine judge assignment and rotations between district courts.[11]

Central to my identification strategy is the *timing* of occurrence and removal of judicial vacancies in district courts. The context above suggests the plausibility of exogeneity in the timing of these events even if assignment of a specific judge to a court could be endogenous to local economic development levels and growth. In the years with recruitment drives, the state-level high courts have an opportunity to address vacancies in their corresponding district courts. When they do, there is a persistent increase in judicial staff by more than one judge per court on average. Conversely, when vacancies occur, they too persist because recruitment drives are relatively rare.

2 Data

2A Court-level Variables: Explanatory Variables

I assemble the universe of 6 million public legal case records from the E-Courts database (Supreme Court of India 2018), spanning all legal cases filed or pending for resolution between 2010 and 2018, from a sample of 195 district courts (see Figure A.4). These districts were selected to ensure an overlap with the location of registered formal sector firms in predominantly non-metropolitan industrial districts

[11] The specific assignment process is based on a seniority-first serial dictatorship mechanism, subject to the specific constraints: non-repeat and no home district assignment. A judge coming up for a reassignment is asked to list 3-4 rank-ordered district court locations for their next posting. The high court committee collates these lists and carries out the assignment algorithm each cycle. First, the senior-most judge is assigned their top ranked location. Next, the second senior-most judge is assigned their top-ranked location as long as it does not conflict with the more senior judge, and so on. In case of conflict, the assignment moves down the ranking order of the more junior judge. Finally, newly recruited judges are assigned randomly to a court with vacancy, also subject to the constraints above. There is a lot of similarity in these processes across states with only minor differences. Therefore, while the assignment process itself may not be convincing as exogenous to local development outcomes, the timing of occurring and removal of vacancies likely is. I test for these empirically by looking for parallel trends in the period prior to these events.

and is representative of other similar districts in India. Each record details the case meta-data as well as lists hearing dates with the corresponding hearing stage.[12]

Judge Headcount and Vacancy: The legal case data also records the courtroom number and the judge designation where a case has been assigned.[13] Since the data represents the universe of legal cases between 2010 and 2018, I am able to identify whether a specific judge post is vacant based on annual workflow observed for that post.

Workflow in a given calendar year corresponding to a specific courtroom (and a judge post) is recorded predominantly as assignment of a newly filed legal case to a specific courtroom. This is because the court registrar assigns new cases to non-vacant courtrooms. If a courtroom is vacant, another judge steps in to continue the business of existing case load but newly filed cases are less likely to be assigned. While I also expand the workflow definition to include case resolution, outcome of a hearing, and passing interim orders as a robustness check, this isn't my preferred method because the in-charge judge continues with the hearings, albeit at a slower pace, underestimating the vacancy rates.

I encode the specific judge post as present if I observe non-zero workflow in a given year and as vacant, otherwise. With this encoding, I generate the number of judges in a district court for each year in my study period, which is consistent with the aggregate data reported in the Law Commission Reports. I calculate the inverse vacancy rates as the percentage of total number of judges in a given year relative to the maximum number of judges in the court during the study period. Note that the denominator in such a measure is imperfectly measured as this maximum number of judges could still mask long-run vacancies. Therefore, specifications using this measure as the dependent variable would likely underestimate the true extent of vacancies in the court.

An important aspect of the e-courts system is that the recording of courtroom's daily business has moved to a digital platform that then periodically updates the e-courts legal case database with the latest status of the case. This follows the central

[12]E-courts is a public facing e-governance program covering the Indian judiciary. The setting up of infrastructure for the computerization of case records started in 2007 and the public-facing website - www.ecourts.gov.in and https://njdg.ecourts.gov.in - went live in late 2014. The fields include date of filing, registration, first hearing, decision date if disposed, nature of disposal, time between hearings, time taken for transition between case stages, litigant characteristics, case issue, among other details.

[13]For example, courtrooms in a district court are numbered 1, 2, 3,... and the judge designations are labeled Principal District Judge (PDJ), Additional District Judge (ADJ) 1, ADJ 2, etc.

objective of the Supreme Court of India's e-courts committee to reform data capture of courts' proceeding directly on digital platforms rather than digitize physical court records at a later point in time. As an analogy, the data generated from e-courts are akin to data uploaded from Computed Aided Surveys (CAI) that has become a commonplace in primary data collection exercises. Data generated thus are more reliable and less likely to have been doctored between the time of an event (i.e. a case hearing) and digitization since such applications minimizes the time lag between the two. This is critical in a context with substantial quality issues with bureaucrat-reported administrative data (Singh 2020).

The number of judges vary within a district court over time due to occurrences and removal of vacancies. Years experiencing addition of new judges are noted as positive staffing change events and years when vacancies occur are marked as negative staffing change events. These staffing changes occur 2-3 times over a span of 10 years, so are neither frequent nor infrequent. However, these highlight the challenges in addressing the capacity constraints in the local frontline judiciary by the higher courts alone and underscore a fundamental problem in the organization structure of the Indian judiciary.[14]

Constructing annual court-level performance variables: I construct court-level annual performance data from individual trial records. I define and construct the key performance variable - rate of backlog resolution (henceforth referred to as disposal rate), as the percentage of total workload or active legal cases resolved in a year. The numerator in this ratio is the number of cases resolved in a year whereas the denominator is the sum of cases that are newly filed and those not yet resolved. This measure is strongly correlated with other possible measures of court performance such as case duration or appeal rates (see Table A.1 for pairwise correlations between the different measures).[15]

[14]Note that this strategy examines changes in court-level judge staffing in aggregate and cannot distinguish individual judge addition from new assignments vs. recruitment or instances of removal from an outgoing judge vs. retirement.

[15]Court workload includes both pending as well as new trials, which on average amounts to 20000 trials per district court. Resolved trials also include those that are dismissed without a final judgement order. The rate of trial resolution is a relevant metric of judicial capacity, especially from the point of view of tied-up factors of production. While trial duration may matter for individual litigant or agent directly involved with the judicial system, annual performance indicators such as the rate of trial resolution measures the extent of congestion and is more appropriate metric of institutional capacity.

2B Firm-level Variables: Outcome Variables

Population of Interest: I focus mainly on incumbent non-financial firms, incorporated before 2010, to measure the impact of local judicial capacity. I do this for two reasons: First, the Code of Civil Procedure, 1908, specifies the relevant court jurisdiction for dispute resolution to be the location of the defendant/complaint respondent. For example, the relevant court would be that corresponding to the location of a borrower in the case of debt-related disputes or that of the defaulting party (could be either the vendor or buyer, depending on who breaks the contractual terms) in the case of a contractual dispute. This rule allows one to match non-financial firms by their registered office location (as also followed in von Lilienfeld-Toal et al. 2012). A large share of firms in India are single-plant firms (Hsieh and Olken 2014) and for such firms, registered office location is also the corporate headquarters and the location of production.[16] Second, by focusing on already incorporated firms, I account for any confounding due to firm entry and exit. Thus, this frame enables examining the role of local judicial capacity on the growth of incumbent firms engaged in the production of real goods and non-financial services. While examining barriers for firm entry and exit is important, studying the role of courts on the growth prospects of incumbent firms is fundamental to understanding the economic development process.

Firm-level data: I use CMIE-Prowess dataset that includes the balance sheets of a sample of registered, formal sector firms to measure annual firm-level outcomes. The data are collated from annual reports, stock exchange reports, and regulator reports for the universe of all listed companies ($\approx$ 5000 listed on Bombay and National Stock Exchanges) and a sample of unlisted public and private companies, representative of the formal sector in India. Since the organized sector accounts for $\approx$ 40% of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), this dataset captures a large share of value addition in the economy. Firm-specific outcomes include production (sales revenue, wage bills, value of capital goods, and raw material expenditure), accounting (profit and loss), and borrowing (working capital and interest expenditure)

[16]Debt and labor disputes are among the main contractual disputes involving firms in the process of production. Many of these contracts are local in order to minimize information asymmetries. Banks lend through their local branches and labor migrates to the location of the firm. This is also documented empirically in Nguyen (2019) who shows that banks lend through their local branch network to minimize adverse selection and moral hazard in the context of banking in the United States. She finds that closure of bank branches led to a substantial decline in credit access for small businesses. Similarly, Burgess and Pande (2005) note that local economies grow with the expansion of banking to underbanked districts in India.

variables. Detailed identifying information in the dataset, including firm name and registered office location, enables me to match them with the court-level dataset.

Sample construction: Of the 49202 firms in the dataset I downloaded from CMIE website, 13298 firms are registered within the jurisdiction of 161 of the 195 sample district courts. Remaining 34 district courts result in no match. 9032 non-financial firms incorporated before 2010 form the sampling frame. Since many of these firms have missing balance sheet data for multiple years in the study period, I focus on a balanced panel. There are two important advantages of using a balanced panel: (a) both to ensure internal validity if missing-ness is non-random as well as to reduce classical measurement error if missing-ness is (implausibly) random, and (b) to help account for firms' time invariant characteristics using firm fixed effects. A total of 393 firms, across multiple 4-digit industrial classification remain in the balanced panel overlapping with 64 districts in the court data and thus form the main sample for analysis. Appendix Figure A.5 describes the firm sample construction process in detail.

I classify firms as small or large firms based on their average asset size in the period prior to 2010. Specifically, I classify those below the top quartile value of pre-2010 assets as small firms and those above 75th percentile as large firms.

Next, I fuzzy-merge the sample firms with the legal case data using firm names and manually verify the resulting matches. About three quarters of the local firms appear as defendants, consistent with the assumption that home district courts are the relevant institution.

Lastly, I also use the entire unbalanced sample of firms, encoding a missing value dummy variable taking value 1 if an outcome measure is not reported for a given year. I use these missing value dummies as outcome variables to check whether data reporting varies with judicial staffing variations.

2C Other District-Level Outcomes

Banking data: I also study financial firms such as banks, but instead of focusing on their firm-level balance sheet variables, I examine total credit lent to industrial borrowers at the district-level, aggregated across the local branches of all commercial banks as reported by the central bank, Reserve Bank of India (RBI). These local aggregates of banking variables are more relevant outcomes to understand access to credit as one of the key underlying mechanisms behind the effects of district court capacity.

Based on qualitative interviews with managers and legal counsels of large banks, banks lend to borrowers only through their local branches, so that the branch-level officials can verify borrower identity, credit needs, and repayment ability.[17] Further, these branches have quotas and targets for lending every year, with additional quotas for specific economic sectors (for example, small and medium enterprises) set by the central bank of India. The details of lending, repayments, and write-offs due to unpaid debt, all are accounted in the "profit and loss statements" (balance sheets) at the branch-level, whose officials face incentives tied to these. Therefore, local judicial capacity also matter for bank branches for their lending operations.

Reported Crime data: To measure the effect on local crime, I use public data on district-level reported crime statistics, classified by whether they are cognizable or non-cognizable, through the National Crime Records Bureau (NCRB). Cognizable crimes are more serious crimes, as such homicides, assault, theft, etc., that do not require prior court orders for the police to carry out investigation. On the other hand, non-cognizable crimes are crimes of lower severity, such as fraud, criminal intimidation, etc., that require a court order signed by a sitting magistrate for the police to investigate.

Nightlights data: Finally, to examine more broad-based impact, I examine the effect of judge staffing variations on district-level annual average Visible and Infrared Imaging Suite (VIIRS) nighttime light measure Annual VNL V2.1 by the Earth Observation Group.

2D Summary Statistics

Panel A of Table 1 presents summary statistics for the court variables. On average, there are 18 district judge posts per district court, with 23 percent vacancy. There are 1.62 instances of judge additions with 2 judges added, and 3.6 instances of vacancies with 3 judges removed per district court over the sample period. Average disposal rate is 14 percent with standard deviation 12, that is, 14% of total workload is resolved in a given year. In other words, it would take nearly seven years to clear all backlog if there were no new litigation. The timestamps on individual cases resolved within

[17] These interviews revealed that lending to any borrower - whether firm or an individual - is through bank branch co-located as the borrower. In the case of individuals, they can only borrow through bank branch in the same district as their residential location. Cross-district borrowing relationships are very rare, if at all.

the study period indicate an average case duration of 420 days (SD 570 days). A key difference between disposal rate and the average case duration is that the former includes the universe of all legal cases within the study period whereas the latter only includes duration for cases that were resolved within this period. Therefore, disposal rate avoids selection concerns in its construction process.

Panels B and C describe credit market and local firm-level outcomes. On average, banks make 9138 loans per year with about USD 4.2 million (INR 310 million) in circulation (outstanding amount) to the industrial sector within the sample districts. The summary on annual firm-level financials indicate that these are large firms, with USD 181 million (INR 13.5 billion) in average sales revenue and USD 10 million (INR 740 million) in average profits. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

3 Research Design

As detailed in Section 1, judge staffing level in a court changes frequently due to addition and removal of judges resulting from recruitments, periodic rotations as well as new vacancies arising from retirements and turnovers. A key identifying assumption required to estimate the causal effect of these staffing changes is that their timings are exogenous. A court can experience staffing changes multiple times during the study period, including both net increases as well as net decreases. Therefore, the empirical strategy must take this multiplicity into account. I use positive changes to draw inferences on the causal effect of judicial staffing improvements and negative changes for the effect of staffing declines.

3A Stacked Difference in Differences Event Study

With a one time, albeit staggered, change in district court's number of judges, the causal effect parameter could be estimated using recent dynamic difference in difference estimators that correctly account for dynamic treatment effects and treatment effect heterogeneity across groups and cohorts (Sant'Anna and Zhao 2020, Sun and Abraham 2021). However, in the context of this paper, district courts experience multiple staffing changes, and in opposing directions, over the study period. My preferred empirical strategy takes into account this multiplicity of events, occurring in different years across district courts, by stacking separate datasets generated for each district-event.

The dataset for an event e within a district d is centered around one period prior to the event with relative yearly event-time bins, including binned end points (clubbing all the years in the dataset outside this effect window). I append all such district-by-event datasets to generate a stacked dataset for analysis, with each event indexed by an event number (this strategy follows Deshpande and Li 2019 that uses event studies around the closing of social security offices and Cengiz et al. 2019 that examines the effect of multiple minimum wage revisions on employment distribution, both in the context of the United States).[18]

Finally, I create binary variables - Pos_{de} and Neg_{de} - to distinguish an event as net positive staffing change (vacancy removal) or a net negative change (vacancy creation), and interact these with the event time bins in the following dynamic difference in differences stacked event-study specification:

$$\begin{aligned} y_{it} &= \sum_{j=-4-,j\neq-1}^{4+} \beta_j^{+} \mathbb{1}\{|t-T_{d,e}|=j\} \text{ x } Pos_{d,e} + \sum_{j=-4-,j\neq-1}^{4+} \beta_j^{-} \mathbb{1}\{|t-T_{d,e}|=j\} \text{ x } Neg_{d,e} \\ &+ \alpha_i + \alpha_e + \alpha_{st} + \epsilon_{it} \end{aligned} \tag{1}$$

where y_{it} is the outcome of either the court or local firm, indexed by i. The specification accounts for unit fixed effect (i.e. district or firm fixed effect), event fixed effect, and state-year fixed effect.

The treated groups are courts with a net positive or a net negative change occurring in a specific calendar year (for e.g., change occurring in calendar year $T_{d,e} = 2013$) relative to the previous year. The control group is the set of districts that don't experience any positive or negative change in the same year but could in the future (i.e., an implementation of staggered net addition or removal). Since there are multiple events, the control group also includes the same district experiencing another positive and/or negative change in the future. 37 districts never experience positive staffing change (never-treated for net addition) whereas every district experiences a negative change at least once within the study period.

The coefficients of interest are $\beta_{j\geq0}^{+}, \beta_{j\geq0}^{-}$ - coefficients on the event-time bins interacted with the positive or negative change dummies, normalized relative to $t=-1$

[18] Event number runs from 1 through 8 for positive events and 10 through 17 for negative events. I generate single event datasets for district courts without any changes. Event ids 0 and 9 are for no positive and no negative change, respectively, in a district court.

(the year prior to the corresponding event), representing the dynamic treatment effect of judge staffing changes. $\beta^{+}_{j<0}, \beta^{-}_{j<0}$, i.e. the coefficients on the interacted term during the pre-period enable testing for any significant pre-trends.

I restrict the effect window to 4 years prior and post with binned endpoints. This completely includes the full tenure of judges in a court. The coefficients within this window are also estimable without loss of precision given the limitations of my data. For inference, I use two-way cluster robust standard errors for estimated event-time coefficients, clustering by both district and event (Bertrand et al. 2004, Abadie et al. 2017).[19]

Causal identification using this design requires the following assumptions: (a) exogeneity of timing, and (b) parallel trends, as the stacked approach correctly accounts for heterogeneous as well as dynamic treatment effects. While the policy of periodic judge reassignment generates plausible exogeneity in the timings of staffing changes, I check for the common trends assumption by examining the presence or absence of pre-trends. The binning of end-points and normalization of event coefficients relative to the year prior to the event(s) relaxes the strong assumptions of no treatment effects outside of the effect window or requiring a never treated group (Schmidheiny and Siegloch 2020).

4 Main Results

In this section, I discuss the reduced form results of judge staffing changes on court's staffing, backlog resolution rate as well as on local firm outcomes. I start by showing the discontinuity in the staffing levels and vacancy rates in Section 4A, followed by discussing the effects on court-level disposal rate in Section 4B and firm-level outcomes in Section 4C.

4A Judge Vacancies

Panels A and B Figure 1 present the regression coefficients on the interacted terms from Equation 1 using both positive and negative changes dummies with judge headcount (Panel A) and inverse vacancy rates (Panel B) as dependent variables. Three features of these graphs are noteworthy: (a) an immediate increase in headcount and

[19] For robustness, I also cluster by state and event in order to account for any spatial correlation between districts arising from the reassignment system.

inverse vacancy rates following positive changes and immediate decline following negative changes, (b) persistence in the effects over a 4-year horizon, and (c) lack of any statistically or economically significant point estimates in the time periods prior to the staffing change. On average, the positive events increase the number of judges by ≈ 2 over a baseline level of 15 judges, increasing the staffing levels by over 13% and reducing vacancy rates by over 15%. The coefficients indicate economically meaningful persistence where the vacancy rates are lower (or higher) by 10 (7) percentage points 3-4 years following the staffing changes.

Table 2 presents the estimates on positive (Columns 1 and 2) and negative (Columns 4 and 5) change events over time in a tabular format. The numbers in the table suggest that the positive staffing changes add around 2 judges on average, whereas negative changes reduce the headcount by 1. These are consistent with a context where recruitment drives are sporadic, and when they occur, multiple judges are recruited per drive. On the other hand, vacancy is typically generated by the retirement of the senior-most judge within a court, and therefore, explains the lack of lumpiness following negative staffing changes.

The discontinuity in judge staffing can be seen across different subsamples of district courts (see Table A.2 by subsets of districts based on their population). Finally, the estimates continue to be significant when I cluster the standard errors by state and event to account for any spatial correlation between district courts arising mechanically from reassignment of judges from one district to another (Figure A.6).

4B Court Performance

The sharp change in the total number of judges and vacancy rates following positive (or negative) change has a corresponding effect on the court's case disposal rate and other case outcome measures as defined in Section 2. Panel C Figure 1 plots the regression coefficients on the event-time bins interacted with positive or negative change dummies as per Equation 1. Disposal rate increases by ≈ 2 percentage points over a baseline of 12.62 percentage points, indicating an increase proportional to the increase in the number of judges. Each additional judge resolves 200 additional trials in a context where the average annual court-level caseload is ≈ 20000 trials.[20] Similar to the

[20] I also confirm these numbers by estimating the specification using number of resolved trials as the dependent variable in Table A.3. I focus on disposal rate as the key measure as it measures backlog resolution in terms of percentage reduction in the number of pending legal cases.

number of judges, the court-level case disposal rate also exhibits a discontinuity in event-time. This clear break in trend suggests a causal relationship between increase in staffing and the judicial capacity of district courts in resolving litigation backlogs.

In contrast, negative staffing changes do not commensurately worsen court disposal rate or the extent of number of resolutions (Figure 1). This result is likely driven by the fact that fewer number of judges turnover relative to those added. Additionally, existing judges are known to step in to take additional charge of workload in courtrooms experiencing vacancy in addition to their assigned workload. Though this could reduce pendency generation due to vacancy, it could plausibly affect the quality of legal services whereby I note an increase in the share of appeal cases from lower courts (Column 6 Table A.3). A district court with lower vacancy where judges are less constrained (i.e., have their regular workload) may preempt filing of frivolous appeal cases from sub-district courts in their jurisdiction.

Columns 3 and 6 of Table 2 present the event study estimates of disposal rate in a tabular format for vacancy removal and creation, respectively. Importantly, the point estimates in the periods prior to the staffing changes are both statistically and economically insignificant. The estimates are also robust to clustering by state and event to account for spatial correlation between districts (Figure A.6).

Finally, I note some heterogeneity in the effects on court-level disposal rate by the underlying district size (which also corresponds to the size of the court). Mid-sized and smaller courts experience larger improvements in case disposal rate following vacancy reduction whereas the negative effects of vacancy creation is mainly driven by large courts (see Table A.4).

4C Local Firms' Production

In this section, I examine the reduced form effects of judicial staffing changes in district courts on the production and financial outcomes of a sample of local formal sector firms. These include profits, sales revenue, wage bills, value of plant and machinery, and raw material expenditures. Given the large right skew in the distributions of these variables, I transform them using inverse hyperbolic sine (arcsine) function. This transformation also helps account for 0s and negative values (specifically in profit), and enable interpreting the coefficients in terms of percentage changes.[21] The sample

[21] Translating coefficients into elasticities could be problematic using inverse hyperbolic sine transformation for small values or if a large fraction of values are zeros (Bellemare and Wichman 2020).

comprises of a balanced panel of incumbent firms in the district that report their annual balance sheet information over the study period as discussed in Section 2B.

The event study estimation shows sizable effects following judicial staffing changes as seen in Figure 2 for vacancy removal and Figure 3 for vacancy creation. Three key features of these graphs are: (a) a gradual increase (or decrease) in the outcome following vacancy removal (or creation), (b) significant long-term effects, and (c) statistically and economically insignificant prior period estimates. The gradual and long-run nature is consistent with the natural time taken for the effects to be visible, for example, through one or more mediating channels of improved contract and law enforcement.

Table 3 and Table 4 present the results in a tabular format for vacancy reduction and creation, respectively. Wage bill, raw material expenditure, and profits increase by around 5%, 3% and 40%, respectively, following vacancy removal over the long run. The effect on sales revenue is modest 1-2% over the period. Since the sample firms are large, formal sector firms to begin with, these effects are plausible and economically meaningful. The relatively large effect on profit can be rationalized by the fact that a part of the increase could be from sources other than production, such as lower expenditure on interest payments or through financial income. Lastly, I find no significant effects on capital investments reflected in the value of plant and machinery (capital goods) following vacancy reduction.

The effects of negative staffing changes generating vacancies are negative but relatively smaller in magnitude. In the long run, wage bill, raw material expenditure, and profits contract by 2%, 5%, and over 20% respectively. The negative effects on sales revenue is also much more prominent, displaying a contraction by close to 3% in the long run. The value of plants and machinery also decreases but the point estimates are imprecise.

One concern is that these estimates could be biased if there are endogenous exits or shut-downs (temporary suspension of production) by competitor firms following judicial staffing changes. Since the sample of firms is restricted to a balanced panel, such exiting firms are not included in the data but nonetheless could affect the sample firms' outcomes through competition or other channels. While this is an important concern, it need not affect the main interpretation of the results if: (a) missingness is uncorrelated with judicial staffing changes or, (b) non-random "missingness" leads

However, in this context, the numbers are sufficiently large that either log or arcsine transformations yield similar results. For example, less than 2% of the working capital or profit values are 0.

to an underestimation in the above results. Data supports explanation (b) where I observe that vacancy reduction is less likely to generate missing observations across the larger (unbalanced) sample of firms and conversely vacancy creation is more likely to generate missing data (see Table A.5 and Table A.6). Even though there is non-random missing observations requiring a sample of balanced panel of firms to ensure internal validity, the direction of the "missingness" suggests a downward bias in the estimates, presenting a lower bound. That is, the observed post-period effects in the balanced sample are in the presence of other formal-sector firms in the area, who are in operation (see Table A.5 and Table A.6). This also suggests that local judicial capacity plausibly could affect the market structure (inducing any slow-downs), which itself is an important economic outcome of interest.[22]

Second, these effects could be mechanical, where firms may be ordered by courts to increase wages, retain workers, or make payments to input vendors (of raw material), and so on. However, I find similar effects among non-litigating firms in the sample as the entire sample, for whom court orders are not applicable and therefore, for whom the effect is plausibly real (Table A.7 and Table A.8, respectively).

Third concern pertains to the local nature of the effect. For example, firms could be litigating in other courts not in the sample and that the functioning of courts other than their corresponding district courts also matter and could bias the estimates if there are strong spatial correlations between courts. I provide two explanations: (a) as discussed before, firms are more likely to be sued in their district court as per procedural law, and (b) I estimate a placebo test where I examine the effect of judicial staffing changes on the outcomes of firms registered in the neighboring districts. Table A.9 and Table A.10 present the results from this placebo test, following vacancy removal and creation, respectively. The point estimates are very small compared to the magnitude of effects seen among local firms and also statistically insignificant, suggesting the local nature of the observed effects.

Further, the results are robust across other sensitivity tests, particularly: (a) dropping top industrial states, and (b) dropping metropolitan districts. If anything, the point estimates become larger and I gain more precision with sales revenue and raw material expenditure (see Table A.11, Table A.12, Table A.13, and Table A.14, respectively). Inference is robust to clustering standard errors by state and event, in

[22]There is no data on formal exits of firms or closure of plants in India since insolvency and liquidation process of formal sector firms is still nascent, at least relative to the study period.

order to account for any spatial correlation between district courts arising out of judge rotation. The effect on wage bills and profits are still significant at 5% in the year(s) following the events (see Table A.15 and Table A.16).

4D Suggestive Broad-Based Impact

Two pieces of evidence suggest that the effect of judicial staffing changes are broad based: (a) fewer (higher) missing data suggesting more firms in operation (shut down) following an increase (decrease) in the number of judges, and (b) suggestive evidence from night lights analysis.

First, I examine a much larger sample of firms across 152 districts, covering most of the districts with industrial activity, where the main outcome variable is whether or not the production and financial variables are reported. This analysis expands the sample of firms to all formal sector firms included in Prowess dataset, thus representative of this sector within India. As discussed in Section 4C and tabulated in Table A.5 and Table A.6 for vacancy reduction and creation respectively, I note that reporting across the outcome variables increases with vacancy reduction and decreases following vacancy creation, suggesting that local judicial capacity could also plausibly affect the short run conditions for firm operations or shut down.

Second, using VIIRS annual average night lights data, I find suggestive positive effects in night lights intensity following an increase in the number of judges and negative effects following a decrease (Table A.17). This analysis complements the results from the formal sector firms sample under the assumption that the nightlights activities would account for variations in the informal and household sector activities and public investments in infrastructure.

5 Mechanisms

Two key features of the context of district judiciary motivate examining local crime and credit market channels as probable mechanisms behind the observed effects on firm-level outcomes: (a) close to 60% of the cases pertain to criminal complaints including bail applications, 25% cases are civil in nature, roughly 10% include insurance claim disputes and the remaining 5% include all other case types (see Figure A.11), and (b) banks are routinely involved in litigation, where the nature of the banking industry and debt contracts frequently require court summons and enforcement. In the legal case data, I observe that about 50% of all commercial banks in India have at least one ongoing litigation during the study period and in 80% of these, banks appear as plaintiff, i.e. the complainant. The value of assets under litigation involving debt recovery disputes are many orders of magnitude larger than other dispute types (see Figure A.11). Finally, parsing judgements from a random subsample of cases involving banks suggests that over 83% of the credit related disputes have outcomes in favor of the bank. This occurs either by undergoing full trial and obtaining a judgement in their favor or by reaching a settlement with the defaulting borrower, leading to its dismissal.

5A Local Crime Rates

I examine the effects on two types of reported crime, classified based on whether or not a court order is required ex-ante for the police to carry out any investigative effort. Specifically, cognizable crime are those that do not require a prior court order for the police to carry out investigation. These include higher order crimes such as murder, theft, abduction, etc. On the other hand, lower order crimes are classified as non-cognizable crimes and require court orders signed by a judge prior to any police investigation.

Table 5 shows reductions in both reported cognizable and non-cognizable crime rates following an increase in the number of judges in a district court. A decrease has a corresponding increase in the reported non-cognizable crime rates but no significant effects on cognizable crime rates. These results suggest that local courts plausibly play an important role in maintaining law and order in coordination with the police in criminal investigation process other than their role in sentencing. This coordination role is consistent with the symmetric results in non-cognizable crime rates (that requires courts and police to work together). On the other hand, the negative effects on cognizable crime rates following an increase in the number of judges could suggest the role of sentencing.

From the perspective of firms' production, it is likely that the threat of lower order crimes such as fraud (for example, with contracts) and criminal negligence (which can affect worker safety, for example) plausibly plays a more direct role in their operations than serious crimes. In Section 5D, I provide a decomposition of the role of crime in affecting firm profits.

5B Local Credit Supply

Next, I examine the effect of judge vacancies on district-level lending. The banking industry is contract-intensive by definition and subsequently, the ability of local courts to resolve the backlog of legal cases, particularly those pertaining to debt recovery, may affect credit supply to firms. First, I examine district-level outcomes: lending by banks to industrial borrowers. Next, I discuss firms' access to credit by examining the reduced form effects of judicial staffing changes on firms' working capital and interest expenditure.[23]

Bank lending I use district-level credit summary data from the Reserve Bank of India to examine the effect on bank lending to all industrial borrowers. Since bank's lending response to improved judicial capacity would likely be a function of the extent of their "exposure" to the enforcement environment, I weight the regression specification in Equation 1 by the number of trials involving banks at the start of the study period.

Panel A Figure 4 presents the event study graph using total number of loans to industrial borrowers across all banks in a district as the outcome variable. Panels B and C break down lending by banking sector, i.e., lending by private and public sector banks respectively. Table 6 is the tabular version of the event-study graphs. Two take-aways from this analysis are: (a) the lack of symmetry - positive changes increase the number of loans, whereas negative staffing changes has no effect on total industrial lending, and (b) the increase is mainly driven by an increase in lending by private sector banks whereas the lack of effect is observed across both the banking sectors following vacancy creation. The increase in lending by private banks needn't be surprising, plausibly driven by an increase in liquidity following debt recovery. On the other hand, liquidity may not be a constraint for public sector banks which enjoys budgetary support from the state or national executive.[24]

There are two plausible reasons why banks respond ex-post to changes in the number of judges in the corresponding district court. First, there is some persistence

[23] Borrowing data is not consistently reported by all firms within the study period and hence, I rely on working capital as an indicator for their ability to finance operating expenses. Working capital mainly consists of excess cash, including borrowings, net of committed payments due within the accounting year.

[24] A large literature such as Khwaja and Mian (2005) and Giné and Kanz (2017) examines the impact of loan write-offs by public sector banks, often used as a political tool, on subsequent misallocation of credit in the economy.

in the increase in judicial capacity (i.e., backlog resolution) following judge addition. This is also a relevant time horizon for short and medium-term loans (for e.g., loans for operating expenses rather than capital expansions), and therefore suggests an increase in short-term lending behavior. Second, timely resolution of debt recovery trials enable banks to recover stuck capital, which increases their liquidity (by lowering provisions they need to make in their profit and loss statements for any debt write-offs). This additional liquidity is likely recirculated as fresh credit (as I will discuss later in this section, noting an immediate improvement in firms' working capital following vacancy reduction).

In order to situate these empirical observations using an economic framework, I adapt commonly used lending models in the literature, such as in Banerjee and Duflo (2010) and Besley and Coate (1995), which I summarize in the next section.

5C Credit Markets and Access to Credit: A Conceptual Framework

A key ingredient of this framework is that a lender (e.g., bank) bases their lending decisions on whether repayment can be enforced through courts. Borrowers need external credit to finance investment in new or existing projects, that has some stochastic probability of success. The lender takes into account borrower wealth towards collateral requirement. Lending takes place only if lender's expected return from lending is greater than the market return. Upon completion of the contract period, the borrower either repays or evades, which is costly. Evasion leads to default, which initiates debt recovery process and subsequently, litigation. This recovery process incurs a cost to both lender and borrower, as a decreasing function in court's effectiveness. That is, lower backlog in courts implies lower litigation related costs, ceteris paribus. Availability of judges has a direct implication on the extent of backlog resolution as discussed in Section 4B.

Some borrowers may choose to litigate if their payoff is higher under litigation. Other borrowers may choose to settle with the lender and avoid continuing the litigation process. A sub-game perfect Nash equilibrium (SPNE) through backward induction suggests that the lender uses a wealth cut-off in their decision to lend. Improvement in contract enforcement environment results in lower interest rates for all borrowers and leads to increased lending to smaller borrowers. The framework is discussed in detail in Appendix A.2.

Since the model is premised on a court's ability to resolve the backlog of litigation, the overall credit mechanism should function when there is a substantial change in backlog resolution. The credit market-level results in Section 5B are consistent with this, where there is an increase in district-level lending to industrial borrowers following reductions in judge vacancies and no significant changes following vacancy creation as the size of the negative change does not generate substantial impact on backlog resolution.

An important implication of this framework is that there are extensive margin changes determining who a bank lends to and the overall price of credit (interest rate) on loans, following medium-run variations in the local judicial capacity. These changes can be driven both by: (a) an improvement in contract enforcement environment, and (b) short-run liquidity effects through increased recovery of defaulted loans. Although I cannot distinguish between these two specific credit market channels, I provide suggestive evidence to bring to attention to the additional likelihood of short-run liquidity effect.

Production behavior: An implication of lower interest rates and an increase in access to credit among smaller firms is that firms would re-optimize their production decisions. In addition to the credit channel, improved courts could also directly benefit firms' production processes through lower transaction costs, for example, with input vendors, or lower hold-up in labor disputes, or lower security costs to protect assets from crime. This implies that, on average, firms expand production and incur lower production and non-production expenses that would impact their production outcomes and balance sheet. As discussed in Section 4C, I note an expansion (contraction) in firms' production and profit following judge vacancy removal (creation).

Additional empirical tests The framework generates additional hypotheses that can be tested in the data.

H1: Wealthier borrowers (firms) are more likely to litigate as defendants.

H2: Lower interest rate for all borrowers.

H3: Increase in lending to smaller borrowers.

Do wealthier firms litigate more? Figure A.13 shows the distribution of trials involving firms as defending litigants, which highlights the following key facts: (a) debt-related trials are many times more than other contract enforcement litigations, (b) highly leveraged firms, defined as those with ex-ante debt-equity ratio greater than 1, form a greater share of defendants, (c) defendant firms have higher ex-ante asset value compared to similarly leveraged non-litigant firm, and (d) ex-ante asset value is much lower among defending firms that are less leveraged compared to high-leveraged defending firms. These empirical observations likely indicate that wealthier defaulters pursue litigation.

Firms' Access to Credit Corresponding to the one-sided effects on district-level lending by banks, I note an increase in firms' working capital and a decrease in interest expenditure following vacancy reduction (Panel A Figure 5 and Columns 6 and 7 of Table 3). Working capital reflects the extent of operating finance, including credit for operational expenditures in contrast to capital loans to finance long-run investments. An increase in working capital, no significant effects on the value of plant and machinery, and a decrease in interest expenditure suggests plausible lowering of the price of operational credit subsequent to judicial capacity improvements. Further, the immediate effect on working capital suggests that capital recovered from debt recovery cases resolved immediately following judge addition could be recirculated to (plausibly known) industrial borrowers, supporting the potential short-run liquidity channel.

Columns 6 and 7 of Table 4 tabulates the event study estimates on working capital and interest expenditure following an increase in judge vacancy. The point estimates are both small and statistically insignificant, suggesting little impact of vacancy creation on firms' access to capital or price of credit they face, consistent with the lack of effects in the overall credit market.

Do smaller firms experience credit expansion? Panel B Figure 5 presents the event study graphs of vacancy removal among the subset of ex-ante smaller, less-leveraged firms. Leverage status along with firm size indicates: (a) fulfillment of firms' demand for debt by firm size, i.e. low leverage status among smaller firms could suggest unmet debt needs, and (b) past access to formal credit. Consistent with the framework, cheaper credit is available to all firms, including smaller firms following judicial capacity improvements and no significant effects following vacancy creation (see Table 7). The timing of effects indicate that the expansion of credit to such firms occur with a lag (i.e., an increase in working capital among such firms is gradual), supporting the proposition that banks take into account improvements in contract enforcement environment for their subsequent lending decisions.

5D Decomposition of Firms' Profit

Lastly, I decompose the reduced form effect on firms' profits into that arising from credit access and from local crime channels. In order to overcome the endogeneity problem in directly using credit or crime variables to estimate their elasticities with respect to firm profits, I use a generalized event study design (Schmidheiny and Siegloch 2020; Freyaldenhoven et al. 2021) using leads and lags of these intermediate variables as follows:

$$y_{it} \;=\; \sum_{j=-3}^{3} \delta_j \Delta x_{i,t-j} + \delta_4 x_{i,t-4} + \delta_{-4}(-x_{i,t+3}) + \alpha_i + \alpha_{st} + \xi_{it} \tag{2}$$

where Δ is the first difference operator and the effect window spans 4 years in the lead and 4 years in the lag. x_{it} is the credit or crime variables for unit i in year t. y_{it} is firm profit. The specification includes unit fixed effect and state-year fixed effect. I normalize using $t = -1$ such that the coefficients δ_j are relative to δ_{-1}. I chose the maximum possible effect window as estimable using the data. $x_{i,t-4}$ and $1 - x_{i,t+3}$ serve as the endpoints. For inference, I cluster standard errors by district. Figure A.15 depicts the corresponding event study graphs for changes in working capital, interest expenditure and local non-cognizable crime rates.

Once I estimate the elasticities using the above design, I apply them to their respective event study reduced form estimates of vacancy removal or creation in the post-period, i.e., from $t = 0$ through $t \geq 4$. Next, I add these across the post period and compare them with the corresponding reduced form effect on profit following changes in judicial staffing in the long run ($t \geq 4$).

Table 8 presents the results from this exercise. The results indicate that firm profits only respond to contemporaneous or lagged values of the mediating variables, and there is little evidence of significant trends in the prior period (the coefficient estimates on the leads are statistically and economically insignificant). As a percentage of the long run effect of judge increase on firms' profit, the suggestive contribution of working capital, interest expenditure and local non-cognizable crime are 51%, 34%, and 8% of respectively. While reduction in the number of judges does not significantly impact the credit channel, an increase in local crime contributes to over 17% of the reduction in profits.

6 Alternate Empirical Strategy

As a robustness test, I exploit the number of judges as continuous-valued "treatment" in a generalized event study framework including leads and lags of the explanatory variable as described in Equation 2 in Section 5D. The unit i using this strategy would refer to a firm for results involving firm-level outcomes or to a district for district-level outcomes. The explanatory variable x in this case will be the number of judges in a district d in a given year t. The identifying assumption relies on "parallel" trends between districts with one more judge in a given year relative to others and homogenous treatment effects. Though using this approach will not produce comparable estimates of the causal effect parameter from the stacked event study approach above, it serves to verify the results from the main design specification qualitatively.

This approach shows similar patterns of effects on court performance (Figure A.7) or firm performance (Figure A.8) or credit mechanisms (Figure A.14). Since the identifying assumptions are stronger than the stacked event study approach, the latter is my preferred estimation strategy.

7 Discussion

7A On Debt Recovery Litigation

The findings in this paper are consistent with Visaria (2009) and von Lilienfeld-Toal et al. (2012) that study the causal effects of gradual introduction of specialized debt recovery tribunals across India. A few things differentiate this paper from this literature. First, debt recovery tribunals are specialized courts with jurisdiction to adjudicate litigation involving higher-valued debts, which would otherwise have been filed in state high courts. In contrast, this paper examines the effectiveness of local (district) courts that adjudicate a variety of debt recovery litigations including those involving smaller debt sizes. Second, this paper examines the capacities of regular civil and criminal courts belonging to the judiciary rather than tribunals that are governed by the executive. Third, the natural experiment employed for causal identification addresses an important concern in the state capacity literature - that of persistent vacancies in the public sector, in contrast to the introduction of additional agencies addressing public services.

Finally, this paper examines an important role of local trial courts in enforcing contracts, complementing their role in enforcing bankruptcy laws as examined by Ponticelli and Alencar (2016) in the context of Brazil. Bankruptcy declaration and processing is currently nascent in India and therefore, lenders rely on district courts for recovering capital in specific debt contracts under default.[25] This paper shows that these local courts play an important role in the functioning of credit market by: (a) enabling banks to recover capital and recirculate credit at a cheaper interest rate to industrial borrowers, (b) enabling firms to expand their working capital, incur lower interest expenditure, indicating access to cheaper credit, that increases their productivity.

7B Benefit-cost analysis

In this section, I present a simple back-of-the-envelope computation of the benefit-cost ratio by employing the reduced form estimates from positive staffing changes, and the costs incurred by the state on additional judges. An implicit assumption I make is that the expenditure on the judges added to district courts is the only cost since these positions are already sanctioned with sunk investments in infrastructure, such as court rooms. That is, these additions are aimed at reducing existing vacancies rather than expanding the *de jure* size of the local judiciary.

In Table A.18, I present the assumptions and the calculated benefit-cost ratio using these estimates. On the benefits side, I use the median values of profits and wage bills among an average of 6 sample firms per district to compute the increase in firm-level surplus and salaried income. Since both formal sector firms and salaried individuals pay corporate and income tax on their net income respectively, I compute the benefit-cost ratio from the perspective of state revenue and expenditure generated at the district-level. I use the corporate tax rate for registered domestic firms in India as specified in the Taxation Laws Amendment Ordinance (2019). I calculate the effective income tax rate on salaried individuals as 7.3 percent based on applying the exemptions and tax-slabs specified in the Union Budget, 2018-19. [26] I also calculate

[25] Any changes in national or state laws affecting the bankruptcy environment are netted out as state-year fixed effects.

[26] These assumptions are motivated by articles in the news media, with sources mentioned in Ta-

the social benefit-cost ratio, which is likely to be a lower bound since I do not account for the benefits and costs accruing to other economic agents including the informal or the household sectors.

On the expenditure side, I calculate the increase in total district-level judge salaries from net increase in the number of judges using the median proposed salary of a district judge in the Second National Judicial Pay Commission. I further inflate the salary to account for fringe costs incurred by the state to cover judges' benefits and allowances, including transport, housing, etc., and account for annual increments. The actual salaries and benefits would be lower than this figure depending on the extent of adoption of these recommendations by each state.

On the benefit side, I compute the discounted net present value of the increase in profits (benefit accruing to firms), wage bills (benefit accruing to the salaried labor force in the district), and the associated tax revenue for each year in the post period using the estimates and tax rates as detailed in Table A.18. I assume the discount rate to be 5% in the base calculation and perform sensitivity analyses using lower and higher discount rates (Table A.19).

Figure 6 shows the distribution of the computed benefit-cost ratios, both from the perspective of tax revenue generated for the state as well as social surplus, along with the 90% confidence intervals. To generate these distributions, I use 1000,000 random draws of the coefficient estimates from a normal distribution with mean equal to the estimated coefficients and standard deviation equal to the standard errors of the coefficients (as per the Central Limit Theorem). This basic computation shows that the benefits are orders of magnitude larger than the costs. For the state, the ratio implies revenues that are over 5 times higher than the expenditure on additional judges on average, whereas the social returns are even higher, implying a return over 30 times the cost. Even the most conservative estimates (with higher discount rate) suggest that the returns to investing in district judicial capacity is high and more than pays for itself.

ble A.18. I calculate the average individual income tax using media reports on average filed annual income of a salaried tax-payer in India for the year 2018-19, which is INR 690,000 or roughly USD 10,000. Applying exemptions, an individual with this income incurs an effective tax rate of 7.3 percent.

8 Conclusion

To conclude, I show that well-functioning frontline judiciary is important for local formal sector development, with implications for overall economic development process. The current status-quo underscores the problem of large backlogs of litigation in such courts in a context where, on average, about a quarter of the judge posts are vacant. Therefore, reducing vacancy by adding more judges is a highly cost-effective intervention, suggesting over 3 times return to public expenditure.

The paper highlights that district courts provide important legal services both to the banking sector and to the police in maintaining law and order. This role of legal service provision facilitates credit circulation in the local economy, which is important for firm productivity through access to credit for operating expenses. To my knowledge, this is the first paper to use disaggregated legal case-level data and exogenous variation in the timing of judicial staffing changes in district courts in India, to understand the role played by courts in the economic development process.

While this paper does not delve into credit misallocation specifically, one could think of capital recovered from resolved debt recovery trials as reducing misallocation. Further research is needed to examine whether lenders extend credit to firms with higher marginal product of capital or higher TFP and how this interacts with the local judicial capacity. For example, examining how functioning of district courts interact with the quality of laws protecting creditor rights can potentially shed light on the mechanisms behind capital misallocation.

References

Abadie, Alberto, Susan Athey, Guido W. Imbens, and Jeffrey Wooldridge, "When Should You Adjust Standard Errors for Clustering?," Working Paper 24003, National Bureau of Economic Research November 2017. Series: Working Paper Series.

Amirapu, Amrit, "Justice delayed is growth denied: The effect of slow courts on relationship-specific industries in India," Working Paper 1706, School of Economics Discussion Papers 2017.

Ashraf, Nava, Oriana Bandiera, and Alexia Delfino, "The Distinctive Values of Bankers," *AEA Papers and Proceedings*, May 2020, *110*, 167–171.

Bandiera, Oriana, Andrea Prat, and Tommaso Valletti, "Active and Passive Waste in Government Spending: Evidence from a Policy Experiment," *American Economic Review*, September 2009, *99* (4), 1278–1308.

_ , **Michael Carlos Best, Adnan Qadir Khan, and Andrea Prat**, "The Allocation of Authority in Organizations: A Field Experiment with Bureaucrats*," *The Quarterly Journal of Economics*, November 2021, *136* (4), 2195–2242.

Banerjee, Abhijit V and Esther Duflo, "Giving Credit Where It Is Due," *Journal of Economic Perspectives*, August 2010, *24* (3), 61–80.

Banerjee, Abhijit V. and Esther Duflo, "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program," *The Review of Economic Studies*, April 2014, *81* (2), 572–607.

Bellemare, Marc F. and Casey J. Wichman, "Elasticities and the Inverse Hyperbolic Sine Transformation," *Oxford Bulletin of Economics and Statistics*, 2020, *82* (1), 50–61.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Differences-In-Differences Estimates?," *The Quarterly Journal of Economics*, February 2004, *119* (1), 249–275.

Besley, Timothy and Stephen Coate, "Group lending, repayment incentives and social collateral," *Journal of Development Economics*, 1995, *46* (1), 1–18.

Bhuller, Manudeep, Gordon B. Dahl, Katrine V. Løken, and Magne Mogstad, "Incarceration, Recidivism, and Employment," *Journal of Political Economy*, July 2019, *128* (4), 1269–1324. Publisher: The University of Chicago Press.

Boehm, Johannes and Ezra Oberfield, "Misallocation in the Market for Inputs: Enforcement and the Organization of Production*," *The Quarterly Journal of Economics*, November 2020, *135* (4), 2007–2058.

Burgess, Robin and Rohini Pande, "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," *American Economic Review*, June 2005, *95* (3), 780–795.

Bó, Ernesto Dal, Frederico Finan, and Martín A. Rossi, "Strengthening State Capabilities: The Role of Financial Incentives in the Call to Public Service*," *The Quarterly Journal of Economics*, August 2013, *128* (3), 1169–1218.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer, "The Effect of Minimum Wages on Low-Wage Jobs*," *The Quarterly Journal of Economics*, August 2019, *134* (3), 1405–1454.

Chemin, Matthieu, "Do judiciaries matter for development? Evidence from India," *Journal of Comparative Economics*, 2009, *37* (2), 230–250.

_ , "Does Court Speed Shape Economic Activity? Evidence from a Court Reform in India," *The Journal of Law, Economics, and Organization*, August 2012, *28* (3), 460–485.

Coviello, Decio, Andrea Ichino, and Nicola Persico, "THE INEFFICIENCY OF WORKER TIME USE," *Journal of the European Economic Association*, 2015, *13* (5), 906–947.

Dasgupta, Aditya and Devesh Kapur, "The Political Economy of Bureaucratic Overload: Evidence from Rural Development Officials in India," *American Political Science Review*, 2020, *114* (4), 1316–1334.

Deshpande, Manasi and Yue Li, "Who Is Screened Out? Application Costs and the Targeting of Disability Programs," *American Economic Journal: Economic Policy*, November 2019, *11* (4), 213–248.

Dhaliwal, Iqbal and Rema Hanna, "The devil is in the details: The successes and limitations of bureaucratic reform in India," *Journal of Development Economics*, 2017, *124* (C), 1–21.

Djankov, Simeon, Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer, "Courts," *The Quarterly Journal of Economics*, May 2003, *118* (2), 453–517.

Dobbie, Will, Jacob Goldin, and Crystal S. Yang, "The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges," *American Economic Review*, February 2018, *108* (2), 201–40.

Duflo, Esther, Rema Hanna, and Stephen P. Ryan, "Incentives Work: Getting Teachers to Come to School," *American Economic Review*, June 2012, *102* (4), 1241–78.

Fenizia, Alessandra, "Managers and Productivity in the Public Sector," *Econometrica*, 2022, *90* (3), 1063–1084. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA19244.

Freyaldenhoven, Simon, Christian Hansen, Jorge Pérez Pérez, and Jesse M. Shapiro, "Visualization, Identification, and Estimation in the Linear Panel Event-Study Design," Working Paper 29170, National Bureau of Economic Research August 2021. Series: Working Paper Series.

Ganimian, Alejandro J, Karthik Muralidharan, and Christopher R Walters, "Augmenting State Capacity for Child Development: Experimental Evidence from India," Working Paper 28780, National Bureau of Economic Research May 2021.

Giné, Xavier and Martin Kanz, "The Economic Effects of a Borrower Bailout: Evidence from an Emerging Market," *The Review of Financial Studies*, 07 2017, *31* (5), 1752–1783.

Hendren, Nathaniel and Ben Sprung-Keyser, "A Unified Welfare Analysis of Government Policies*," *The Quarterly Journal of Economics*, 03 2020, *135* (3), 1209–1318.

Hsieh, Chang-Tai and Benjamin A. Olken, "The Missing "Missing Middle"," *Journal of Economic Perspectives*, September 2014, *28* (3), 89–108.

Johnson, Simon, John McMillan, and Christopher Woodruff, "Property Rights and Finance," *The American Economic Review*, 2002, *92* (5), 1335–1356.

Khwaja, Asim Ijaz and Atif Mian, "Do Lenders Favor Politically Connected Firms? Rent Provision in an Emerging Financial Market*," *The Quarterly Journal of Economics*, 11 2005, *120* (4), 1371–1411.

Kondylis, Florence and Mattea Stein, "Reforming the Speed of Justice: Evidence from an Event Study in Senegal," *The World Bank Working Paper Series*, 2018, p. 65.

Muralidharan, Karthik and Venkatesh Sundararaman, "Contract Teachers: Experimental Evidence from India," Working Paper 19440, National Bureau of Economic Research September 2013.

Nguyen, Hoai-Luu Q., "Are Credit Markets Still Local? Evidence from Bank Branch Closings," *American Economic Journal: Applied Economics*, January 2019, *11* (1), 1–32.

Norris, Samuel, Matthew Pecenco, and Jeffrey Weaver, "The Effect of Parental and Sibling Incarceration: Evidence from Ohio," *Working Paper*, February 2020.

North, Douglass C., "The New Institutional Economics," *Journal of Institutional and Theoretical Economics (JITE) / Zeitschrift für die gesamte Staatswissenschaft*, 1986, *142* (1), 230–237.

Nunn, Nathan, "Relationship-Specificity, Incomplete Contracts, and the Pattern of Trade," *The Quarterly Journal of Economics*, May 2007, *122* (2), 569–600.

of India, Ecourts Supreme Court, "eCourt India Services," 2018.

of India, No. 245 The Law Commission, "Arrears and Backlog: Creating Additional Judicial (wo)manpower," Technical Report 245, Government of India July 2014.

Ponticelli, Jacopo and Leonardo S. Alencar, "Court Enforcement, Bank Loans, and Firm Investment: Evidence from a Bankruptcy Reform in Brazil," *The Quarterly Journal of Economics*, August 2016, *131* (3), 1365–1413.

Porta, Rafael La, Florencio Lopez-de-Silanes, Andrei Shleifer, and Robert W. Vishny, "Law and Finance," *Journal of Political Economy*, December 1998, *106* (6), 1113–1155.

Project, The World Justice, "WJP Rule of Law Index," 2021.

Rajan, Raghuram G. and Luigi Zingales, "Financial Dependence and Growth," *The American Economic Review*, 1998, *88* (3), 559–586.

Sant'Anna, Pedro H. C. and Jun Zhao, "Doubly robust difference-in-differences estimators," *Journal of Econometrics*, November 2020, *219* (1), 101–122.

Schmidheiny, Kurt and Sebastian Siegloch, "On Event Studies and Distributed-Lags in Two-Way Fixed Effects Models: Identification, Equivalence, and Generalization," SSRN Scholarly Paper ID 3571164, Social Science Research Network, Rochester, NY 2020.

Singh, Abhijeet, "Myths of official measurement: Auditing and improving administrative data in developing countries," *Research on Improving Systems of Education (RISE) Working Paper*, 2020, *42.*

Sun, Liyang and Sarah Abraham, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, December 2021, *225* (2), 175–199.

Visaria, Sujata, "Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India," *American Economic Journal: Applied Economics*, 2009, *1* (3), 59–81.

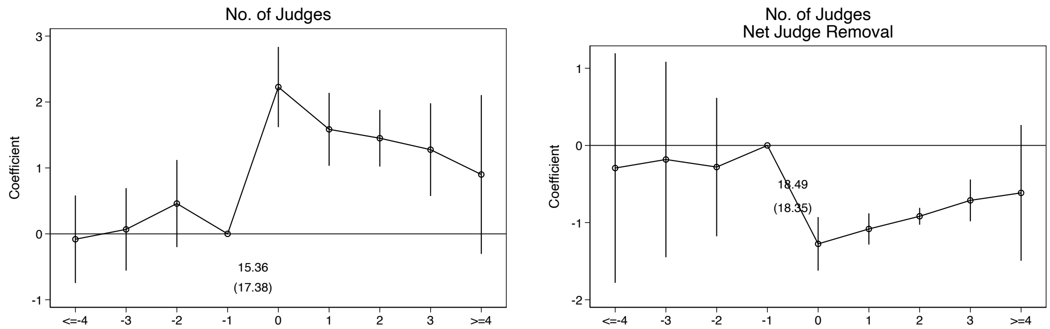
von Lilienfeld-Toal, Ulf, Dilip Mookherjee, and Sujata Visaria, "THE DISTRIBUTIVE IMPACT OF REFORMS IN CREDIT ENFORCEMENT: EVIDENCE FROM INDIAN DEBT RECOVERY TRIBUNALS," *Econometrica*, 2012, *80* (2), 497–558.

Yang, Crystal S., "Resource Constraints and the Criminal Justice System: Evidence from Judicial Vacancies," *American Economic Journal: Economic Policy*, November 2016, *8* (4), 289–332.

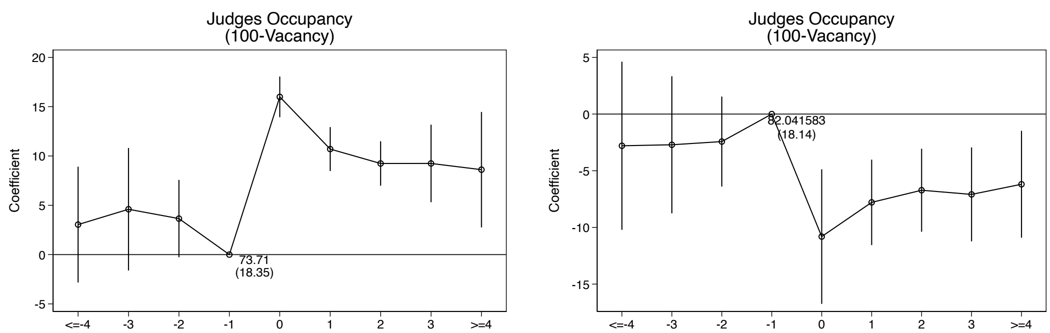
9 Figures

Figure 1: Removal and Creation of Vacancy and Court Performance

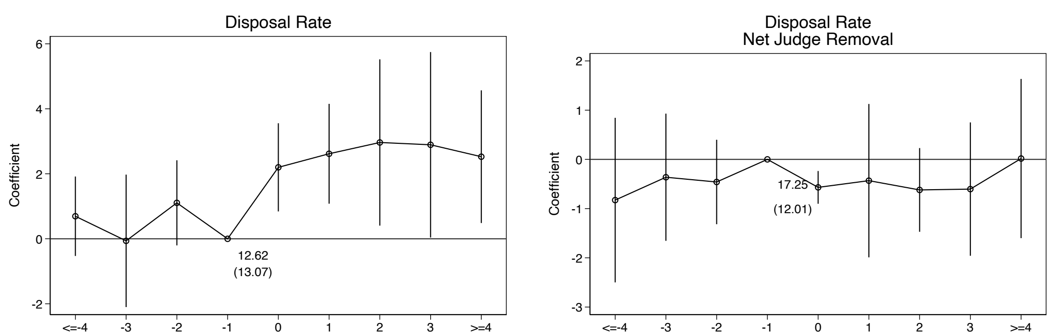
Panel A: Judge Headcount



Panel B: Inverse Vacancy Rate

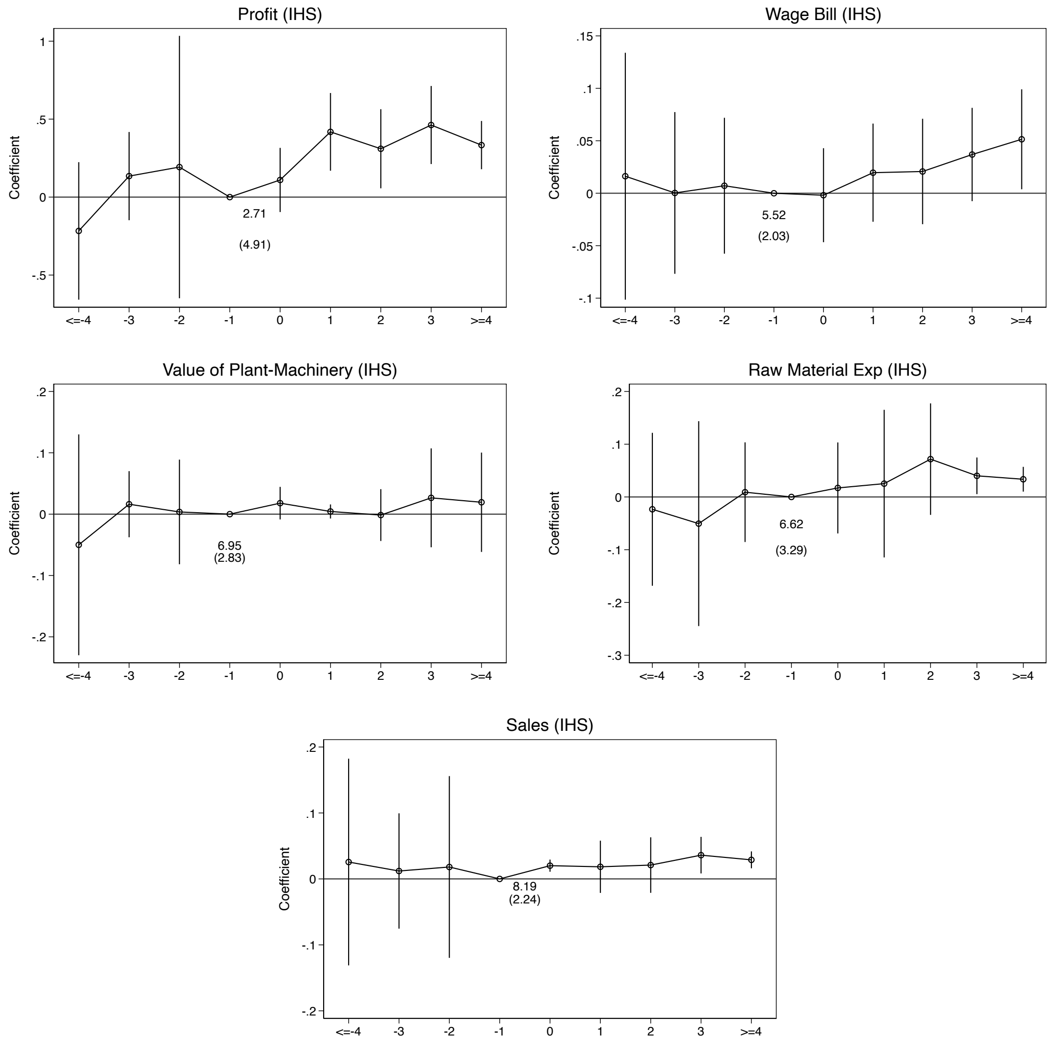


Panel C: Court-Level Disposal Rate



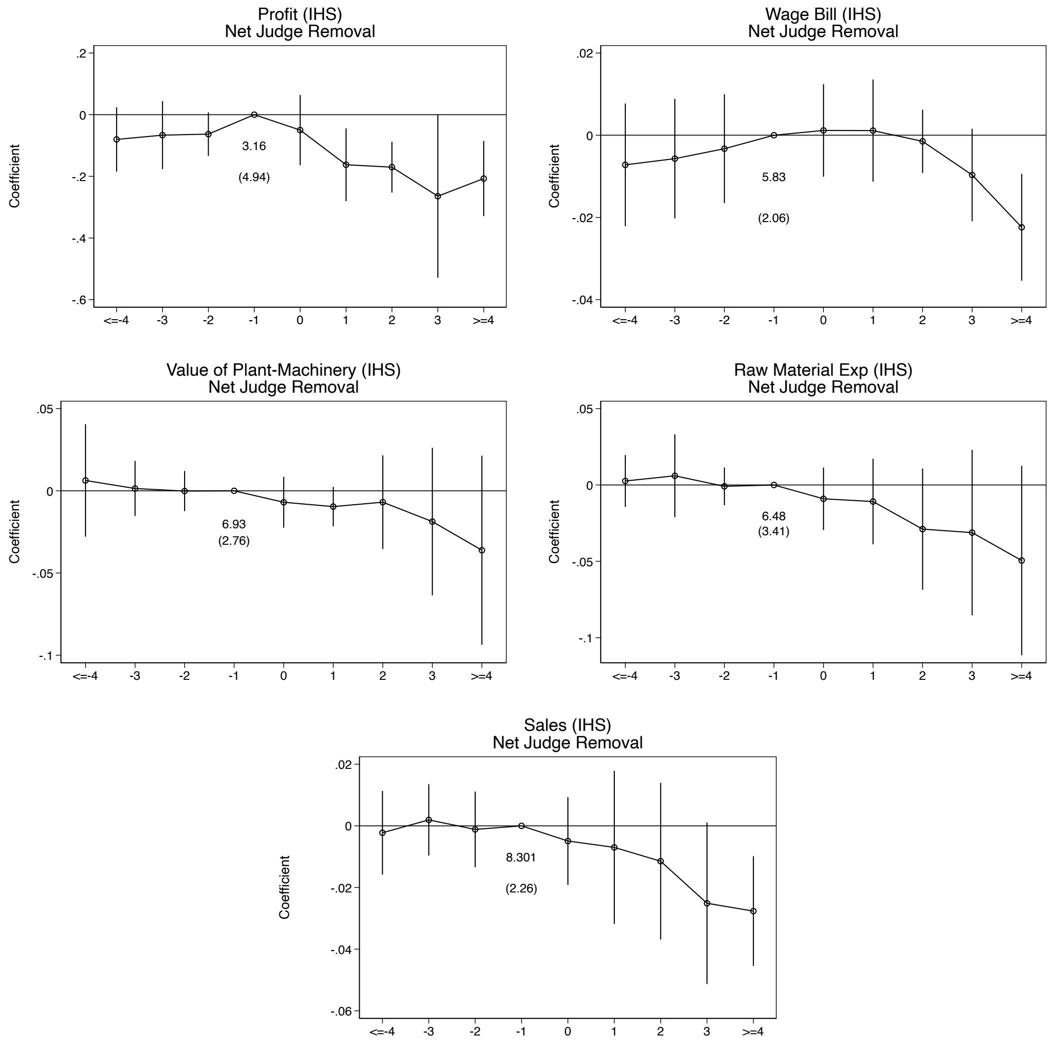
Notes: The figures plot the event study interaction coefficients for positive and negative staffing changes from estimating Equation 1 using total number of judges (Panel A), inverse vacancy rates (Panel B) and disposal rate (expressed in percentage terms in Panel C) as dependent variables, respectively. In all the figures, the end-points take into account relative event-bins outside the effect window in the data. The coefficients are all normalized to the period prior to the event. Standard errors are clustered by district and event. Error bars present 95% confidence interval.

Figure 2: Local Firms' Production: Removal of Vacancy



Notes: The figures above plot the event studies coefficients on positive staffing change event-time interaction dummies from estimating Equation 1 for firm-level variables. The outcome variables are transformed using inverse hyperbolic sine function to account for 0s and negative values observed in the balance-sheet data. The first row presents the coefficients with profits and wage bills as the dependent variables. The dependent variables in second row are the value of capital goods (plant/machinery) and raw material expenditure, respectively. The last row presents the effects on sales revenue. In all the figures, the end-points take into account relative event-bins outside the effect window in the data. The coefficients are all normalized to the period prior to an event and standard errors are clustered by district and event. Error bars present 95% confidence interval.

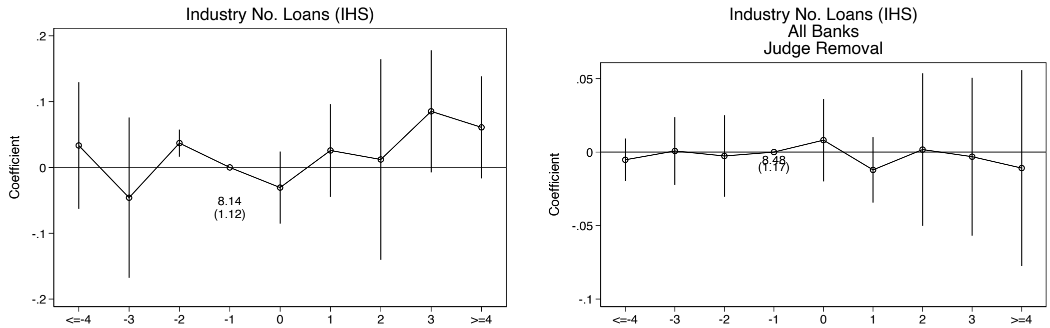
Figure 3: Local Firms' Production: Creation of Vacancy



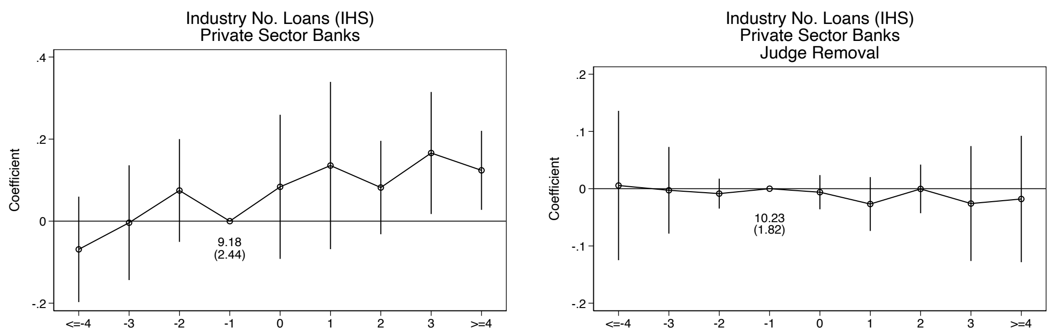
Notes: The figures above plot the event studies coefficients on negative staffing change event-time interaction dummies from estimating Equation 1 for firm-level variables. The outcome variables are transformed using inverse hyperbolic sine function to account for 0s and negative values observed in the balance-sheet data. The first row presents the coefficients with profits and wage bills as the dependent variables. The dependent variables in second row are the value of capital goods (plant/machinery) and raw material expenditure, respectively. The last row presents the effects on sales revenue. In all the figures, the end-points take into account relative event-bins outside the effect window in the data. The coefficients are all normalized to the period prior to an event and standard errors are clustered by district and event. Error bars present 95% confidence interval.

Figure 4: District Credit Outcomes: Removal of Vacancy

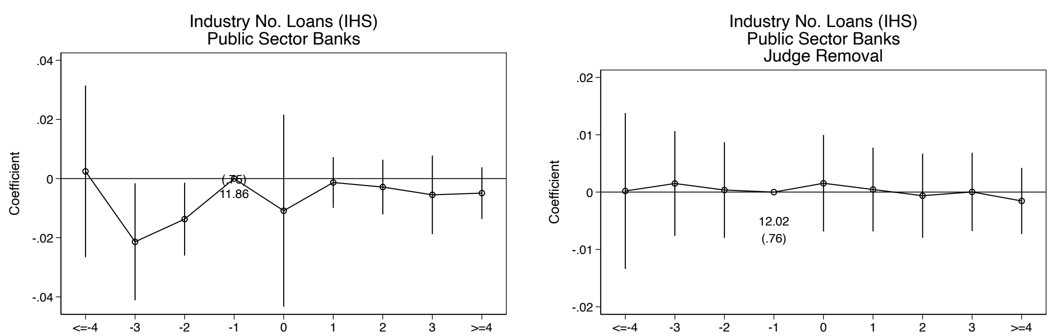
Panel A: Overall Lending



Panel B: Lending by Private Sector Banks

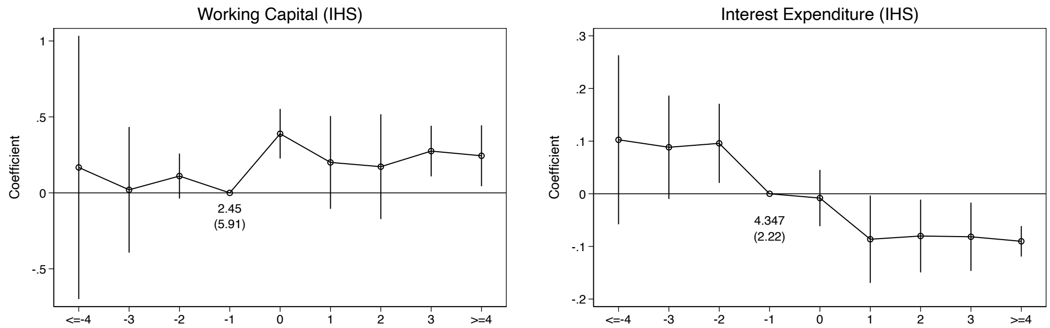


Panel C: Lending by Public Sector banks

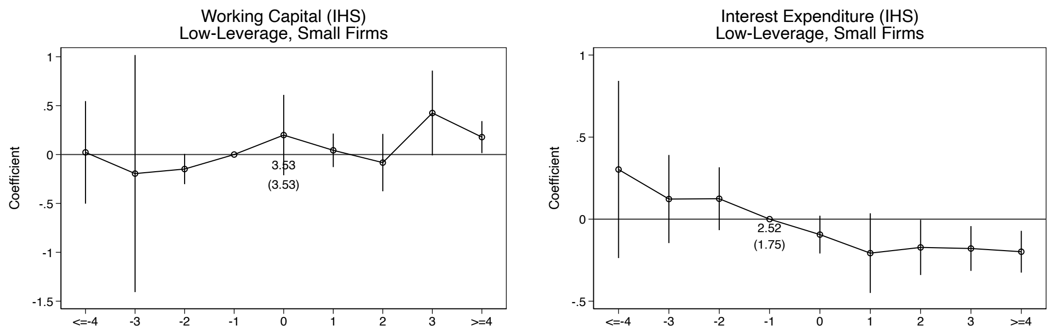


Notes: Panel A presents effects on overall lending by all banks branches within a district to industrial borrowers, noting the effects of both vacancy removal (left) and creation (right). Panels B and C break down the lending results by banking sector, i.e. private or public sector banks. These district-level regressions are weighted by the number of active bank cases before the start of the study period. Error bars present 95% confidence interval.

Figure 5: Firm Credit Outcomes: Removal of Vacancy
Panel A: Firm-level Working Capital and Interest Expenditure - All Sample Firms

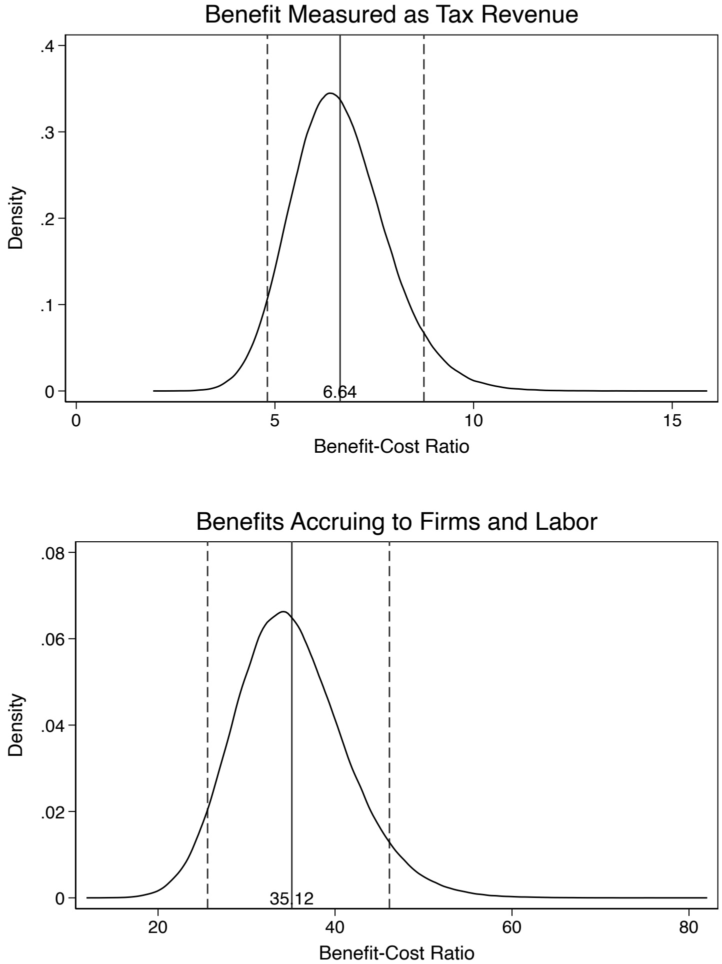


Panel B: Subsample of Low-Leverage, Small Sized Firms



Notes: Panel A presents effects of judge vacancy removal on working capital and interest expenditure for all firms and Panel B for the subset of small-sized less-leveraged firms. Error bars present 95% confidence interval.

Figure 6: Benefit-Cost Ratio



Notes: Average benefit-cost ratio from tax-revenue perspective is 6.64, with 90% confidence interval [4.81, 8.75]. The ratio computed using benefit accruing to firms and labor is 35.12, with 90% confidence interval [25.6, 46.15]. These are calculated through bootstrapping procedure with 1000,000 draws from random normal distributions using the parameter estimates from net judge additions and their standard errors on total number of judges, profits, and wage bill. Standard errors of the benefit-cost ratios are calculated as bootstrapped standard errors.

10 Tables

Table 1: Summary Statistics

	(1)					
	No. of Units	Observations	Mean	Std Dev	Min	Max
Panel A: Court Variables						
Total Judge Posts	195	1755	18	19	1	108
100-Vacancy(%)	195	1723	77	21	10	100
No. Net Judge Increases	195	195	1.621	1.153	0	6
Δ Judge (+ve) (per event)	158	158	2.31	2.54	1	24
No. Net Judge Decreases	195	195	3.6	1.66	1	8
Δ Judge (-ve) (per event)	195	195	3.67	3.97	1	33
Disposal Rate (%)	195	1755	14	12	0	86
Case Duration (days)	195	5706852	420	570	0	4022
Panel B: Bank Lending						
No. Industry Loans	192	1719	9188.2	15602.58	30	188456
Outstanding Amount (real terms, million INR)	192	1719	310.3	1130.19	0.023	15569.2
Panel C: Sample Firms						
Wage Bill (in real terms, million INR)	393	3537	640.9	939.2	0	4645.76
Plant value (real terms, million INR)	393	3537	3867.6	7052.8	0	36506.9
Raw Mat Exp (real terms, million INR)	393	3537	3687.3	5797.7	0	28694.6
Revenue from Sales (real terms, million INR)	393	3537	8421.6	12085.3	0	59319.2
Accounting Profits (in real terms, million INR)	393	3537	371.2	811.5	-1897.1	3388.14
Working Cap (in real terms, million INR)	393	3537	537	1873.3	-5611.1	7099.9
Interest Exp (in real terms, million INR)	393	3537	231.5	460.9	0	2933.6
Panel D: All Local Firms						
Wage Bill (in real terms, million INR)	9032	87837	200.4	641.6	0	22059.97
Plant value (real terms, million INR)	9032	87837	1853.4	7521.4	0	178171.8
Raw Mat Exp (real terms, million INR)	9032	87837	1156.7	3685.9	0	94930
Revenue from Sales (real terms, million INR)	9032	87837	2887.3	8392.9	0	190978
Accounting Profits (in real terms, million INR)	9032	87837	54.4	585.6	-9645.3	10908.1
Working Cap (in real terms, million INR)	9032	87837	106.2	1255.2	-20041.9	23886.2
Interest Exp (in real terms, million INR)	9032	87837	129.4	450.5	0	11225.9

Notes: Panel A summarizes the court-level variables computed from trial-level disaggregated data. Panel B summarizes district-level bank lending to industries. Panels C and D summarize firm-level variables for incumbent firms in the sample, i.e. firms incorporated before 2010, separately for the balanced panel and for all firms, respectively. All monetary variables are measured in INR million as reported in Prowess database, in real terms using 2015 as the base year.

Table 2: Court Outcomes and Judge Vacancy Changes

	Vacancy (1) No. of Judges	Removal (2) 100 - Vacancy Rate	(3) Disposal Rate	(4) No. of Judges	Vacancy (5) 100 - Vacancy Rate	Creation (6) Disposal Rate
Event x <=-4	-0.0821	3.041	0.694	-0.293	-2.796	-0.827
	(0.307)	(2.717)	(0.566)	(0.689)	(3.432)	(0.774)
Event x -3	0.0678	4.598	-0.0628	-0.182	-2.708	-0.363
	(0.289)	(2.874)	(0.943)	(0.586)	(2.799)	(0.598)
Event x -2	0.460	3.650	1.106	-0.280	-2.427	-0.459
	(0.306)	(1.816)	(0.606)	(0.415)	(1.838)	(0.397)
Event x 0	2.228	15.99	2.199	-1.276	-10.81	-0.569
	(0.282)	(0.954)	(0.628)	(0.161)	(2.748)	(0.154)
Event x 1	1.585	10.70	2.617	-1.082	-7.790	-0.432
	(0.256)	(1.031)	(0.711)	(0.0937)	(1.745)	(0.721)
Event x 2	1.451	9.240	2.964	-0.918	-6.719	-0.621
	(0.199)	(1.043)	(1.184)	(0.0505)	(1.696)	(0.394)
Event x 3	1.277	9.243	2.893	-0.712	-7.086	-0.604
	(0.326)	(1.820)	(1.320)	(0.125)	(1.917)	(0.627)
Event x >=4	0.900	8.612	2.526	-0.615	-6.193	0.0171
	(0.558)	(2.710)	(0.945)	(0.407)	(2.183)	(0.748)
Observations	9162	9162	9162	9162	9162	9162
No. Districts	195	195	195	195	195	195

Notes: This table presents the estimates from Equation 1 using court-level outcomes, equivalent to Figure 1. Columns 1-3 present estimates following judge vacancy reduction (net judge increase) whereas Columns 4-6 present those following judge vacancy creation (net judge reduction). All court-level specifications include district and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 3: Local Firms' Outcomes: Removal of Judge Vacancy

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Pos x <=-4	0.0162	-0.0500	-0.0234	0.0256	-0.217	0.167	0.103
	(0.0535)	(0.0818)	(0.0658)	(0.0712)	(0.200)	(0.394)	(0.0729)
Pos x -3	0.000279	0.0162	-0.0505	0.0120	0.135	0.0202	0.0883
	(0.0350)	(0.0245)	(0.0882)	(0.0397)	(0.129)	(0.188)	(0.0446)
Pos x -2	0.00715	0.00361	0.00903	0.0181	0.193	0.111	0.0957
	(0.0294)	(0.0388)	(0.0429)	(0.0626)	(0.382)	(0.0673)	(0.0341)
Pos x 0	-0.00187	0.0179	0.0171	0.0201	0.110	0.389	-0.00813
	(0.0203)	(0.0120)	(0.0392)	(0.00418)	(0.0935)	(0.0742)	(0.0243)
Pos x 1	0.0196	0.00435	0.0253	0.0184	0.418	0.200	-0.0864
	(0.0213)	(0.00520)	(0.0636)	(0.0180)	(0.113)	(0.139)	(0.0377)
Pos x 2	0.0207	-0.00149	0.0717	0.0210	0.310	0.172	-0.0802
	(0.0228)	(0.0192)	(0.0480)	(0.0191)	(0.115)	(0.157)	(0.0314)
Pos x 3	0.0369	0.0266	0.0401	0.0360	0.462	0.275	-0.0817
	(0.0202)	(0.0366)	(0.0158)	(0.0126)	(0.114)	(0.0757)	(0.0295)
Pos x >=4	0.0514	0.0194	0.0336	0.0289	0.334	0.244	-0.0903
	(0.0216)	(0.0368)	(0.0107)	(0.00581)	(0.0703)	(0.0911)	(0.0131)
Observations	22752	22752	22752	22752	22752	22752	22752
No. Firms	393	393	393	393	393	393	393
No. Districts	64	64	64	64	64	64	64

Notes: This table presents the estimates from Equation 1 using firm-level outcomes, equivalent to Figure 2, for judge vacancy removal. IHS refers to inverse hyperbolic sine function. Using logarithmic transformation instead of arcsine yields similar estimates. I restrict the firms sample to a balanced panel in order to ensure no endogenous missing values of firm-level outcomes. All firm-level specifications include firm and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 4: Local Firms' Outcomes: Creation of Judge Vacancy

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Neg x <=-4	-0.00720	0.00629	0.00261	-0.00225	-0.0803	-0.0779	0.0251
	(0.00678)	(0.0155)	(0.00772)	(0.00616)	(0.0474)	(0.0398)	(0.0112)
Neg x -3	-0.00570	0.00140	0.00601	0.00193	-0.0664	-0.0151	0.00411
	(0.00661)	(0.00761)	(0.0123)	(0.00526)	(0.0501)	(0.0725)	(0.00978)
Neg x -2	-0.00328	-0.000139	-0.000887	-0.00116	-0.0631	0.0266	-0.00900
	(0.00601)	(0.00555)	(0.00561)	(0.00557)	(0.0322)	(0.0877)	(0.00460)
Neg x 0	0.00116	-0.00697	-0.00905	-0.00492	-0.0499	-0.0356	-0.00827
	(0.00511)	(0.00702)	(0.00930)	(0.00647)	(0.0518)	(0.0932)	(0.0174)
Neg x 1	0.00113	-0.00960	-0.0109	-0.00699	-0.162	0.0252	-0.00239
	(0.00564)	(0.00546)	(0.0127)	(0.0113)	(0.0536)	(0.0856)	(0.0157)
Neg x 2	-0.00149	-0.00692	-0.0289	-0.0115	-0.170	0.00525	-0.00874
	(0.00350)	(0.0129)	(0.0180)	(0.0115)	(0.0374)	(0.0600)	(0.0110)
Neg x 3	-0.00967	-0.0187	-0.0312	-0.0251	-0.264	-0.0679	-0.00507
	(0.00511)	(0.0204)	(0.0246)	(0.0119)	(0.120)	(0.0230)	(0.0187)
Neg x >=4	-0.0224	-0.0361	-0.0495	-0.0277	-0.207	0.0580	-0.0126
	(0.00591)	(0.0261)	(0.0282)	(0.00808)	(0.0554)	(0.118)	(0.0204)
Observations	22752	22752	22752	22752	22752	22752	22752
No. Firms	393	393	393	393	393	393	393
No. Districts	64	64	64	64	64	64	64

Notes: This table presents the estimates from Equation 1 using firm-level outcomes, equivalent to Figure 3, for judge vacancy creation. IHS refers to inverse hyperbolic sine function. Using logarithmic transformation instead of arcsine yields similar estimates. I restrict the firms sample to a balanced panel in order to ensure no endogenous missing values of firm-level outcomes. All firm-level specifications include firm and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 5: Local Recorded Crime and Judge Vacancy Changes

	Vacancy	Removal	Vacancy	Creation
	(1) Cognizable Crime (IHS)	(2) Non-Cognizable Crime (IHS)	(3) Cognizable Crime (IHS)	(4) Non-Cognizable Crime (IHS)
Event x <=-4	-0.00938	0.00550	0.0268	-0.0160
	(0.00558)	(0.0417)	0.0168	-0.0128
Event x -3	-0.0129	-0.0223	0.0168	-0.0128
	(0.0113)	(0.0340)	(0.0112)	(0.0281)
Event x -2	-0.00414	-0.0105	0.00682	-0.00100
	(0.00512)	(0.0165)	(0.00602)	(0.0194)
Event x 0	-0.00926	-0.00279	0.00332	0.0280
	(0.00392)	(0.0414)	(0.00268)	(0.0356)
Event x 1	-0.0109	-0.0246	-0.00321	0.0578
	(0.0105)	(0.0191)	(0.00412)	(0.0206)
Event x 2	-0.0212	0.0149	-0.00902	-0.0113
	(0.00473)	(0.0257)	(0.00476)	(0.0263)
Event x 3	-0.0273	-0.101	-0.0147	0.0590
	(0.00785)	(0.0213)	(0.00440)	(0.0363)
Event x >=4	-0.0257	-0.00650	-0.0106	0.0676
	(0.00901)	(0.0537)	(0.00692)	(0.0222)
Observations	9101	9101	9101	9101
No. Districts	195	195	195	195

Notes: I use annual district-level reported crime data by the National Crime Records Bureau (NCRB), under the Ministry of Home, Government of India. All the crime variables are based on reported crimes under the Indian Penal Code (IPC). Cognizable Crime include crimes that do no require a court order for the police to complete their investigation. Non-cognizable crimes are those that require a court order from a sitting magistrate to carry forth any investigative effort by the police. Columns 1-2 present estimates following judge vacancy reduction (net judge increase) whereas Columns 3-4 present those following judge vacancy creation (net judge reduction) as per Equation 1. All specifications include district and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 6: Industrial Loans by Banking Sector

	Vacancy Removal			Vacancy Creation		
	(1) All Banks	(2) Public Sector Banks	(3) Private Sector Banks	(4) All Banks	(5) Public Sector Banks	(6) Private Sector Banks
Event x <=-4	0.0334	0.00243	-0.0688	-0.00525	0.000196	0.00556
	(0.0437)	(0.0132)	(0.0584)	(0.00658)	(0.00617)	(0.0592)
Event x -3	-0.0460	-0.0214	-0.00378	0.000752	0.00150	-0.00277
	(0.0553)	(0.00898)	(0.0635)	(0.0104)	(0.00415)	(0.0344)
Event x -2	0.0369	-0.0137	0.0747	-0.00265	0.000364	-0.00858
	(0.00935)	(0.00559)	(0.0569)	(0.0126)	(0.00379)	(0.0119)
Event x 0	-0.0306	-0.0109	0.0837	0.00811	0.00154	-0.00614
	(0.0249)	(0.0148)	(0.0798)	(0.0128)	(0.00382)	(0.0136)
Event x 1	0.0258	-0.00133	0.136	-0.0121	0.000454	-0.0268
	(0.0320)	(0.00389)	(0.0926)	(0.0101)	(0.00332)	(0.0213)
Event x 2	0.0121	-0.00286	0.0819	0.00171	-0.000625	-0.000413
	(0.0693)	(0.00420)	(0.0517)	(0.0236)	(0.00333)	(0.0193)
Event x 3	0.0852	-0.00549	0.166	-0.00314	0.0000327	-0.0259
	(0.0422)	(0.00604)	(0.0676)	(0.0244)	(0.00310)	(0.0456)
Event x >=4	0.0609	-0.00491	0.124	-0.0109	-0.00154	-0.0180
	(0.0353)	(0.00396)	(0.0437)	(0.0303)	(0.00262)	(0.0501)
Observations	5670	5670	5670	5670	5670	5670
No. Districts	110	110	110	110	110	110

Notes: I use annual district-level credit data to industrial borrowers aggregated across all banks, and by banking sector, by the Reserve Bank of India (RBI). Columns 1-3 present estimates following judge vacancy reduction (net judge increase) whereas Columns 4-6 present those following judge vacancy creation (net judge reduction) as per Equation 1. All specifications are weighted by the number of active cases involving banks in a district and include district and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 7: Small Firms' Access to Credit

	Vacancy	Removal	Vacancy	Creation
	(1)	(2)	(3)	(4)
	Working Cap. (IHS)	Interest Exp (IHS)	Working Cap. (IHS)	Interest Exp (IHS)
	Low Lev Small Firms	Low Lev Small Firms	Low Lev Small Firms	Low Lev Small Firms
Event x <=-4	0.0222	0.303	-0.156	0.0146
	(0.238)	(0.245)	(0.102)	(0.0261)
Event x -3	-0.195	0.123	-0.0468	-0.00744
	(0.551)	(0.122)	(0.0739)	(0.0198)
Event x -2	-0.148	0.124	-0.0357	-0.0118
	(0.0701)	(0.0870)	(0.0437)	(0.0259)
Event x 0	0.199	-0.0941	-0.0343	0.00958
	(0.187)	(0.0522)	(0.0843)	(0.0216)
Event x 1	0.0431	-0.207	0.0330	0.0339
	(0.0778)	(0.110)	(0.0683)	(0.0295)
Event x 2	-0.0826	-0.172	0.0868	0.0290
	(0.133)	(0.0764)	(0.0582)	(0.0236)
Event x 3	0.425	-0.179	-0.0374	0.0512
	(0.197)	(0.0620)	(0.0373)	(0.0405)
Event x >=4	0.178	-0.198	0.0591	0.0675
	(0.0743)	(0.0578)	(0.0815)	(0.0648)
Observations	6210	6210	6210	6210
No. Firms	105	105	105	105
No. Districts	30	30	30	30

Notes: This table presents the estimates from Equation 1 using working capital and interest expenditure as the dependent variables for the subset of ex-ante less-leveraged low asset size firms. Columns 1 and 2 are tabular equivalent to figures in Panel B Figure 5. Columns 3 and 4 present the event-study estimates for judge vacancy creation. The specifications include firm fixed and state-year fixed effect. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 8: Decomposition - Firm Profits

	Credit	Credit	Crime
	Working Cap (IHS) (1)	Interest Exp (IHS) (2)	Non-Cognizable Crime (IHS) (3)
t+3	0.0167	0.0208	0.0848
	(0.0265)	(0.124)	(0.187)
Δt+3	-0.0193	0.0198	-0.122
	(0.0257)	(0.0924)	(0.250)
Δt+2	-0.0217	-0.00426	-0.0176
	(0.0140)	(0.0596)	(0.237)
Δt	0.162	-0.417	-0.125
	(0.0360)	(0.243)	(0.241)
Δt-1	0.165	-0.389	0.0423
	(0.0403)	(0.234)	(0.307)
Δt-2	0.137	-0.379	-0.351
	(0.0345)	(0.232)	(0.187)
Δt-3	0.128	-0.335	-0.302
	(0.0417)	(0.223)	(0.291)
t-4	0.126	-0.347	-0.313
	(0.0575)	(0.235)	(0.164)
Percent Δ Profit	50.74	33.73	{7.97,17.42}
Observations	3048	1325	3029
No. Firms	391	322	391
No. Districts	64	55	64

Notes: The column names in this table refer to mediating variables whose leads and lags are noted as row headers. The dependent variable is arcsine firm profits. I employ a distributed lag specification as in Equation 2 to estimate the elasticities of these mediating variables on firms' profit. The coefficients are normalized relative to the explanatory variable from period $t + 1$. The contribution of each of these specific mechanisms as a percent change in long run profit due to positive judge staffing changes are noted in the last row. Additionally for crime, I also note the contribution to the contraction in firms' profits following negative staffing changes. Since credit outcomes do not change for these negative events, their contribution is construed to be 0. The event study graphs corresponding to the table above are in Figure A.15.

Appendix
For Online Publication Only

A.1 Data Appendix

A.1.A. Outcome variables

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

1. Bank Lending: Bank lending variables are from RBI data warehouse on Indian Economy (https://dbie.rbi.org) on district-wise number of loans and total outstanding amount (in INR Crore) aggregated annually across 27 scheduled commercial banks (national-level banks).

2. Working Capital: As all firms do not consistently report total borrowing, I use working capital as an indicator of credit use. Sufficient working capital is an indication that a firm will be able to fund its day-to-day operating expenditure.

3. Interest Expenditure: This includes firms' interest payment on all borrowing - long-term and short-term borrowing, trade credit, debentures, interest on taxes, etc.

Impact variables: Following variables represent inputs, production, and value addition mapping, onto firm's production decisions.

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

2. Accounting profits (income net of expenditure): I generate this variable by subtracting total expenditure reported by the firm from total reported income.

3. Wage bill: This captures total payments made by the firm to all its employees, either in cash or kind. This includes salaries/wages, social security contributions, bonuses, pension, etc.

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

5. Raw material expenditure: This captures total expenditure on raw materials by adding purchases reported in a given year to the value of net stock (opening - closing).

A.1.B. Matching firms with trial data

I follow the steps below to match firms with registered trials in the e-courts database:[1]

1. Identify the set of trials involving firms on either sides of the litigation (i.e. either as a plaintiff/petitioner, or as a defendant/respondent, or as both) using specific naming conventions followed by firms during registration. Common patterns include firm names starting with variants of "M/S", ending with variants of "Ltd", and so on. This results in 1.2 million trials, or 20% of the trial dataset being identified as those involving firms.

2. Create a set of unique firms appearing in above dataset. I note that same firm could appear as a litigant in more than one district. 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 trial data in step 2 with firm names as they appear in Prowess dataset using common patterns with the aid of regular expressions. This also accounts for 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 trial dataset as "State Bank of India", "SBI", S.B.I", and similar variants. I map all these different spellings to the same entity "State Bank of India".

4. Remove matches where firm names are used as landmark in the addresses of litigants. To do this, I detect prefix words such as "opposite to" "above", "below", "near", and "behind" followed by a firm name.

[1]Note that the firms can be engaged in litigation in any district other than their registered office location. Specifically, banking firms have ongoing trials in the court corresponding to the jurisdiction of the borrower. For matching, therefore, I employ a nested approach following above heuristics. I only retain one-to-one match between a firm and a trial.

5. Create primary key as the standardized name, from step 3 to match with both trial as well as Prowess 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.

A.2 A model of credit market with enforcement costs

A.2.A. Credit Market

I follow and extend the credit contract model in Banerjee and Duflo (2010) to include probability of litigation at a given rate of trial resolution in the corresponding district court. Specifically, I consider a lender-borrower sequential game with lender's choice to enforce debt contract through litigation. This is similar to the role of social sanctions in the group liability model discussed in Besley and Coate (1995). The solution to the game provides an optimal contract that details the interest rate schedule and a wealth threshold for lending.

At the start, borrower needs to invest, K, in a project which returns $f(K)$. Their exogenous wealth endowment is W. They needs an additional $K_B = K - K_M$ from the lender to start the project, where K_M is the amount they raises from the market. Borrower repays RK_B at the end of the contract period, where $R = 1 + r > 1$ incorporates the interest rate r. The project succeeds with probability s, upon which the borrower decides to repay or evade. Evasion is costly as the borrower incurs an evasion cost ηK_B leading to a payoff $f(K) - \eta K_B$. The lender loses the entire principal, $-K_B$. Repayment results in $f(K) - RK_B$ as payoff to the borrower and the lender earns RK_B. On the other hand, the borrower automatically defaults if her project fails, in which case the lender can choose to litigate to monetize borrower's assets to recover their loan. This game is depicted in Figure A.12. Litigation is costly and lender incurs a cost, $C_L(\gamma) > 0, \frac{\partial C_L}{\partial \gamma} < 0$, as a function of judicial capacity, γ. The borrower can also choose to litigate with costs, $C_B(\gamma) > 0, \frac{\partial C_B}{\partial \gamma} < 0$, or settle out of court. Once the lender chooses to litigate and borrower accepts, lender wins with a very high probability. The intuition behind the relationship behind enforcement costs and judicial capacity can be explained by the fact that the litigants need to spend on travel, logistics, and lawyer fees over the duration of the trial, which is longer when the judicial capacity is lower.[2]

When borrower's project fails, they litigate only if the value of their assets net litigation costs is positive. At the same time, the lender seeks to liquidate part of the borrower's assets, δW, to recover the loan, where δ is the depreciation rate. Lender earns a payoff of $\Gamma\delta W - C_L(\gamma)$ under litigation, where $\Gamma < 1$ is the fraction of the disputed amount that the court is able to help recover. The borrower earns a payoff $\Gamma\delta W - E[C_B(\gamma)]$, where their litigation cost $C_B(\gamma)$ is unknown ex-ante. Therefore, the condition for the borrower to accept litigation instead of opting to settle, given project failure, is

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

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

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

This gives a minimum wealth threshold, W^*, for lending. Under project success, the borrower can choose to default if they can successfully evade. However, default gives rise to the possibility of litigation. In this situation, borrower will litigate if

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

K_B mainly depends on the project and has an ex-ante distribution given by CDF, $G(.)$. R is fixed by the lender. This gives a distribution of firms willing to litigate under default as $1 - G(\tilde{W})$. Therefore, by backward induction, litigation will be lender's weakly dominant strategy if

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

[2] 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^* and setting the interest rate schedule. The returns from lending to ensure adequate recovery of loan under default gives the following schedule:

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

The contract design thus generates a set of borrowers that will $\{default, litigate\}$ and another set that will either $\{default, settle\}$ or $\{repay\}$ based on their ex-ante wealth $\tilde{W}$ and project size K_B. Finally, lender's participation constraint is given by

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

The timing of the game where the lender and borrower decide on their strategies are depicted as an extensive form game in Figure A.12.

Proposition 1: Litigation response from borrower As judicial capacity, γ, increases, the wealth threshold for litigation decreases. That is, $\frac{\partial \tilde{W}}{\partial \gamma} < 0$.

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

Constraints (2) and (5) define the credit contract. Additionally $R \geq \phi$ else the lender would rather invest in external markets than engaging in lending. This gives the relationship between returns - R, borrowing - K_B, and the wealth threshold for lending - W^*, as depicted in Figure A.12.

Proposition 2: Credit market response to judicial capacity As judicial capacity, γ, increases, the credit market response varies as follows:

1. Effect on W^* is negative. That is, an increase in judicial capacity lowers the threshold of wealth required for lending.

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

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

Proof for Proposition 2: Differentiating (2) and (5) with respect to γ yields the expressions for $\frac{\partial R}{\partial \gamma}$ and $\frac{\partial W^*}{\partial \gamma}$ as below. For the distribution functions, I assume $g(\tilde{W}), f(\tilde{W}) \to 0$ since only large firms engage in litigation.

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

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

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

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

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

A.2.B. Firm Production

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

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

where w_1 and w_2 are the unit costs of inputs X_1 and X_2, $m_i(\gamma)$ is the monitoring costs arising in the production process, which weakly decreases with improvements in judicial capacity, i.e. $\frac{\partial m_i}{\partial \gamma} \leq 0$. i represents firm size based on their initial wealth endowment, denoted by S for small firms and by L for large ones. Further, I assume that fixed costs form a large share of monitoring costs for small firms such that $\frac{\partial m_S}{\partial \gamma} \approx 0$ whereas for large firms, $\frac{\partial m_L}{\partial \gamma} < 0$ reflecting a lowering of the variable cost. $K_i = K_M + K_B$, is the total capital available to finance production, including borrowing from bank K_B as in Banerjee and Duflo (2014). From the credit market model above, we know that as judicial capacity, γ, improves, banks begin to lend to smaller firms and the overall interest rate on bank lending, $R(\gamma, .)$ drops.

Proposition 3: Effects of judicial capacity on firm production As judicial capacity, γ, increases, the firm responds as follows:

1. Optimal input use X_1, X_2 increases on an average.
2. Output increases on an average.
3. Heterogeneity in effects on profits is as follows:
   (a) For large firms, L, optimal inputs and profits increase if decrease in monitoring costs and cheaper credit more than offsets the increase in input expenditure.
   (b) For marginal small firms, S, optimal inputs and profits increase if increase in borrowing is sufficiently large to offset the increase in input expenditure.
   (c) For inframarginal small firms, S, optimal inputs and profits remain unchanged because borrowing and monitoring costs for these firms remain unchanged.

Proof for Proposition 3: From the credit model, borrowing increases with an increase in judicial capacity i.e. $\frac{\partial K_i}{\partial \gamma} > 0$ for the marginal borrowers, i.e. those with $W \approx W^* - \epsilon$, with $\epsilon > 0$, a small positive real number.

Constrained Optimization:

$$\mathcal{L} = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - m_i(\gamma) + \lambda\big(K_i - w_1X_1 - w_2X_2 - m_i(\gamma)\big)$$

FOC:

$$\frac{\partial \mathcal{L}}{\partial X_1} = pQ_{x_1} - w_1 - w_1\lambda = 0$$
$$\frac{\partial \mathcal{L}}{\partial X_2} = pQ_{x_2} - w_2 - w_2\lambda = 0$$
$$\frac{\partial \mathcal{L}}{\partial \lambda} = K_i - w_1X_1 - w_2X_2 - m_i(\gamma) = 0$$

To examine how the optimal production choices vary with exogenous variation in the institutional quality parameter, γ, I use Implicit Function Theorem where X_1, X_2, λ are endogenous variables and γ is exogenous to the firm's problem. A key distinction arises based on whether the firm belongs to the group of small or large firms. For

$i = S$ and $W \approx W^* - \epsilon$, $K_i = K_M + K_B$ when γ increases. For $i = L$, $\frac{\partial K_i}{\partial \gamma} = 0$. Applying Cramer's Rule:

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

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

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

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

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

$\frac{\partial g^*}{\partial \gamma} > 0$ if marginal benefits from an improvement in judicial capacity exceeds marginal cost, in which case, welfare improves. If this is not true, then the welfare effect is potentially ambiguous. Heterogeneity based on firm size distribution imply:

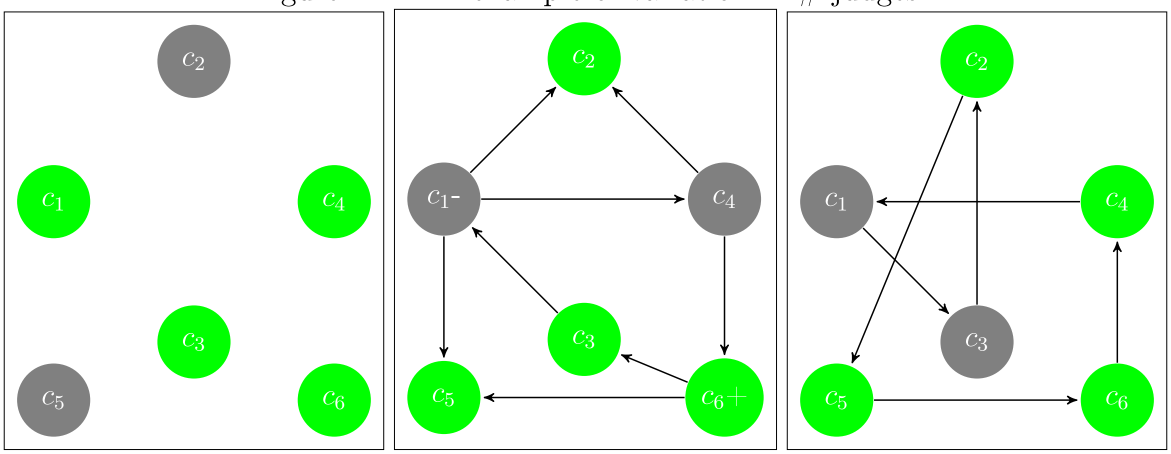
1. For large firms, $i = L$, the marginal benefit $0 - \frac{\partial m_L}{\partial \gamma}$ is mainly due to reduction in monitoring costs since there is no change in their borrowing from banks. If this reduction in monitoring costs is greater than the marginal increase in input costs, then profits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

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

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

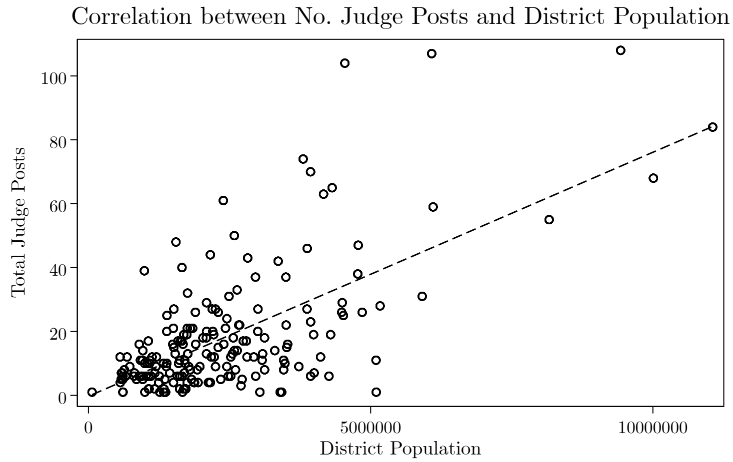
A.3 Appendix: Figures

Figure A.1: An example of variation in # judges

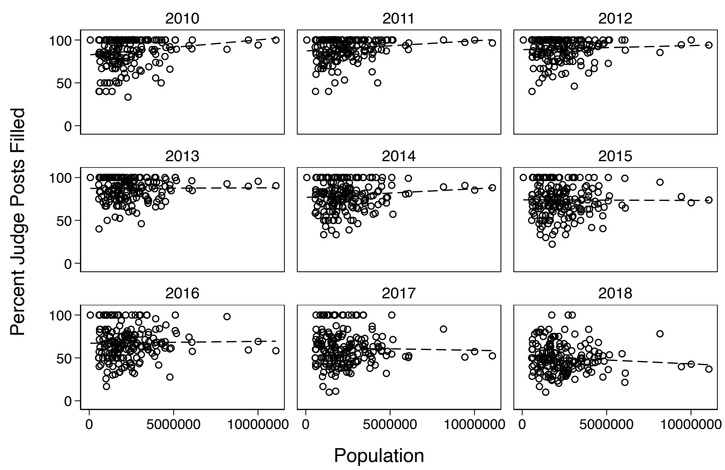


Notes: A node refers to a district court. Green node implies no judge vacancy and gray node implies judge vacancy. A directed arrow indicates the movement of judge from origin district court to the newly assigned destination court. The + and − inside the nodes indicate addition of a newly recruited judge and retirement, respectively.

Figure A.2: Total Number of Judge Posts and District Population
Panel A: Court-size and district population

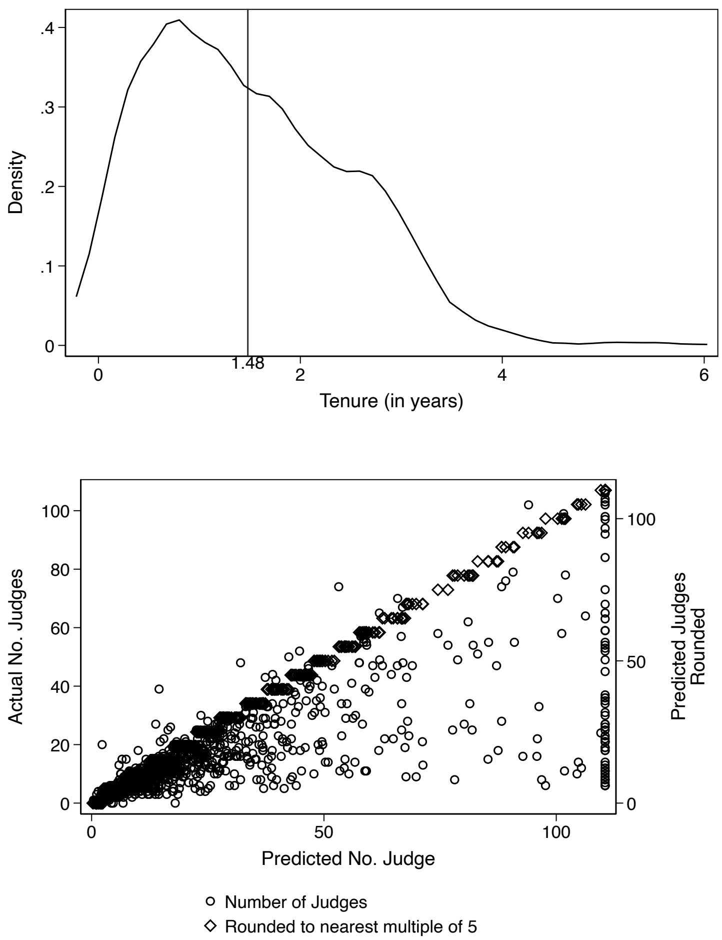


Panel B: Inverse Vacancy-rates over time and district population



Notes: Y axis in Panel A presents total number of judge posts across the sample courts. Y axis in Panel B presents 100-vacancy rate (%) by year across the sample courts. X-axis in both figures is the district population as measured in 2011 census.

Figure A.3: Judge tenure and assignment



Notes: For the top panel, I use data on judge start date and end date in a given district court, available mainly for the Principal District Judge (PDJ) from a subset of the sample court websites displaying this information. In the bottom panel, I plot the observed number of judges in a district court-year on the left y-axis, predicted number of judges based on the Law Commission Report No. 245 on the x-axis, and the predicted number rounded to the nearest multiple of 5 on the right y-axis. If the high courts followed the algorithm subject to integer rounding, the relationship between observed number of judges and predicted number of judges should follow a step function as shown.

Figure A.4: Sample district courts

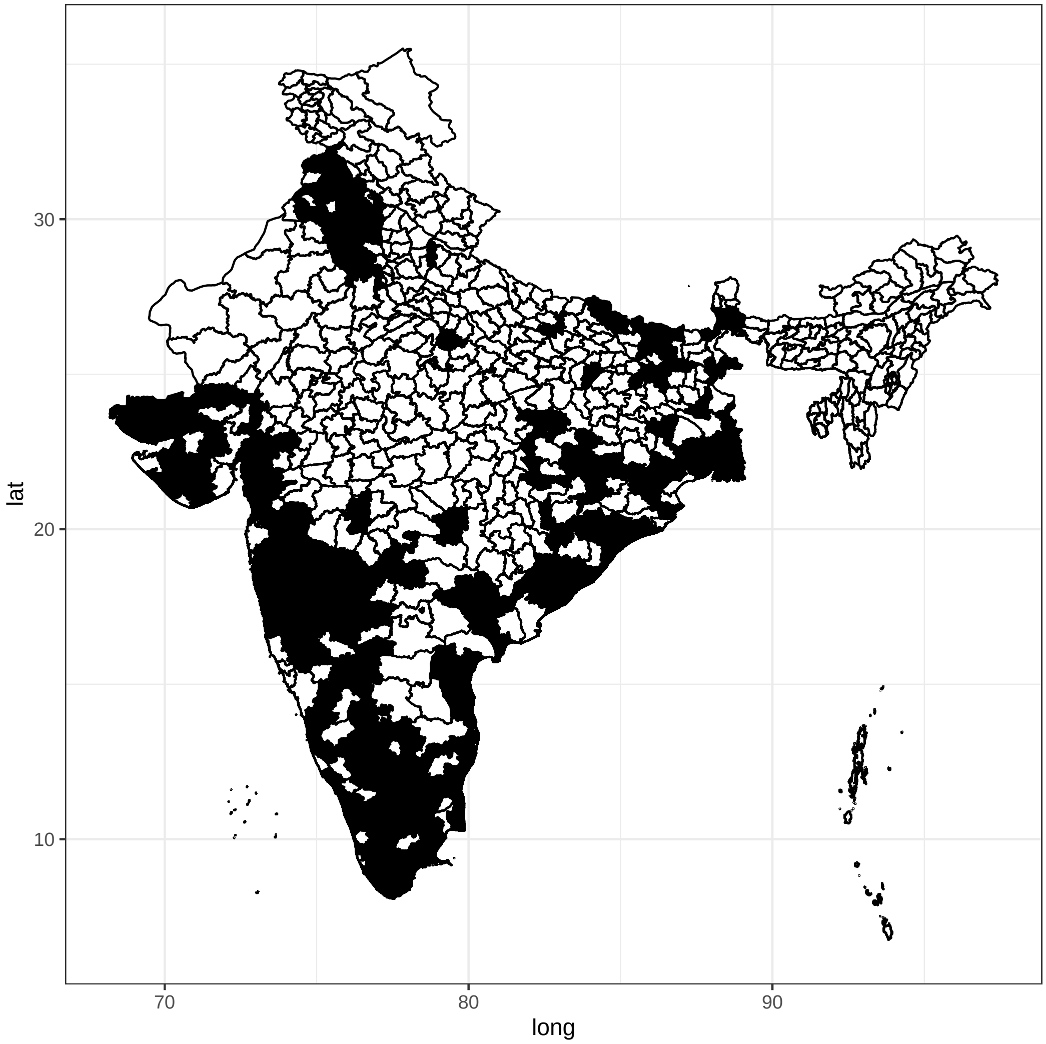


Figure A.5: Construction of sample of firms

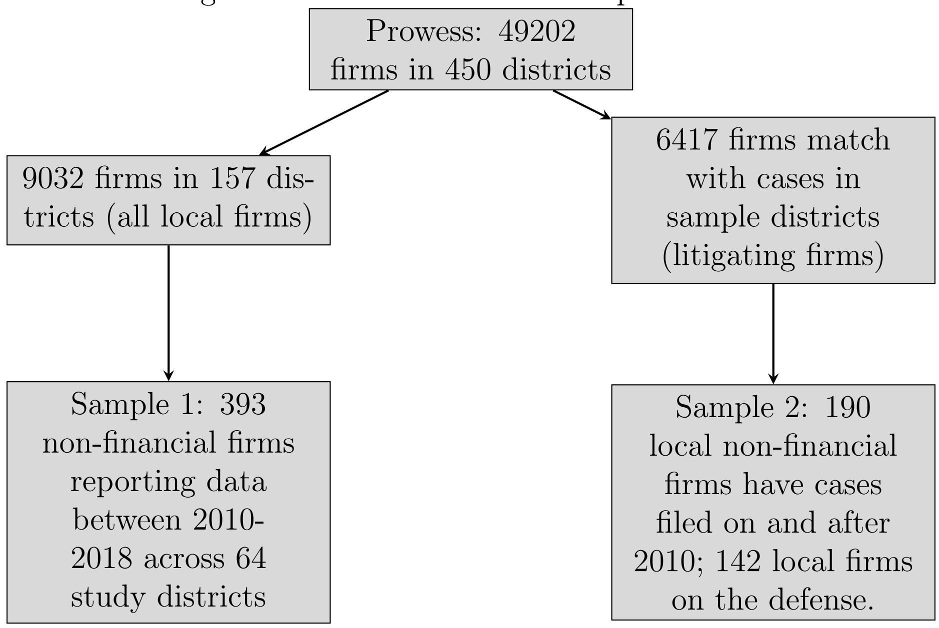
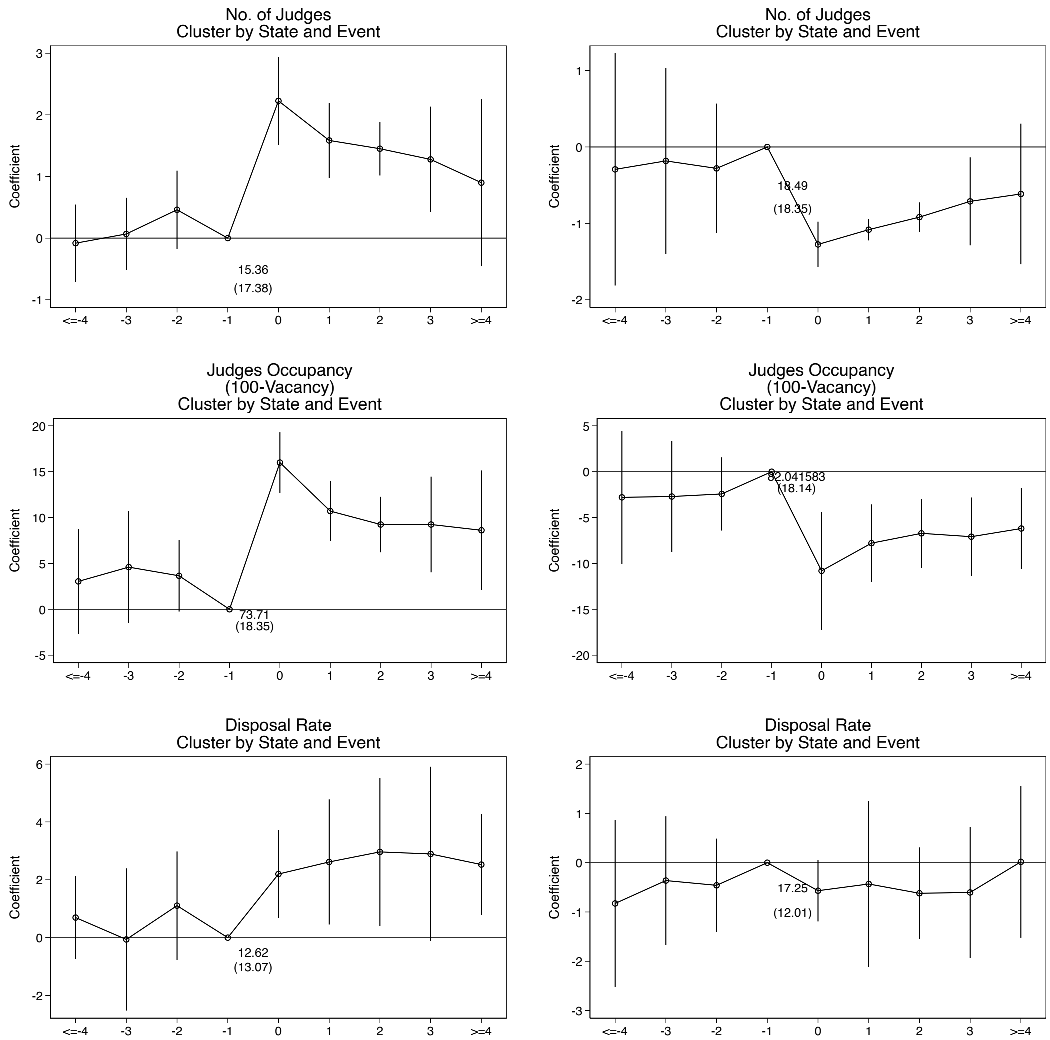
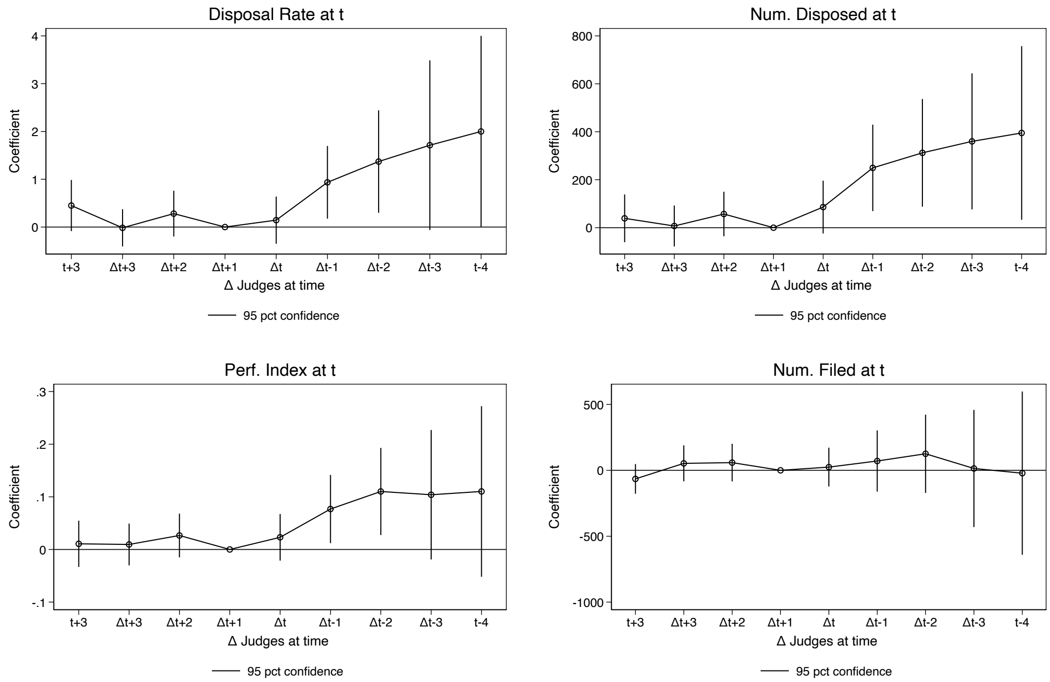


Figure A.6: Court Outcomes: Inference Robustness



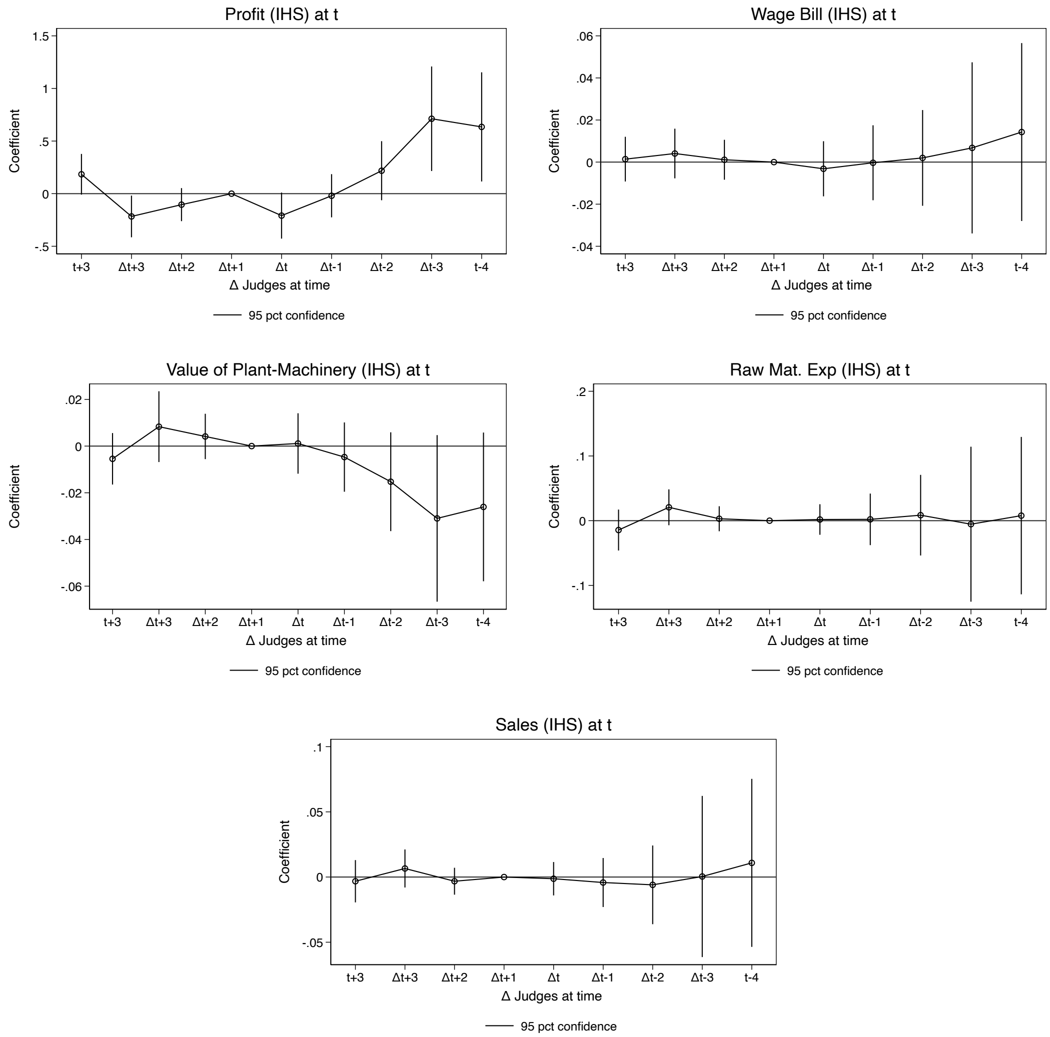
Notes: The figures plot the event study interaction coefficients from estimating Equation 1. Standard errors are clustered by state (instead of district) and event. Error bars present 95% confidence interval.

Figure A.7: Court Outcomes: Continuous Explanatory Variable



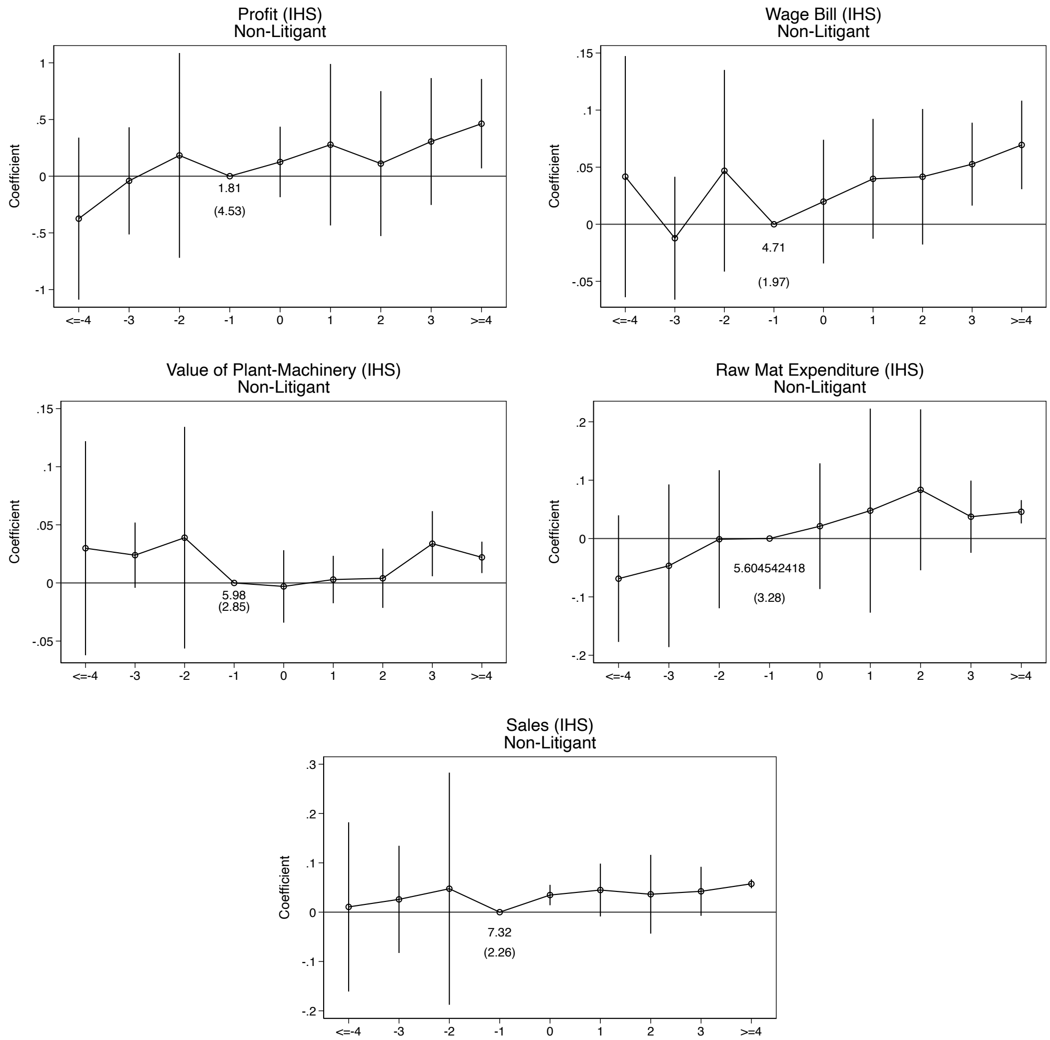
Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the court-level outcomes are measured at t as in Equation 2. In addition to disposal rate, the analysis includes cases resolved, new cases filed, and an index incorporating other possible court-level performance outcomes including appeals, dismissals, and percent uncontested. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

Figure A.8: Firm-Level Outcomes: Continuous Explanatory Variable



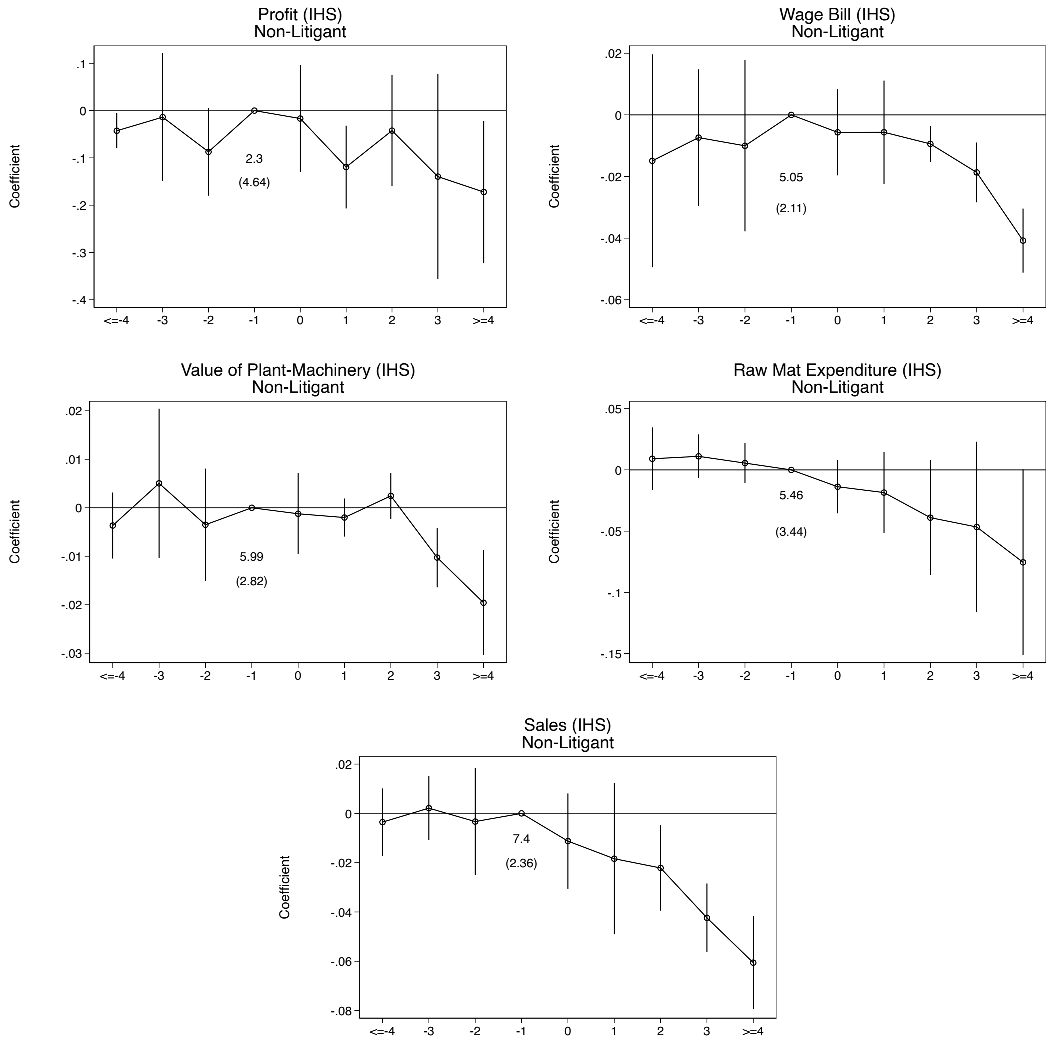
Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the firm-level outcome is measured at t as in Equation 2. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

Figure A.9: Subset of Non-Litigating Firms: Vacancy Removal



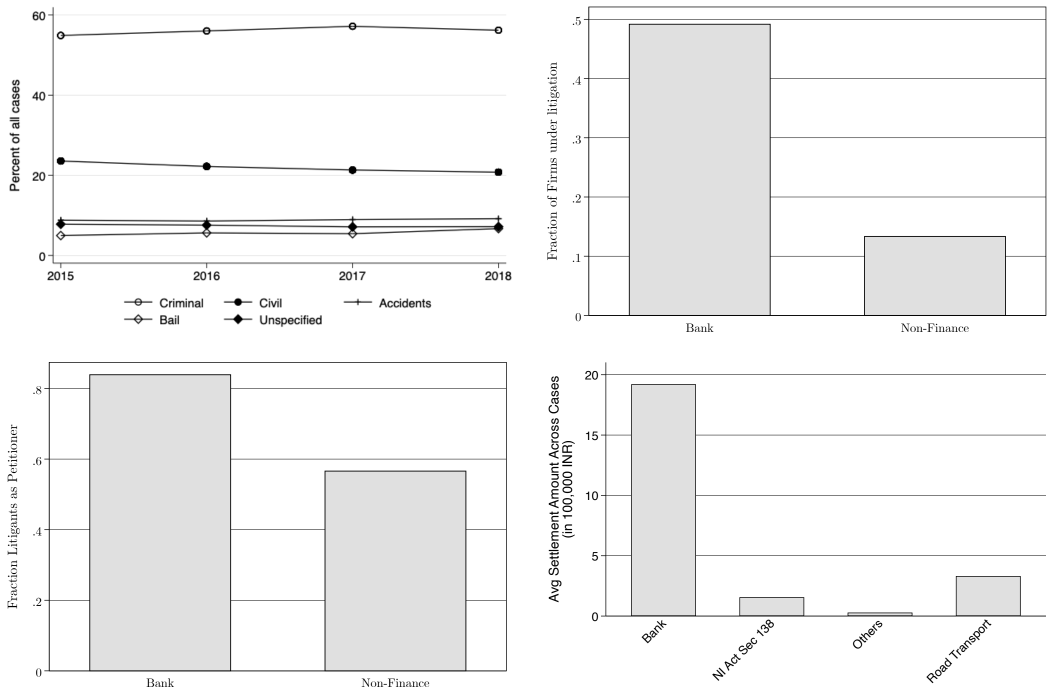
Notes: These graphs reproduce the reduced form graphs from Figure 2 but only using the subsample of non-litigating firms. Each estimate includes 95% confidence interval. Standard errors are clustered by district and event.

Figure A.10: Subset of Non-Litigating Firms: Vacancy Creation



Notes: These graphs reproduce the reduced form graphs from Figure 3 but only using the subsample of non-litigating firms. Each estimate includes 95% confidence interval. Standard errors are clustered by district and event.

Figure A.11: Case-Types, Debt Litigations, and Settlement Amounts



Notes: Top-left figure presents the composition of cases in district courts. The second figure in the top panel presents the fraction of all firms in Prowess data belonging to either banking sector or non-finance sector (for e.g., manufacturing, services, trade and transportation, etc.) with at least one trial in the trial-level dataset. Bottom-right panel presents the fraction of these litigating firms appearing as the plaintiff (petitioner). Data on settlement amount in the bottom panel are from codified judgement documents from one court only for illustration.

Figure A.12: Model: Credit and Litigation

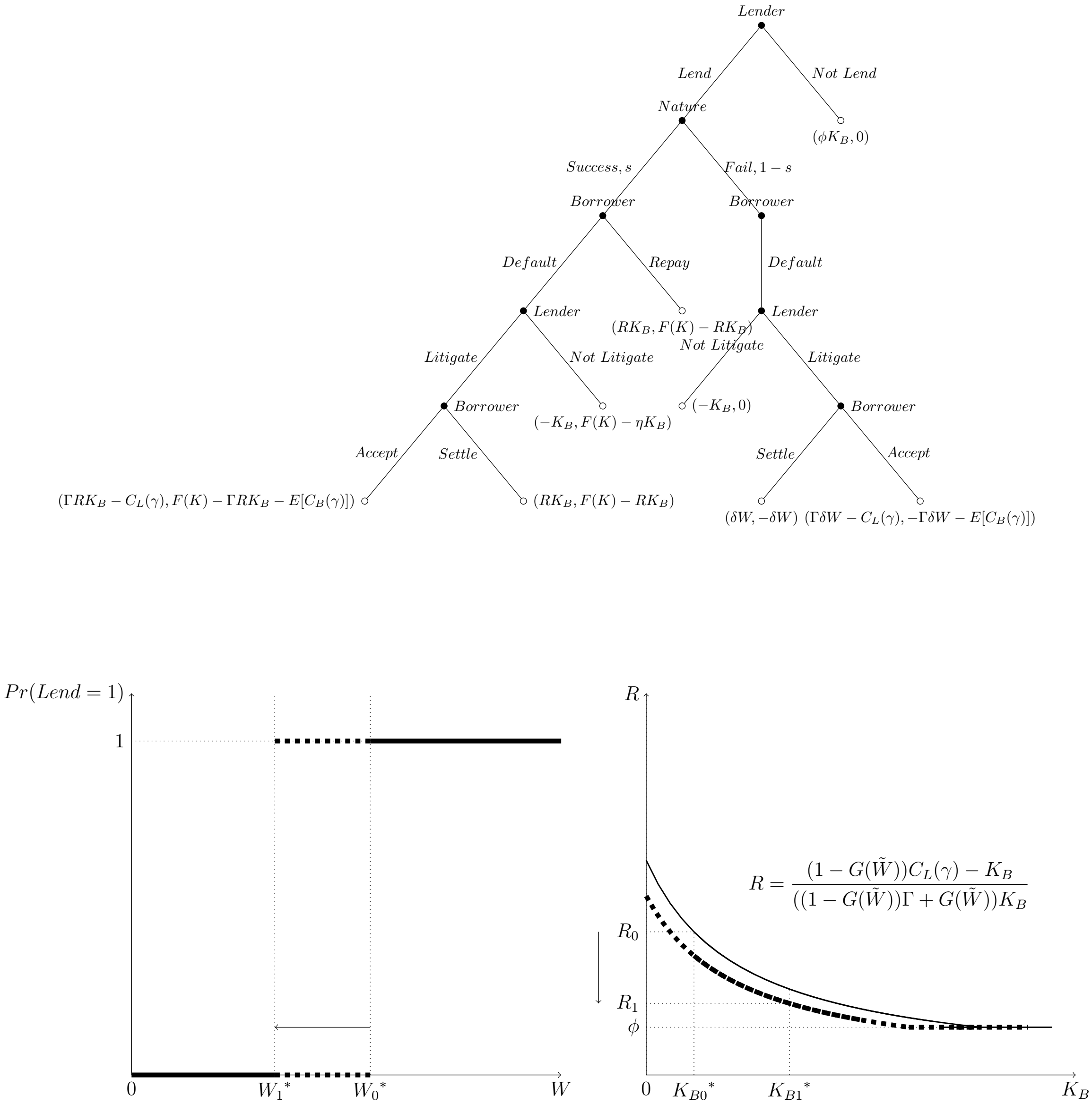
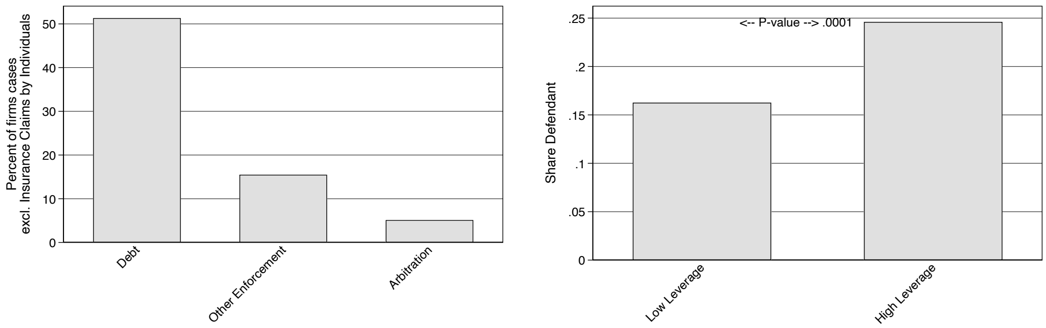
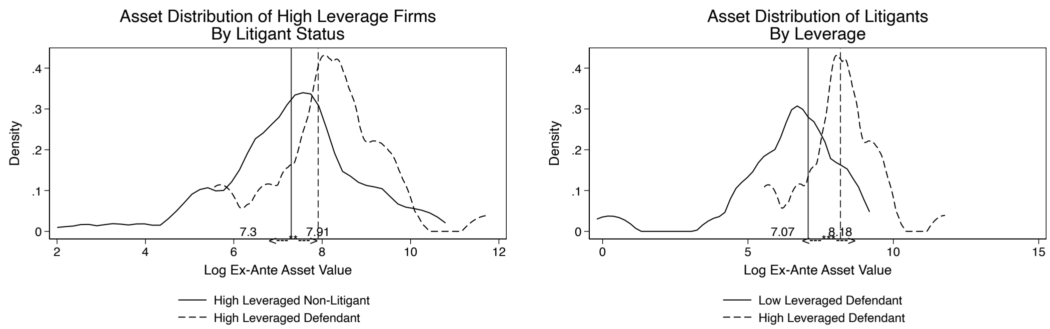


Figure A.13: Litigation Behavior

Panel A: Firms' Cases in Courts

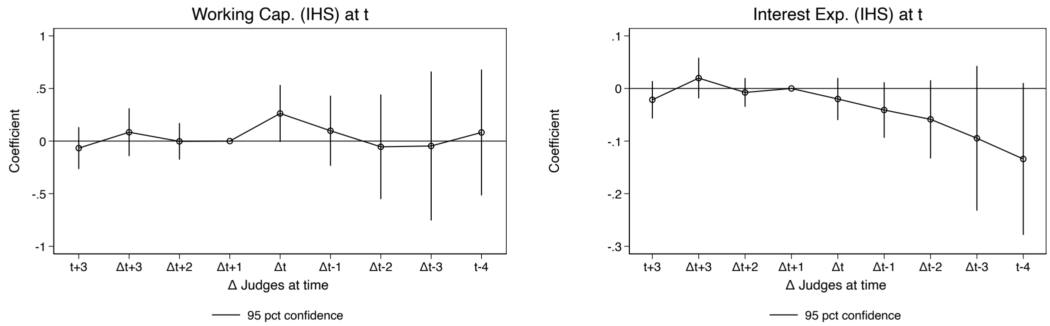


Panel B: Wealth Distribution

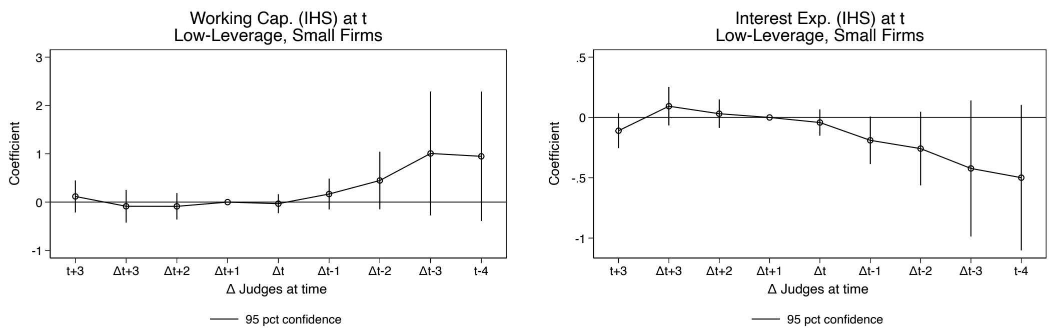


Notes: Panel A presents the share of trials involving non-financial firms by dispute type (left) and leverage (right). Trials involving financial sector firms, including banks, are excluded. Panel B presents the kernel densities of local non-financial firms' ex-ante total asset value by: (a) litigation status among high leverage firms (left), and (b) leverage status among the defending firms (right). The lines represent the average asset values with statistical significance of this difference as noted.

Figure A.14: Firms' Credit Outcomes: Continuous Explanatory Variable
Panel A: Firm-level Working Capital and Interest Expenditure - All Sample Firms

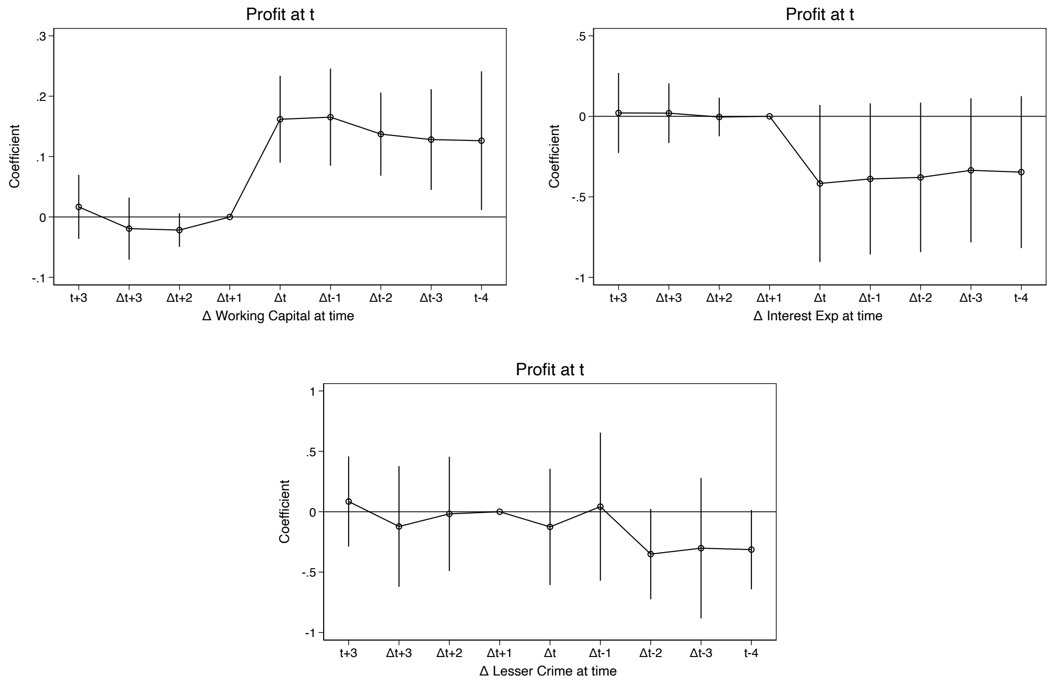


Panel B: Subsample of Low-Leverage, Small Sized Firms



Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the outcome is measured at t as in Equation 2. Panel A presents the coefficients using firm-level working capital and interest expenditure across all firms in the main sample. Panel B presents the coefficients using outcomes on the subsample of low-leverage, small-sized firms. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

Figure A.15: Decomposition of Firm Profits



Notes: The figures present the generalized event study estimates relative to working capital from $t+1$ when the profit is measured at t as in Equation 2. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

A.4 Appendix: Tables

Table A.1: Pairwise Correlations Between Different Measures of Court Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disposal Rate (1)	1.00						
Number Filed (2)	0.2689	1.00					
Number Disposed (3)	0.2497	0.8820	1.00				
Case Duration (4)	-0.1912	-0.1448	-0.0465	1.00			
Share Uncontested (5)	-0.1078	0.1172	0.1225	0.0555	1.00		
Share Dismissed (6)	0.1317	0.0188	-0.0268	-0.1258	0.0932	1.00	
Share Appealed (7)	-0.0811	-0.1593	-0.1787	0.0284	-0.2087	0.2174	1.00
Observations	1755						

Notes: All measures of court performance are constructed using the trial-level data, aggregated by court-year. Case duration is measured in number of days. Share uncontested is the percentage of resolved cases that are not contested by either of the litigants. Share dismissed is the percentage of resolved cases that are dismissed without full trial and judgement order. Share appealed is the percentage of newly filed cases that are appeals against decisions from lower courts within the district court's jurisdiction.

Table A.2: Heterogeneity in Judge Staffing Levels

	Vacancy	Removal			Vacancy	Creation
	(1)	(2)	(3)	(4)	(5)	(6)
	1st Tercile Population	2nd Tercile Population	3rd Tercile Population	1st Tercile Population	2nd Tercile Population	3rd Tercile Population
Event x <=-4	0.658	-0.122	-0.174	0.126	-0.0597	-0.464
	(0.556)	(0.604)	(0.826)	(0.487)	(0.449)	(0.396)
Event x -3	0.251	0.217	-0.160	0.134	-0.157	-0.264
	(0.345)	(0.501)	(0.400)	(0.385)	(0.468)	(0.388)
Event x -2	0.323	0.500	0.680	-0.0462	-0.189	-0.426
	(0.247)	(0.406)	(0.443)	(0.272)	(0.326)	(0.390)
Event x 0	1.491	1.742	2.848	-1.134	-1.112	-1.273
	(0.273)	(0.297)	(0.653)	(0.238)	(0.184)	(0.319)
Event x 1	0.894	0.928	2.509	-1.021	-0.938	-1.102
	(0.264)	(0.117)	(0.695)	(0.372)	(0.200)	(0.241)
Event x 2	0.922	0.628	2.501	-0.834	-0.941	-0.971
	(0.242)	(0.117)	(0.920)	(0.510)	(0.215)	(0.131)
Event x 3	0.423	0.569	2.932	-0.466	-0.937	-0.984
	(0.562)	(0.326)	(0.357)	(0.627)	(0.174)	(0.198)
Event x >=4	-0.139	0.833	2.166	0.0194	-0.982	-0.913
	(0.876)	(0.386)	(0.127)	(0.758)	(0.261)	(0.421)
Observations	2988	3042	2988	2988	3042	2988
No. Districts	71	64	57	71	64	57

Notes: This table presents the event study reduced form estimates of judge staffing changes on the number of judge in a year using different subsets of the sample by underlying district population.

Table A.3: Caseload Outcomes

	Vacancy	Removal			Vacancy	Creation
	(1) No. Filed	(2) No. Resolved	(3) Perc. Appeal	(4) No. Filed	(5) No. Resolved	(6) Perc. Appeal
Event x <=-4	260.0	436.0	-0.500	-36.81	-152.6	0.384
	(161.5)	(213.1)	(0.496)	(153.6)	(204.0)	(0.471)
Event x -3	65.23	93.38	0.196	-23.92	-80.41	-0.0926
	(105.7)	(98.07)	(0.533)	(128.4)	(217.5)	(0.272)
Event x -2	177.3	143.5	0.923	-68.69	-119.0	0.0816
	(67.19)	(148.9)	(0.385)	(125.0)	(158.5)	(0.192)
Event x 0	243.7	270.6	0.143	-91.27	-163.7	0.0248
	(156.7)	(137.8)	(0.334)	(72.22)	(58.00)	(0.555)
Event x 1	215.3	173.2	-0.180	44.04	-0.897	0.00462
	(308.8)	(268.8)	(0.357)	(68.87)	(104.7)	(0.521)
Event x 2	472.0	386.3	-0.982	-8.926	-50.67	0.343
	(338.3)	(338.6)	(0.491)	(111.2)	(156.3)	(0.502)
Event x 3	436.9	436.6	-0.251	-27.97	-126.4	0.151
	(329.3)	(516.8)	(0.547)	(135.2)	(221.6)	(0.377)
Event x >=4	442.2	398.7	-0.548	16.49	42.24	0.518
	(316.6)	(399.2)	(0.403)	(180.2)	(250.9)	(0.295)
Observations	9162	9162	9162	9162	9162	9162
No. Districts	195	195	195	195	195	195

Notes: This table presents the estimates from Equation 1 using other court-level outcomes including a breakdown of caseload by newly filed and resolved as well as the composition of cases that are appeals from lower courts. Columns 1-3 presents estimates for vacancy removal and Columns 4-6 for vacancy creation. All court-level specifications include district fixed effect. Standard errors are clustered by district and event.

Table A.4: Heterogeneity in Court Performance: Disposal Rate

	Vacancy	Removal			Vacancy	Creation
	(1) 1st Tercile Population	(2) 2nd Tercile Population	(3) 3rd Tercile Population	(4) 1st Tercile Population	(5) 2nd Tercile Population	(6) 3rd Tercile Population
Event x <=-4	0.901	-0.206	0.0257	-1.190	-1.000	0.0712
	(1.840)	(0.818)	(0.991)	(1.620)	(0.569)	(0.853)
Event x -3	-0.519	-2.373	1.114	-0.290	-0.674	-0.553
	(1.728)	(1.191)	(0.865)	(2.146)	(0.672)	(0.765)
Event x -2	0.667	0.544	1.155	-0.857	-0.465	-0.415
	(1.637)	(0.912)	(0.985)	(1.228)	(0.632)	(0.426)
Event x 0	1.766	1.605	1.329	-0.209	-0.173	-0.988
	(0.830)	(0.709)	(0.655)	(0.276)	(0.261)	(0.276)
Event x 1	2.062	1.985	1.560	-0.739	-0.180	-0.585
	(0.784)	(2.478)	(0.843)	(0.402)	(1.048)	(0.611)
Event x 2	2.043	3.425	1.450	-0.208	-0.508	-1.091
	(0.920)	(2.549)	(0.864)	(0.280)	(1.086)	(0.636)
Event x 3	2.257	3.074	0.941	-0.437	-0.511	-0.989
	(1.318)	(1.682)	(1.187)	(0.875)	(0.855)	(0.456)
Event x >=4	1.693	3.422	0.300	-0.0554	0.643	-0.513
	(1.515)	(1.407)	(1.306)	(0.432)	(1.286)	(0.738)
Observations	2988	3042	2988	2988	3042	2988
No. Districts	71	64	57	71	64	57

Notes: This table presents the event study reduced form estimates of staffing changes on court-level disposal rate using different subsets of the sample by underlying district population.

Table A.5: Vacancy Removal and Missing Firm-Level Data

	(1) Wage Bill (Missing)	(2) Plant Value (Missing)	(3) Raw Mat (Missing)	(4) Sales (Missing)	(5) Profit (Missing)	(6) Working Cap. (Missing)	(7) Interest Exp (Missing)
Pos x <=-4	0.00106	0.00171	0.00916	0.00610	0.000377	-0.00158	0.000776
	(0.00438)	(0.000868)	(0.00667)	(0.00473)	(0.000754)	(0.00224)	(0.00645)
Pos x -3	-0.00588	0.00221	-0.000704	-0.000637	0.00351	-0.00147	0.00203
	(0.00546)	(0.00461)	(0.00561)	(0.00731)	(0.00177)	(0.00187)	(0.00638)
Pos x -2	0.00225	0.00348	0.00382	0.00228	-0.000224	-0.000940	0.00591
	(0.00313)	(0.00168)	(0.00468)	(0.00285)	(0.00266)	(0.00139)	(0.00172)
Pos x 0	-0.00889	-0.00310	-0.00774	-0.0110	-0.00267	-0.00244	-0.00471
	(0.00381)	(0.00197)	(0.00367)	(0.00483)	(0.00115)	(0.00126)	(0.00465)
Pos x 1	-0.00916	-0.00442	-0.00592	-0.00620	-0.000915	-0.00160	-0.00165
	(0.00341)	(0.00180)	(0.00428)	(0.00419)	(0.000752)	(0.000589)	(0.00656)
Pos x 2	-0.0111	-0.00938	-0.00460	-0.00888	-0.00188	-0.00205	-0.00915
	(0.00343)	(0.00214)	(0.00437)	(0.00282)	(0.000673)	(0.000491)	(0.00919)
Pos x 3	-0.0117	-0.00221	-0.00321	-0.00960	-0.00171	-0.00161	-0.00940
	(0.00366)	(0.00155)	(0.00555)	(0.00230)	(0.000854)	(0.00100)	(0.00631)
Pos x >=4	-0.0114	-0.00499	-0.00467	-0.00736	0.000623	-0.00195	-0.0146
	(0.00352)	(0.00164)	(0.00639)	(0.00200)	(0.000732)	(0.000392)	(0.00665)
Observations	238401	238401	238401	238401	238401	238401	238401
No. Firms	7534	7534	7534	7534	7534	7534	7534
No. Districts	152	152	152	152	152	152	152

Notes: This table presents the estimates from Equation 1 for judge vacancy reduction using all registered formal sector firms in the district, with missing data variable encoded as 1 if a firm does not report the corresponding variable for a given year. Standard errors are clustered by district and event.

Table A.6: Vacancy Creation and Missing Firm-Level Data

	(1) Wage Bill (Missing)	(2) Plant Value (Missing)	(3) Raw Mat (Missing)	(4) Sales (Missing)	(5) Profit (Missing)	(6) Working Cap. (Missing)	(7) Interest Exp (Missing)
Neg x <=-4	-0.000405	0.000301	-0.00298	-0.00199	-0.00105	-0.0000105	0.00156
	(0.000412)	(0.000655)	(0.00299)	(0.000538)	(0.000107)	(0.0000468)	(0.000453)
Neg x -3	-0.000449	-0.000137	-0.00227	-0.00215	-0.00101	0.000235	0.000469
	(0.000757)	(0.000650)	(0.00234)	(0.000901)	(0.000503)	(0.000173)	(0.000464)
Neg x -2	-0.000891	-0.000586	-0.00157	-0.00102	-0.000955	-0.0000314	-0.00103
	(0.00133)	(0.000400)	(0.00211)	(0.00137)	(0.000684)	(0.000153)	(0.000888)
Neg x 0	0.00180	0.000392	0.00256	0.00226	0.000503	0.000433	0.000449
	(0.00166)	(0.000492)	(0.00238)	(0.00161)	(0.000649)	(0.000179)	(0.000752)
Neg x 1	0.00339	0.000743	0.00373	0.00284	-0.0000510	0.000205	0.0000261
	(0.000691)	(0.000680)	(0.00179)	(0.000749)	(0.000468)	(0.000112)	(0.00126)
Neg x 2	0.00460	0.00246	0.00499	0.00502	0.000961	0.000417	0.00403
	(0.000609)	(0.00103)	(0.00147)	(0.000673)	(0.000727)	(0.000216)	(0.00131)
Neg x 3	0.00497	0.000480	0.00579	0.00697	0.000773	0.000492	0.00422
	(0.000570)	(0.00108)	(0.00207)	(0.000694)	(0.000398)	(0.000188)	(0.00177)
Neg x >=4	0.00544	0.00194	0.00779	0.00653	0.000558	0.000232	0.00629
	(0.000591)	(0.00164)	(0.00278)	(0.000778)	(0.000298)	(0.000176)	(0.00211)
Observations	238401	238401	238401	238401	238401	238401	238401
No. Firms	7534	7534	7534	7534	7534	7534	7534
No. Districts	152	152	152	152	152	152	152

Standard errors in parentheses

Notes: This table presents the estimates from Equation 1 for judge vacancy creation using all registered formal sector firms in the district, with missing data variable encoded as 1 if a firm does not report the corresponding variable for a given year. Standard errors are clustered by district and event

Table A.7: Vacancy Removal and Non-Litigating Firms

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Pos x <=-4	0.0417	0.0299	-0.0688	0.0107	-0.374	-0.480	0.152
	(0.0480)	(0.0418)	(0.0493)	(0.0779)	(0.325)	(0.326)	(0.0700)
Pos x -3	-0.0122	0.0239	-0.0467	0.0259	-0.0410	0.160	0.121
	(0.0244)	(0.0128)	(0.0633)	(0.0494)	(0.215)	(0.181)	(0.0556)
Pos x -2	0.0469	0.0389	-0.00119	0.0475	0.183	0.0577	0.161
	(0.0401)	(0.0433)	(0.0538)	(0.107)	(0.410)	(0.152)	(0.0427)
Pos x 0	0.0198	-0.00299	0.0211	0.0347	0.126	0.397	-0.0104
	(0.0246)	(0.0142)	(0.0489)	(0.00938)	(0.141)	(0.128)	(0.0305)
Pos x 1	0.0398	0.00294	0.0478	0.0448	0.278	0.0526	-0.0975
	(0.0238)	(0.00926)	(0.0795)	(0.0243)	(0.324)	(0.112)	(0.0206)
Pos x 2	0.0416	0.00400	0.0835	0.0363	0.111	0.134	-0.0568
	(0.0270)	(0.0116)	(0.0627)	(0.0363)	(0.290)	(0.237)	(0.0152)
Pos x 3	0.0526	0.0338	0.0374	0.0423	0.306	0.0993	-0.0564
	(0.0165)	(0.0127)	(0.0281)	(0.0226)	(0.254)	(0.161)	(0.0339)
Pos x >=4	0.0695	0.0220	0.0459	0.0575	0.463	0.0999	-0.105
	(0.0176)	(0.00614)	(0.00907)	(0.00413)	(0.179)	(0.265)	(0.0170)
Observations	11727	11727	11727	11727	11727	11727	11727
No. Firms	203	203	203	203	203	203	203
No. Districts	44	44	44	44	44	44	44

Notes: This table presents the estimates from Equation 1 for judge vacancy reduction using the subset of non-litigating balanced panel of firms in the district. Non-litigating is defined as whether a firm in the sample is found to have a legal case in the sample courts during the study period. Standard errors are clustered by district and event.

Table A.8: Vacancy Creation and Non-Litigating Firms

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Neg x <=-4	-0.0149	-0.00366	0.00909	-0.00354	-0.0426	0.0296	0.0465
	(0.0157)	(0.00309)	(0.0116)	(0.00621)	(0.0169)	(0.0817)	(0.0143)
Neg x -3	-0.00737	0.00504	0.0111	0.00212	-0.0138	-0.0240	0.0250
	(0.0101)	(0.00700)	(0.00815)	(0.00589)	(0.0614)	(0.158)	(0.0140)
Neg x -2	-0.0100	-0.00350	0.00556	-0.00332	-0.0871	0.0569	-0.00447
	(0.0126)	(0.00527)	(0.00746)	(0.00984)	(0.0422)	(0.127)	(0.0156)
Neg x 0	-0.00567	-0.00124	-0.0138	-0.0112	-0.0168	-0.0348	-0.0110
	(0.00635)	(0.00380)	(0.00988)	(0.00878)	(0.0514)	(0.0794)	(0.0168)
Neg x 1	-0.00563	-0.00202	-0.0185	-0.0184	-0.119	0.0705	-0.0111
	(0.00762)	(0.00179)	(0.0151)	(0.0139)	(0.0398)	(0.0769)	(0.0155)
Neg x 2	-0.00942	0.00245	-0.0390	-0.0221	-0.0424	-0.0259	-0.0239
	(0.00265)	(0.00216)	(0.0213)	(0.00787)	(0.0534)	(0.0832)	(0.00853)
Neg x 3	-0.0187	-0.0103	-0.0466	-0.0424	-0.140	-0.0694	-0.0285
	(0.00442)	(0.00279)	(0.0316)	(0.00633)	(0.0986)	(0.0603)	(0.0181)
Neg x >=4	-0.0408	-0.0196	-0.0755	-0.0606	-0.172	-0.0383	-0.0398
	(0.00472)	(0.00491)	(0.0345)	(0.00859)	(0.0685)	(0.0654)	(0.0142)
Observations	11727	11727	11727	11727	11727	11727	11727
No. Firms	203	203	203	203	203	203	203
No. Districts	44	44	44	44	44	44	44

Standard errors in parentheses

Notes: This table presents the estimates from Equation 1 for judge vacancy creation using the subset of non-litigating balanced panel of firms in the district. Non-litigating is defined as whether a firm in the sample is found to have a legal case in the sample courts during the study period. Standard errors are clustered by district and event.

Table A.9: Neighboring Districts Firms' Outcome and Vacancy Removal (Placebo)

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap (IHS)	(7) Int Exp (IHS)
Pos x <=-4	-0.0117	-0.00305	-0.00259	-0.00801	-0.0391	-0.105	0.00680
	(0.0106)	(0.00637)	(0.00564)	(0.00929)	(0.0514)	(0.0527)	(0.00261)
Pos x -3	-0.00614	0.00343	0.000131	0.00175	-0.0278	-0.0488	0.00842
	(0.00770)	(0.00354)	(0.00452)	(0.00800)	(0.0429)	(0.0330)	(0.00451)
Pos x -2	0.00292	0.00619	0.00874	0.00220	0.0430	-0.0317	0.00465
	(0.0114)	(0.00293)	(0.0102)	(0.00493)	(0.0354)	(0.0198)	(0.00863)
Pos x 0	-0.000792	0.00160	-0.000159	0.000863	-0.0362	-0.0325	0.00141
	(0.00672)	(0.00266)	(0.00481)	(0.00423)	(0.0218)	(0.0355)	(0.00388)
Pos x 1	-0.000467	-0.00201	-0.000318	-0.00115	-0.0269	-0.0181	0.00336
	(0.00563)	(0.00183)	(0.00443)	(0.00446)	(0.0258)	(0.0199)	(0.00308)
Pos x 2	0.00539	0.00541	-0.00991	-0.0110	-0.0351	-0.000400	0.00544
	(0.00427)	(0.00369)	(0.00666)	(0.00559)	(0.0368)	(0.0345)	(0.00553)
Pos x 3	-0.00723	0.00714	-0.0240	-0.00638	-0.104	0.0146	-0.00258
	(0.00650)	(0.00320)	(0.00804)	(0.00508)	(0.0475)	(0.0240)	(0.00375)
Pos x >=4	0.00504	0.000668	-0.00877	-0.00554	-0.0344	0.0213	0.00150
	(0.0108)	(0.00325)	(0.00598)	(0.00987)	(0.0680)	(0.0314)	(0.00319)
Observations	35049	35049	35049	35049	35049	35049	35049
No. Firms	597	597	597	597	597	597	597
No. Districts	99	99	99	99	99	99	99

Notes: This table presents the estimates from Equation 1 for judge vacancy removal, using firm-level outcomes in districts neighboring the sample court districts. The regressions include firm fixed effects, neighbor district fixed effects and state-time trends. Standard errors are clustered by district and event.

Table A.10: Neighboring Districts Firms' Outcome and Vacancy Creation (Placebo)

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap (IHS)	(7) Int Exp (IHS)
Neg x <=-4	-0.00872	-0.00271	0.00774	0.00515	0.0267	-0.0555	0.00423
	(0.0103)	(0.00410)	(0.00627)	(0.00964)	(0.0688)	(0.0375)	(0.00470)
Neg x -3	-0.00509	-0.00470	0.00829	0.0000129	-0.0110	-0.0359	0.00431
	(0.00576)	(0.00283)	(0.00547)	(0.00479)	(0.0535)	(0.0223)	(0.00728)
Neg x -2	0.000469	-0.000556	0.00103	-0.00152	-0.0158	-0.00676	0.00424
	(0.00359)	(0.00144)	(0.00349)	(0.00346)	(0.0269)	(0.0321)	(0.00431)
Neg x 0	-0.00166	-0.000180	-0.00104	-0.00167	0.00737	0.0184	0.00134
	(0.00292)	(0.00533)	(0.00492)	(0.00632)	(0.0224)	(0.0368)	(0.00172)
Neg x 1	-0.00471	0.00610	-0.00446	-0.0117	-0.0343	0.00303	0.000545
	(0.00531)	(0.00308)	(0.00562)	(0.0105)	(0.0491)	(0.0498)	(0.00874)
Neg x 2	-0.00603	0.00251	-0.00580	-0.00366	-0.0328	-0.0257	-0.00139
	(0.00543)	(0.00313)	(0.00336)	(0.00769)	(0.0624)	(0.0206)	(0.00497)
Neg x 3	0.00679	0.00248	-0.00394	-0.00768	-0.0578	-0.0387	0.00876
	(0.00685)	(0.000904)	(0.00855)	(0.00661)	(0.0632)	(0.0558)	(0.00646)
Neg x >=4	0.00600	0.00896	-0.00736	0.00822	-0.00678	-0.126	0.00446
	(0.00765)	(0.00245)	(0.00298)	(0.00588)	(0.0434)	(0.104)	(0.0112)
Observations	35049	35049	35049	35049	35049	35049	35049
No. Firms	597	597	597	597	597	597	597
No. Districts	99	99	99	99	99	99	99

Notes: This table presents the estimates from Equation 1 for judge vacancy creation, using firm-level outcomes in districts neighboring the sample court districts. The regressions include firm fixed effects, neighbor district fixed effects and state-time trends. Standard errors are clustered by district and event.

Table A.11: Dropping Industrial States: Vacancy Removal

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Pos x <=-4	0.0336	-0.0837	0.0104	-0.00766	0.223	0.232	0.0429
	(0.0719)	(0.139)	(0.0364)	(0.105)	(0.281)	(0.537)	(0.0571)
Pos x -3	0.00852	0.0219	-0.00255	0.00525	0.716	0.149	0.0632
	(0.0331)	(0.0470)	(0.0486)	(0.0383)	(0.168)	(0.155)	(0.0442)
Pos x -2	0.0341	-0.0256	0.0177	0.0126	0.0742	0.145	0.0770
	(0.0275)	(0.0281)	(0.0112)	(0.0762)	(0.362)	(0.220)	(0.0336)
Pos x 0	0.0209	0.0259	0.0191	0.0279	0.192	0.452	0.0220
	(0.00754)	(0.0155)	(0.00550)	(0.0124)	(0.101)	(0.0695)	(0.0375)
Pos x 1	0.0292	0.00441	0.0555	0.0442	0.354	0.325	-0.0661
	(0.0103)	(0.0118)	(0.0156)	(0.0160)	(0.116)	(0.0599)	(0.0293)
Pos x 2	0.0399	-0.00209	0.0619	0.0593	0.188	0.366	-0.0473
	(0.0107)	(0.0278)	(0.0208)	(0.0145)	(0.225)	(0.0254)	(0.0408)
Pos x 3	0.0573	0.0186	0.0493	0.0649	0.446	0.586	-0.0347
	(0.00799)	(0.0328)	(0.0185)	(0.0108)	(0.146)	(0.0600)	(0.0201)
Pos x >=4	0.0622	0.00895	0.0345	0.0398	0.196	0.464	-0.0587
	(0.0186)	(0.0404)	(0.0408)	(0.0147)	(0.0772)	(0.0947)	(0.00461)
Observations	8631	8631	8631	8631	8631	8631	8631
No. Firms	149	149	149	149	149	149	149
No. Districts	44	44	44	44	44	44	44

Notes: This table presents the event study reduced form estimates of positive staffing changes on the main firms sample after dropping large, industrial states from the sample.

Table A.12: Dropping Industrial States: Vacancy Creation

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Neg x <=-4	-0.0322	-0.00182	-0.0193	-0.0181	-0.188	-0.216	0.0444
	(0.0149)	(0.0290)	(0.0176)	(0.0180)	(0.129)	(0.0307)	(0.0101)
Neg x -3	-0.0195	-0.00795	-0.0110	0.00604	-0.262	-0.0722	0.0193
	(0.00951)	(0.0148)	(0.00976)	(0.0162)	(0.0718)	(0.288)	(0.0161)
Neg x -2	-0.0191	-0.00126	-0.00660	-0.00724	-0.160	-0.0199	-0.0174
	(0.00873)	(0.0131)	(0.00509)	(0.0167)	(0.132)	(0.154)	(0.0227)
Neg x 0	-0.000568	-0.0164	-0.00954	-0.0166	-0.171	-0.104	-0.0237
	(0.00928)	(0.0157)	(0.0160)	(0.0162)	(0.159)	(0.188)	(0.0328)
Neg x 1	0.00474	-0.0183	-0.0225	-0.0360	-0.382	-0.00374	0.00109
	(0.0102)	(0.0100)	(0.0237)	(0.0143)	(0.0965)	(0.173)	(0.0340)
Neg x 2	-0.00722	-0.0149	-0.0405	-0.0651	-0.500	-0.152	-0.00367
	(0.0163)	(0.0249)	(0.0384)	(0.0137)	(0.102)	(0.174)	(0.0166)
Neg x 3	-0.0290	-0.0359	-0.0539	-0.0994	-0.777	-0.362	-0.0219
	(0.0248)	(0.0490)	(0.0614)	(0.0304)	(0.215)	(0.0840)	(0.0313)
Neg x >=4	-0.0571	-0.0922	-0.0833	-0.109	-0.471	-0.189	-0.0146
	(0.0252)	(0.0680)	(0.0604)	(0.0318)	(0.0763)	(0.166)	(0.0177)
Observations	8631	8631	8631	8631	8631	8631	8631
No. Firms	149	149	149	149	149	149	149
No. Districts	44	44	44	44	44	44	44

Notes: This table presents the event study reduced form estimates of negative staffing changes on the main firms sample after dropping large, industrial states from the sample.

Table A.13: Dropping Largest Districts: Vacancy Removal

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Pos x <=-4	0.00512	-0.0626	-0.0264	0.00673	-0.251	0.253	0.0908
	(0.0665)	(0.108)	(0.0777)	(0.0833)	(0.258)	(0.440)	(0.0600)
Pos x -3	-0.00157	0.00833	-0.0640	0.00726	0.163	0.132	0.0706
	(0.0415)	(0.0353)	(0.102)	(0.0441)	(0.152)	(0.236)	(0.0334)
Pos x -2	0.000595	-0.00513	0.0110	0.0191	0.105	0.108	0.0810
	(0.0290)	(0.0382)	(0.0455)	(0.0726)	(0.407)	(0.109)	(0.0274)
Pos x 0	0.00133	0.0181	0.0428	0.0275	0.0877	0.319	-0.00654
	(0.0201)	(0.0137)	(0.0207)	(0.00645)	(0.112)	(0.0755)	(0.0285)
Pos x 1	0.0212	-0.00245	0.0450	0.0306	0.424	0.267	-0.103
	(0.0167)	(0.00982)	(0.0425)	(0.0143)	(0.142)	(0.175)	(0.0300)
Pos x 2	0.0280	-0.00481	0.0927	0.0454	0.260	0.262	-0.0804
	(0.0135)	(0.0266)	(0.0289)	(0.0137)	(0.132)	(0.195)	(0.0371)
Pos x 3	0.0460	0.0269	0.0580	0.0566	0.457	0.306	-0.0963
	(0.00817)	(0.0452)	(0.0134)	(0.00797)	(0.109)	(0.0989)	(0.0261)
Pos x >=4	0.0463	0.0152	0.0374	0.0330	0.217	0.225	-0.109
	(0.0172)	(0.0462)	(0.0233)	(0.00922)	(0.0633)	(0.0995)	(0.0114)
Observations	11916	11916	11916	11916	11916	11916	11916
No. Firms	217	217	217	217	217	217	217
No. Districts	61	61	61	61	61	61	61

Notes: This table presents the event study reduced form estimates of positive staffing changes on the main firms sample after dropping large, metropolitan districts from the sample.

Table A.14: Dropping Largest Districts: Vacancy Removal

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Neg x <=-4	-0.0141	0.00185	-0.00562	-0.00799	-0.185	-0.126	0.0502
	(0.0114)	(0.0210)	(0.0123)	(0.0102)	(0.0792)	(0.0760)	(0.00924)
Neg x -3	-0.0137	0.000103	0.00633	0.00177	-0.162	-0.0273	0.0137
	(0.0124)	(0.0122)	(0.0220)	(0.0100)	(0.0786)	(0.137)	(0.00949)
Neg x -2	-0.00720	0.000730	-0.00600	-0.00410	-0.121	0.0794	-0.0115
	(0.0129)	(0.0109)	(0.0104)	(0.0113)	(0.0969)	(0.0954)	(0.0168)
Neg x 0	-0.0000545	-0.0121	-0.0239	-0.0121	-0.102	-0.0322	-0.0243
	(0.00970)	(0.0157)	(0.0208)	(0.0116)	(0.128)	(0.199)	(0.0301)
Neg x 1	0.00183	-0.0127	-0.0249	-0.0186	-0.348	0.0280	-0.0106
	(0.00842)	(0.0138)	(0.0240)	(0.0167)	(0.0744)	(0.145)	(0.0294)
Neg x 2	-0.00585	-0.00723	-0.0637	-0.0392	-0.321	-0.0467	-0.0341
	(0.00627)	(0.0243)	(0.0323)	(0.0136)	(0.0966)	(0.0807)	(0.0258)
Neg x 3	-0.0232	-0.0325	-0.0647	-0.0682	-0.554	-0.173	-0.0310
	(0.00838)	(0.0381)	(0.0436)	(0.0185)	(0.144)	(0.0697)	(0.0398)
Neg x >=4	-0.0428	-0.0722	-0.0988	-0.0697	-0.352	0.150	-0.0415
	(0.00942)	(0.0446)	(0.0591)	(0.0139)	(0.0620)	(0.199)	(0.0227)
Observations	11916	11916	11916	11916	11916	11916	11916
No. Firms	217	217	217	217	217	217	217
No. Districts	61	61	61	61	61	61	61

Notes: This table presents the event study reduced form estimates of negative staffing changes on the main firms sample after dropping large, metropolitan districts from the sample.

Table A.15: Removal of Vacancy and Firms' Outcomes: Clustering by State and Event

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Pos x <=-4	0.0162	-0.0500	-0.0234	0.0256	-0.217	0.167	0.103
	(0.0417)	(0.0667)	(0.0464)	(0.0726)	(0.204)	(0.416)	(0.0600)
Pos x -3	0.000279	0.0162	-0.0505	0.0120	0.135	0.0202	0.0883
	(0.0310)	(0.0172)	(0.0686)	(0.0369)	(0.340)	(0.235)	(0.0462)
Pos x -2	0.00715	0.00361	0.00903	0.0181	0.193	0.111	0.0957
	(0.0339)	(0.0368)	(0.0267)	(0.0558)	(0.339)	(0.0783)	(0.0348)
Pos x 0	-0.00187	0.0179	0.0171	0.0201	0.110	0.389	-0.00813
	(0.0179)	(0.0166)	(0.0312)	(0.00576)	(0.114)	(0.0866)	(0.0276)
Pos x 1	0.0196	0.00435	0.0253	0.0184	0.418	0.200	-0.0864
	(0.0184)	(0.00621)	(0.0482)	(0.0210)	(0.0892)	(0.156)	(0.0383)
Pos x 2	0.0207	-0.00149	0.0717	0.0210	0.310	0.172	-0.0802
	(0.0234)	(0.0211)	(0.0447)	(0.0302)	(0.0811)	(0.136)	(0.0472)
Pos x 3	0.0369	0.0266	0.0401	0.0360	0.462	0.275	-0.0817
	(0.0220)	(0.0345)	(0.0279)	(0.0224)	(0.0605)	(0.147)	(0.0588)
Pos x >=4	0.0514	0.0194	0.0336	0.0289	0.334	0.244	-0.0903
	(0.0259)	(0.0359)	(0.0188)	(0.0147)	(0.102)	(0.138)	(0.0566)
Observations	22752	22752	22752	22752	22752	22752	22752
No. Firms	393	393	393	393	393	393	393
No. Districts	64	64	64	64	64	64	64

Notes: This table presents the event study reduced form estimates of positive staffing changes on the main firms sample with standard errors clustered by state and event.

Table A.16: Creation of Vacancy and Firms' Outcomes: Clustering by State and Event

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)	(6) Working Cap. (IHS)	(7) Interest Exp (IHS)
Neg x <=-4	-0.00720	0.00629	0.00261	-0.00225	-0.0803	-0.0779	0.0251
	(0.00675)	(0.0108)	(0.0100)	(0.00233)	(0.0877)	(0.0506)	(0.0328)
Neg x -3	-0.00570	0.00140	0.00601	0.00193	-0.0664	-0.0151	0.00411
	(0.00867)	(0.00625)	(0.00990)	(0.00503)	(0.0741)	(0.0564)	(0.0213)
Neg x -2	-0.00328	-0.000139	-0.000887	-0.00116	-0.0631	0.0266	-0.00900
	(0.00590)	(0.00405)	(0.00564)	(0.00341)	(0.0410)	(0.0667)	(0.0155)
Neg x 0	0.00116	-0.00697	-0.00905	-0.00492	-0.0499	-0.0356	-0.00827
	(0.00542)	(0.00932)	(0.00676)	(0.00718)	(0.0541)	(0.0959)	(0.0168)
Neg x 1	0.00113	-0.00960	-0.0109	-0.00699	-0.162	0.0252	-0.00239
	(0.00586)	(0.0108)	(0.0108)	(0.0147)	(0.0656)	(0.0695)	(0.0188)
Neg x 2	-0.00149	-0.00692	-0.0289	-0.0115	-0.170	0.00525	-0.00874
	(0.00530)	(0.0104)	(0.0165)	(0.0230)	(0.0843)	(0.0872)	(0.0248)
Neg x 3	-0.00967	-0.0187	-0.0312	-0.0251	-0.264	-0.0679	-0.00507
	(0.00633)	(0.0183)	(0.0221)	(0.0291)	(0.116)	(0.0994)	(0.0340)
Neg x >=4	-0.0224	-0.0361	-0.0495	-0.0277	-0.207	0.0580	-0.0126
	(0.0108)	(0.0396)	(0.0236)	(0.0305)	(0.120)	(0.186)	(0.0488)
Observations	22752	22752	22752	22752	22752	22752	22752
No. Firms	393	393	393	393	393	393	393
No. Districts	64	64	64	64	64	64	64

Notes: This table presents the event study reduced form estimates of negative staffing changes on the main firms sample with standard errors clustered by state and event.

Table A.17: Judicial Vacancies and Nightlights

	Vacancy Removal	Vacancy Creation
	(1) Avg. Nightlights (IHS)	(2) Avg. Nightlights (IHS)
Event x <=-4	-0.105	0.0315
	(0.0751)	(0.0322)
Event x -3	-0.0570	0.0201
	(0.0491)	(0.0213)
Event x -2	0.00240	-0.0136
	(0.00753)	(0.0288)
Event x 0	0.00893	-0.00139
	(0.0165)	(0.0166)
Event x 1	0.0234	-0.0203
	(0.0275)	(0.0207)
Event x 2	0.0353	-0.0127
	(0.0392)	(0.0178)
Event x 3	0.0369	-0.00840
	(0.0386)	(0.0169)
Event x >=4	0.0584	-0.0382
	(0.0559)	(0.0399)
Observations	6993	6993
No. Districts	192	192

Notes: I use VIIRS annual average nightlights data from Colorado Mines Earth Observatory from 2012-2018. I use district GIS shapefiles to compute the average nightlight intensity within the polygon for each year in the data. The empirical specification includes district and state-year fixed effects. Standard errors are clustered by district and event.

Table A.18: Cost-benefit Calculation

Parameter	Value	Units	Source
No. Firms per District	6	Number	Sample
Median Profit	79.21	Million INR	Sample
Median Wage Bill	240.74	Million INR	Sample
Corporate Tax Rate	22	Percent	Sec115BAA Taxation Laws Amendment Ordinance (2019)
Effective Income Tax Rate	7.3	Percent	LiveMint
Discount Rate	5	Percent	Assumption
Annual Per Judge Salary + Other costs	3.33	Million INR	Second National Judicial Pay Commission
Benefit-Cost (Tax Revenue)	6.64 1.21	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social)	35.12 6.3	Ratio	Calculation Bootstrapped SE

Notes: I focus on the event of positive staffing change to compute benefit-cost ratios. I calculate effective income tax incidence on salaried individual tax payer using average reported annual income of INR 690,000 and the applicable progressive tax slab on this reported income: income upto INR 500,000 is exempt and the remaining INR 190,000 is taxed at 20%. This gives an effective average tax incidence of 7.3%. Corporate tax rate of 22% is the rate applicable on reported corporate income for domestic companies. Bootstrapped standard error in square brackets from 1000,000 random draws.

Table A.19: Cost-benefit Sensitivity Analysis

Parameter	**Mean/CI**	**Units**	**Source**
Benefit-Cost (Tax Revenue) ($\delta = 0.03$)	7.16 [1.28]	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social) ($\delta = 0.03$)	37.93 [6.685]	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Tax Revenue) ($\delta = 0.1$)	5.52 [1.052]	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social) ($\delta = 0.1$)	29.16 [5.47]	Ratio	Calculation Bootstrapped SE

Notes: In this table, I use different values of discount rate - both lower and higher than the preferred discount rate used in Table A.18. I report the average benefit-cost ratio for each of these different discounting scenarios along with their bootstrapped standard errors in parentheses.