Front-line Courts As State Capacity: Evidence From India

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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, I show that the timing of judge staffing changes 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 resolves court backlog by 10 percent. In a context with high levels of backlog, this capacity improvement enables credit circulation through local bank-branch balance sheet effects from debt recoveries. With better access to credit, productivity of local formal sector firms increases, generating a benefit-cost ratio exceeding 3. On the other hand, new vacancies reduce firm productivity and increase reported crimes such as small-scale thefts.(*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 al. 2003). Contract and law 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; Laeven and Woodruff 2007; 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 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 sub-national courts in providing essential legal services such as dispute resolution. 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. Front-line courts such as district or county courts, with jurisdiction over the smallest administrative unit, are the relevant institutions that play this role. This paper documents that capacities in such institutions vary even across small geographic units and over time, with substantial productivity and welfare implications (Acemoglu and Dell 2010).

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Availability of adequate number of judges is a key constraint. Staff vacancies and its sporadic redressal is a fundamental problem in bureaucratic organizations worldwide. This situation is not only exclusive to India and other developing economies but also common among the judiciary in many OECD countries (Yang 2016; Sadka et al. 2018). District courts in India have over 10 million legal disputes 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 study the downstream economic consequences of the removal and creation of judge vacancies in district courts in India. Using timestamps and meta data across the universe of legal case records (6 million) from a sample of district courts between 2010 and 2018, I construct a court-level panel dataset on staffing (number of judges) and performance (number of cases filed and resolved, and the rate of backlog resolution). In a context with prevalent corruption and questionable official data, my data construction is based on recorded workflow and is more reliable relative to bureaucrat-reported aggregate data on courts (Olken and Pande 2012; Singh 2020). I link this dataset with both district-level and firm-level economic outcomes over the same time period to examine the implications of judge staffing changes and highlight the role played by district courts in facilitating contracts and productive activities within a local economy.

For causal identification, I exploit the timing of judge staffing changes resulting from recruitments, retirements, and rotation of judges between courts, using a stacked event study design in the presence of fixed effects (Sant'Anna and Zhao 2020, Sun and Abraham 2021). State-level policies on retirement at 60 years of age, sporadic and often failed recruitment drives, and frequent rotation of judges between district courts imply that the timings of net staffing changes in a court are plausibly exogenous, and generate sharp and persistent discontinuities in the number of judges and vacancy rates. While some courts experience a positive change, others experience negative or no change at all. This creates two types of treatment groups over the multiple staffing events - those experiencing a net increase in the number of judges and those experiencing a net decrease, along with a counterfactual group without such changes. Additionally, no one agent - the judiciary, the executive, or the elected representatives - alone controls these judge staffing policies, which often requires close coordination between two or more agents, unlike in the context of general administration bureaucrats (Iyer and Mani 2012; Khan et al. 2019). This further adds to the uncertainty in the timing of these changes. Assuringly, I find no significant economically meaningful determinants of judge staffing changes across a range of corresponding district-level, time-varying demographic, economic, or political variables. Further, I find that there are no significant trends in the prior period across the key outcomes as a support for the parallel trends assumption. I employ a number of robustness

[1]Pending case data as of 2019 from both India and US district and county 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.

checks including estimating the reduced form results with an alternate approach using the number of judges as a continuous-valued explanatory variable in a generalized event study design.

To examine the economic consequences, I merge formally registered firms' annual production and financial data - sales revenue, wage bill, asset value, and profits - with the court-level dataset by mapping the firms' district of registration to the corresponding court's jurisdiction. Firms, including those in the formal sector, largely rely on local markets to meet their production needs such as financing from local branches of financial institutions (Nguyen 2019; Rigol and Roth 2021) and protection from common crime such as theft and embezzlement (Bandiera 2003). District courts play an important role in facilitating these types of local market transactions: First, they aid in debt recovery with liquidity implications through banks' branch-level balance sheets effects (Castellanos et al. 2018; Breza and Kinnan 2021). This is critical in a context where credit supply is constrained due to policies such as local lending quotas and other financing frictions between and within financial institutions as documented by a vast literature in finance (Khwaja and Mian 2008; Paravisini 2008; Schnabl 2012; Castellanos et al. 2018; Rigol and Roth 2021). Second, they provide court orders to investigate crimes that the police alone cannot initiate, which is particularly important for firms in protecting their stock of raw material, inventory, and capital goods. Thus, these immediate, transactional roles of such courts have important implications for firms' access to credit, operations, and ultimately productivity. I verify these plausible mechanisms by examining district-level credit circulation, crime reporting, and nightlights data as well as firm-level data on working capital, interest, and raw material expenditures.

I document three main results. First, I find a significant impact on court-level outcomes when there is a net increase in the number of judges. These include a persistent effect on reducing vacancy, an increase in the number of resolutions by 200 cases per judge added, and an increase in the backlog disposal rate by 20 percent (2-3 percentage points) each year over the next four years. On the other hand, negative staffing changes have roughly half the effect size on reducing the staffing levels, and thus have commensurately smaller effects on court's backlog disposal rate. This non-symmetry arises from different realizations of staffing changes resulting from the interplay between recruitment, rotation, and retirement.

Second, profits, wage expenditures, and sales revenue of local firms increase following positive changes and decrease following negative changes in judge staffing. I find that the average wage bill and the average profit increase by around 5% and 40%, respectively, when more judges are added in net. On the other hand, a decrease in the number of judges has a negative effect: wage bill and profits contract by around 2 and 20% respectively. I take a number of precautions and perform different robustness checks to confirm these results. For the main analysis, I focus on a balanced panel of incumbent firms, reporting balance sheet data for each year in the study period, to ensure internal validity. However, this raises an important concern whether the estimated effects are due to sample construction, particularly if the composition of excluded firms in the district vary over time that could be correlated with both judge staffing changes and sample firms' outcomes. I address this in several ways. One, I find positive effects on new firm incorporations and total firms in the district following net judge addition but no effect following net reduction. This suggests that the incumbent firm-level results are observed even in the presence new firm entry with no changes in firm exit in the district, which are important economic outcomes themselves. Two, I find similar effects qualitatively, using the larger, unbalanced panel data. However, I find that data for many variables are missing non-randomly - that is, data reporting is correlated with judge staffing changes without any pre-period trends. While the latter is assuring, the former suggests that using the unbalanced panel will not produce unbiased estimates of the causal effect and I abstain from using it for my main analysis. Three, I show that these effects are also seen among a subset of firms with no legal cases across the entire study period. This supports the fact that the estimates capture beyond any immediate effects due to case resolution for the litigating firms. More broadly, I find suggestive positive effects on district night light intensity following net addition and negative effects following net reduction in the number of judges. Finally, I note that these effects are only observed among local firms and not among firms in the neighboring districts where the district court has no jurisdiction, suggesting that these effects are not due to any spurious correlation in the data. Importantly, these suggest broad-based, real economic implications of local judicial capacity.

Third, I find evidence in support of courts' role in facilitating local markets by resolving legal disputes. I note an immediate increase in firms' working capital, raw material expenditure, and a reduction in interest expenditure following net judge addition. At the market (district)-level, I find an increase in aggregate lending by banks to industrial borrowers and a drop in reported crime rates following positive staffing changes. This correlation between improved legal dispute resolution and credit circulation is consistent with Ponticelli and Alencar (2016) in the context of better bankruptcy enforcement. 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 (such as small-scale thefts). While this asymmetry in the credit mechanism may be perplexing, natural lags in recognizing defaults and subsequent accumulation of debt-recovery cases in courts (Ashraf et al. 2020; Breza and Kinnan 2021) could suggest why I don't note a decline in firms' credit access following net judge reductions within the study timeframe. In contrast, an increase in lower-order crimes requiring court-police coordination could increase the costs of property protection for firms, consistent with a decline in firms' production outcomes in line with Johnson et al. (2002).[2]

To situate these findings in economic theory, I develop a conceptual framework that builds on standard lending models by introducing variation in the quality of contract enforcement by 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

[2]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. However, once cases are filed in a court, the timing of resolution has more immediate implications on recovery and liquidity through branch-level balance sheet effect. I discuss these in greater detail in Section 1.

low ex-ante leverage, following net judge additions. This suggests that an expansion of cheaper credit is important to support the scale of firms' operations through working capital, especially in developing economies like India where firms are both credit constrained and credit rationed (Banerjee and Duflo 2014). Subsequently, firms' profitability change both in the presence of credit availability and lower operating costs. Following these modeling assumptions, I find that profits have large negative elasticity with respect to interest expenditure. Importantly, these mechanisms highlight that district courts' dispute resolution services aid the functioning of local markets and thus are important to the economic development process.

These findings highlight substantial public and social benefits generated by reducing judge vacancies in the frontline judiciary. A back of the envelope calculation of the benefit-cost ratio shows large returns. I measure benefits accruing only to sample firms (through corporate profit) and their employees (through taxable 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 hiring more judges can generate over 3 times tax revenue relative to its cost considering even the most conservative estimate. The social return is orders of magnitude higher. Importantly, this paper documents that marginal changes to judicial staffing levels in frontline courts generate persistent, long-run implications for local economic development. It is likely that substantive changes in personnel policies such as increasing the steady-state staffing levels or upgrading court infrastructure may have different implications, and remain as open questions for future research.

This paper contributes to three strands of the literature. First, this shows that frontline courts of law are important for local economic development through an expansion of formal sector economic activity. In this regard, this paper complements existing literature (Chemin 2009a,b, 2012; Ponticelli and Alencar 2016; Amirapu 2017; Kondylis and Stein 2018) by highlighting the role of the smallest unit of the judiciary. The literature hitherto has either taken an aggregate approach - exploiting cross-sectional variations in court efficiency measures arising from procedural law, or focused narrowly on a small number of courts, reflecting a lack of micro-data at scale. Using large-scale disaggregated data on legal case records, I contribute a novel district-level panel data on local judicial capacity in India, linking staffing changes with case backlogs in courts. As noted in Sadka et al. (2018), using disaggregated case-level data provide significant advantages in both data construction for subsequent analysis as well as help shed light on important, yet under-documented mechanisms including that of local state capacity, and the transactional role of courts in markets.

Second, this paper underscores staff vacancies in the judiciary as a barrier to effective state capacity. A growing body of literature has noted a significant relationship between staffing constraints and service delivery (Dal Bó et al. 2013) in sectors ranging from finance (Rigol and Roth 2021), education (Muralidharan and Sundararaman 2013), public administration (Coviello et al. 2015; Khan et al. 2015; Dasgupta and Kapur 2020; Fenizia 2022), and early childhood development (Ganimian et al. 2021).[3] This paper extends the state capacity literature beyond the executive to

[3]Among this literature, Ganimian et al. (2021) compute a benefit-cost ratio, albeit using strong assumptions

examine the implications of constraints within the sub-national judiciary.

Finally, this paper highlights the role of courts in credit circulation through debt recovery. Faster and efficient debt recovery has been a core focus of many policy reforms, including creation of specialized tribunals aiming to improve business environment as documented in Visaria (2009); von Lilienfeld-Toal et al. (2012); Lichand and Soares (2014). Despite this, general courts of law continue to be the final authority on dispute resolution, creating heavy reliance on local courts by the financial sector. Institutions supporting the development of a strong financial sector are fundamental for firm and economic growth through access to credit (Rajan and Zingales 1998; Burgess and Pande 2005; Castellanos et al. 2018; Breza and Kinnan 2021) and inputs (Boehm and Oberfield 2020). This paper shows that courts help unlock capital tied-up in legal disputes when judge vacancy is resolved, generating balance sheet effects at local bank branches. In the presence of financing frictions preventing costless movement of capital between banks or between regions, the resulting liquidity can affect the local supply of credit for industrial use. While vacancy creation does not generate a symmetric reduction in credit due to lags in recognizing defaults and filing of legal cases, local firms' productivity suffers through other transaction costs.

The rest of the paper is organized as follows. Section 1 discusses the context, detailing both the judicial organization structure and how this interacts with local credit market and crime environments. 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 the broader implication of local judicial capacity using back of the envelope benefit-cost analysis in Section 6. Section 7 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). 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, with state-level high courts and the Supreme Court of India setting policies and managing the internal functioning of the judiciary. In this paper, I examine the functioning of district-level general courts of law, which are often the first interface of the judicial system. Specifically, I study the District and Sessions Court (hereinafter called district court, similar to county courts in many common law countries), which is typically the court of first

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.

instance for many types of legal disputes, including those involving 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.[4]

Due to separation of powers, the judiciary needs to coordinate with both the executive and the legislature for effective rule of law. While the judiciary alone is responsible for managing its organization structure, it relies on the executive for financing and needs to take into account new laws and amendments by the legislature. 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.

1A Judicial Staffing

The number of judges relative to India'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 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, including the scale of my study time period. Figure A.1 (Panel A) shows a strong, albeit imperfect correlation between district population and the number of judge posts.

In addition to low judge strength-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 (Panel A Figure A.1). 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 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

[4]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.

recommendations are not followed in practice. Further, the recruitment drives are implemented sporadically, with varying success rates.[5]

District judges are senior legal professionals, 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, and are either rotated out or retire at the end of their tenure in a given court, where they reach 60 years in age. The state high courts determine judge assignment and rotations between district courts.[6]

Thus, three personnel policies - recruitments, retirements, and rotation between courts - affect the net change in the number of judges in a court over time. Figure A.2 presents a schematic to show this dynamic and how this affects judge staffing in a court over time. This also suggests that the period between two shock-generating years are a function of the composition of incumbent judges - their tenure lengths, age distribution, and assignment of new recruits. Therefore, central to my identification strategy is the *timing* of the net staffing changes that affect judge vacancy rates in district courts. The context discussed here suggests the plausible exogeneity in the timing of these events that affect the total number of judges in a given court even if assignment of a specific judge to a court could be endogenous to local firm or district-level economic outcomes in levels or growth.

1B Courts and Bank Credit Circulation

A key aspect of the district judiciary is its importance in the functioning of the financial sector. By the nature of the industry itself, financial sector enterprises such as banks rely on these courts for execution orders in the case of last resort recovery. Local nature of contracts and contract enforcement is thus central. As per bank managers and their legal counsels, banks lend to borrowers only through their local branches so that the branch-level officials can verify borrower identity, credit needs, and repayment ability. This co-location requirement with the borrower is important in the context of this paper irrespective of whether the borrower is a firm or a private individual. For enterprise borrowers, this coincides with their registered office, whereas in the case of individuals, this corresponds to their verifiable residential location. Cross-district borrowing relationships are

[5] The Law Commission 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 (Panel B, Figure A.1).

[6] The specific assignment process for determining which judges are to be rotated where 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, subject to the home district constraint. 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 net judge staffing changes likely is. I test for these empirically by looking for parallel trends in the period prior to these events.

not common, and plausibly does not occur at all.

Credit supply in India continues to be dominated by public sector banks, where credit is delivered through their local branch offices. Private sector banks also follow a similar model. Additionally, both private and public sector banks are regulated by the central bank - Reserve Bank of India, and follow national-level monetary and lending policies. Important among these policies are branch-level lending quotas and targets per year, with additional quotas for specific economic sectors (for example, small and medium enterprises or agricultural borrowers). Therefore, even when a specific branch is part of large public or private-sector bank spanning national or international markets, the amount of credit for circulation is typically determined based on local targets.

Each branch maintains annual balance sheet, recording profits and losses generated from their operations. The details of lending, repayments, and write-offs due to unpaid debt, all are accounted in these documents. Branch managers face career incentives based on their performance tied to lending targets as well as the overall health of their branch's balance sheets. These managers are also the authorized representatives of the bank in legal cases, where the specific court's jurisdiction is predetermined by the legal procedure. Write-offs due to non-payments enter as expenditures whereas recovered capital as income. Thus, whenever pending legal cases in courts pertaining to unpaid debts are resolved, recoveries from following court's execution orders are considered income, and serve as positive liquidity shock to the branch.

Bulk of the lending portfolio of banks in India are loans to individuals and households for consumption outside of agricultural loans.[7] Unsurprisingly, most of the defaults also arise from defaults of personal and agricultural loans. Income shocks to individuals lead to defaults such as non-payment of credit card dues (unsecured loans), mortgage payments, and non-payment on other such loan products. The quantum of the total write-off from such defaults, when aggregated over multiple individual borrowers in the absence of strong individual-level bankruptcy regulations in India, imply that there are potentially large write-offs for the bank. Enabling settlements among such defaults is particularly important for the health of local branch balance sheet. To illustrate with an example, each pre-trial mediation and arbitration session yields about USD 240,000 in recovery-induced liquidity at the district-level. Summing across 4-6 sessions in a year, this generates about USD 1-1.5 million in recovery on an annual basis per district, which serves as a positive liquidity shock to the local branch balance sheet.[8]

This context on banking reveal two important facts relevant for this paper: (a) defaults are common, especially from the bulk of loans to private individuals/households, and (b) resolution or settlement of debt recovery cases in district courts generates branch-level balance sheet effects. In contrast, delays in debt recovery resolution does not necessarily affect the workflow of recognizing and filing such litigation nor does it affect the balance sheet, which already accounts for the write-off

[7]Calculated using district and sector-level lending data across all banks, made available through data repository at the Reserve Bank of India. Agricultural loans are disbursed to farming households with agricultural land under cultivation. Agriculture is also considered priority sector under the central bank's lending policy.

[8]Calculated based on the official statistics by the National Legal Services Authority for sessions held in district courts across India, which is available at https://nalsa.gov.in/statistics.

at the time of default.

1C Courts and Law Enforcement

The district courts are general courts of law, which means that every kind of legal dispute, whether civil or criminal, are tried in these courts. Capacity of these courts are also important for containing crime, which in turn could affect economic productivity in the area. However, courts and law enforcement, i.e. police, have to coordinate and work together in containing crime. While police play a more direct role in violent crimes, the bulk of crimes are non-violent, and less serious in nature, where the functioning of courts is important from the perspective of protection of property and thus, economic activity.

Importantly, a large bulk of criminal cases in district courts are what are known as "summary trial" cases. A few examples of these according to the Code of Criminal Procedure are (a) "Offense of theft, under section 379, section 380 or section 381 of the Indian Penal Code, 1860, where the value of the property that has been stolen does not exceed two thousand rupees.", (b) "Offenses relating to receiving or retaining stolen property, under section 411 of the Indian Penal Code, 1860, where the value of the property does not exceed two thousand rupees.", and (c) "Offenses relating to assisting in the concealment or disposal of a stolen property, under section 414 of the Indian Penal Code, 1860, where the value of such property does not exceed two thousand rupees." The monetary value may be updated from time to time through amendments to procedural law, but the main import is that a large bulk of criminal cases pending in district courts pertain to protection of property from thefts and embezzlement.

2 Data and Sample Construction

2A Court-level Variables: Explanatory Variables

I assemble the universe of 6 million public legal case records from the E-Courts database, spanning all legal cases filed or pending for resolution between 2010 and 2018, from a sample of 195 district courts (Figure A.3). These districts were selected to ensure an overlap with the location of registered formal sector firms across non-metropolitan industrial districts and are 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.[9]

Judge Headcount and Vacancy: In addition to timestamps, the meta-data also records the courtroom number and the judge designation where a case has been assigned.[10] Leveraging the

[9]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.

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

fact that the data represents the universe of legal cases between 2010 and 2018, I enumerate judges within a court over the study period based on annual workflow observed for a given courtroom, which has an assigned judge. I describe this construction in detail below. Finally, I categorize vacancy based on the difference in the number of judges relative to the maximum within the study period.

I enumerate judges within a court in a given calendar year if I observe newly filed cases in that year assigned to courtrooms. The court registrar assigns new cases to all incumbent judges, who have assigned courtrooms, immediately after filing and verification of an application by petitioner(s). When an incumbent judge moves (either due to rotation or retirement) with no incoming judge, that specific courtroom remains vacant and no new cases are assigned to the courtroom. The existing workload at the time of vacancy is transferred to other judges/courtrooms within the court. While I also expand the workflow definition to include case resolution, outcome of a hearing, and passing interim orders as a robustness check, using these isn't my preferred method for constructing the number of judges precisely because existing workload at the time of the vacancy is reassigned to other judges, creating biases in the enumeration.

Following this algorithm, I generate the number of judges in a district court for each year in my study period. These numbers generate a similar aggregate measure at the state-level, as reported in the Law Commission Reports. I also calculate vacancy rate as the relative shortfall in the number of judges in a given calendar year relative to the maximum number of observed judges in the court within the study period. This construction of vacancy rate assumes that the maximum number of judges is indeed the total number of posts, and is agnostic to long-run vacancies or an increase in the number of posts in a court. To be conservative, I restrict all my analyses using annual changes in the number of judges rather than changes in vacancy rates, which requires additional assumptions.

In the absence of data repositories of district judge tenures and their biographies, this construction contributes an important measure of local judicial staffing levels and capacity. Since the launch of the e-courts system, each courtroom's daily business is directly recorded on a digital platform that then periodically updates the e-courts legal case database with the latest status of cases heard on a given day. This follows the central 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.[11]

Constructing annual court-level performance variables: I construct court-level annual performance measures using timestamps 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 including pending legal cases that are resolved in a calendar year.

[11] 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).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.

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 filed in the past years but have not yet been 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).[12]

2B Firm-level Outcomes

Population of Interest: I focus mainly on incumbent non-financial firms, incorporated before 2010, with registered office in the same district as the court's 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 and cannot be endogenously selected by the petitioner/plaintiff (i.e. forum shopping is not allowed). This is particularly relevant for debt contracts where the relevant court is one corresponding to the location of the debtor.[13] Second, by focusing on already incorporated firms, I account for any confounding due to firm entry and exit using a balanced panel and firm fixed effect. While the analysis using this sampling frame restricts the interpretation of the effects to incumbent firms, I use other datasets to measure more broad-based effects of local judicial capacity.

Firm-level data: I use CMIE-Prowess dataset that includes the balance sheets of the universe of listed firms and a sample of unlisted but registered formal sector firms to measure annual firm-level outcomes. This specific sector accounts for $\approx$ 40% of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), and therefore 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) variables. Detailed identifying information in the dataset, including firm name and registered office location, enables me to match them with the court-level dataset.

Firm sample construction: Of the 49202 firms on the CMIE website in 2018, 9032 incumbent non-financial sector firms have registered offices in 157 of the 195 sample court districts. Remaining 38 district courts result in no match. 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, and (b)

[12]Court workload includes both pending as well as new trials, which is around 20000 cases per district court. Resolved trials also include those that are dismissed without a final judgement order. Disposal rate is a relevant metric of judicial capacity relative to average or other moments of case duration that necessarily have a selection component in what cases are resolved. Focusing on disposal rate is also important from the point of view of the volume of tied-up factors of production. While trial duration may matter for individual litigant directly involved with the judicial system, annual performance indicators such as the disposal rate measures the extent of congestion and is more appropriate metric of institutional capacity.

[13]Debt disputes are among the main contractual disputes involving firms in the process of production. These contracts are local in order to minimize information asymmetries. Banks lend through their local branches. 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. They find 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.

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. I carry out supplementary analysis and robustness tests using the unbalanced panel of firms as well. Appendix Figure A.4 describes the firm sample construction process in detail.

2C District-Level Outcomes

Banking data: I examine total lending (number of loans) 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). District-level aggregates of bank-lending is one of the important outcomes to understand access to credit as one of the key underlying mechanisms.

Reported Crime data: To explore effects on local crime, I use public data on district-level reported crime statistics by National Crime Records Bureau (NCRB). I leverage crime reporting classified into serious crimes such as murders, homicides - those causing injuries to human life - and remaining categories classified as other crimes, which mainly include lesser crimes including small-valued thefts that are typically tried "summarily" by courts (as described in the context section above). Specifically, these crimes also require a court order for the police to investigate before filing a case in the court.

Nightlights data: Finally, to examine more broad-based impact, I use Visible and Infrared Imaging Suite (VIIRS) nighttime light measure Annual VNL V2.1 by the Earth Observation Group and compute the pixel average within the district boundary.

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. Over the study period 2010-2018, net judge additions occur 1.62 times with 2 judges added on average and net removals occur about 3.6 times with 3 judges removed on average across the district courts in my sample. Average disposal rate is 14 percent with standard deviation 12, that is, 14% of total workload is resolved in a given year. The timestamps on individual cases resolved within 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. Therefore, disposal rate avoids selection concerns in its construction process and is the main first stage outcome of interest.

Panels B and C describe credit market and local firm-level outcomes. On average, banks make 9188 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 103 million (INR 8.4 billion) in average sales revenue and USD 4.5 million (INR 371 million) in average profits. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

3 Research Design and Empirical Strategy

As detailed in Section 1, judge staffing levels 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 Cengiz et al. 2019 that examines the effect of multiple minimum wage revisions on employment distribution in the context of the United States).[14]

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:

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

[14] 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.

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 $\beta^{+}_{j\geq 0}, \beta^{-}_{j\geq 0}$ - coefficients on the event-time bins interacted with the positive or negative change dummies, normalized relative to $t = -1$ (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.[15]

I restrict the effect window to 4 years prior and post with binned endpoints. This is to account for the maximal tenure length of a judge 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).[16]

Causal identification using this design requires the following assumptions: (a) exogeneity of timing, and (b) parallel trends, as the stacked approach 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 any differential trends in the prior period. 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).

3B 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 (Schmidheiny and Siegloch 2020; Freyaldenhoven et al. 2021) as described in Equation 2 below:

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

[15] I simulate treatment effect estimation using this estimator in Figure A.5, showing that the estimator recovers the treatment effect without bias.

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

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 number of judges in district i in year t. y_{it} is the unit-level outcome variable, where i refers to district with district-level outcomes and a firm with firm-level outcomes. 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.

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 the same causal effect parameter from the stacked event study approach above, I use this approach to verify the results qualitatively.

3C Exogeneity of Staffing Changes

A key advantage of dynamic difference in difference strategy is visual representation of the differential trends in the prior period. However, this empirical test is only a necessary but not a sufficient condition for establishing the validity of the research design. While the fixed effects in the main specification Equation 1 - accounting for the smallest geographic and/or economic unit - absorb all time-invariant unobservable potential confounders of the timing of the staffing changes, and state-year dummies account for state-specific flexible time trends, there could be other time-varying confounders of staffing changes. However, a key challenge is availability of data, disaggregated even at the district-level with annual periodicity. Given these challenges, I leverage multiple rounds of population census, economic census, and electoral data in the decade prior to my study period to obtain potential time varying confounders that could determine which districts are likely to experience judicial staffing changes.

In the absence of annual periodicity of these other potential confounders, I exploit long differences specification where I regress long-run changes in judge staffing levels (i.e. between 2010 and 2018) on changes in population, number of establishments, employment in manufacturing, demographic composition (caste, literacy, and urbanization), and electoral outcomes as important determinants (i.e. as RHS variables). Table 2 presents the results from this linear prediction exercise. To aid easier interpretation of the coefficients, all dependent and independent variables are transformed into % changes relative to their baseline values (i.e. the earliest period of data availability). None of the individual coefficients are statistically significant nor do they jointly do well in predicting which districts are likely to experience larger staffing changes.

4 Reduced Form Effects of Judicial Staffing Changes

4A Judge Headcount and Vacancy Rate

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) - (100-vacancy in %) - as dependent variables. Three features of these graphs are noteworthy: (a) an immediate increase/decrease in headcount and inverse vacancy rates following the changes, (b) persistence, albeit a gradual decay 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 percentage points. Negative events decrease the number of judges by ≈ 1, implying a 5.5% decrease in levels and 10 percentage point increase in vacancy. The coefficients indicate economically meaningful persistence, albeit with a gradual decay given the frequency of turnovers, where the vacancy rates are lower (or higher) by 10 (7) percentage points 3-4 years following the staffing changes. The asymmetry between positive and negative changes is consistent with a context where recruitment drives are sporadic and lumpy. 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.

Table A.2 presents the estimates on positive (Columns 1 and 2) and negative (Columns 4 and 5) change events over time in a tabular format. These effects on judge staffing can be seen across different subsamples of district courts (see Table A.3 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

Panel C Figure 1 plots the regression coefficients on the event-time bins interacted with positive or negative change dummies as per Equation 1 using annual court-level case disposal rate as the dependent variable. This outcome increases by ≈ 2 percentage points over a baseline rate of 12.62% of existing workload, following positive staffing changes and does not respond significantly following a negative change. Each additional judge resolves 200 additional trials in a context where the average annual court-level caseload is ≈ 20000 trials.[17] A clear break in trend following positive changes suggests a causal relationship between increase in staffing and the capacity of district courts in resolving litigation backlogs.

The lack of a negative performance result following negative staffing changes is likely driven by the fact that fewer number of judges turnover relative to those added and that existing workload at the time of vacancy is transferred to other judges in the court. Despite this muted effect on disposal rate, increased vacancy 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.4). A district court with lower vacancy where judges are less constrained (i.e., have their regular workload) may preempt filing

[17] I also confirm these numbers by estimating the specification using number of resolved trials as the dependent variable in Table A.4. I focus on disposal rate as the key measure as it measures backlog resolution in terms of percentage reduction in the number of existing workload legal cases.

of frivolous appeal cases from sub-district courts in their jurisdiction. Additionally, courts with increased vacancy may not be able to coordinate well with the law enforcement agencies, including the local police, in containing lower order crimes such as thefts, which do not yet become a legal case in the court.

Columns 3 and 6 of Table A.2 present the event study estimates on disposal rate in a tabular format for net increase and net decrease in judge staffing, 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 treatment effect heterogeneity by 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 are mainly driven by large courts (see Table A.5).

4C Robustness: First Stage

A concern with the estimated effects on court performance is if there are any mechanical correlations between coding of the staffing change events with the disposal rate or other measures of court performance. Note that the staffing change is only constructed using filing of new litigation, and thus should have little mechanical correlation with case resolutions or backlog from past years. In order to address concerns arising from construction of the events, I estimate the effects of judicial staffing changes on court performance using Equation 2, which includes leads and lags of continuous valued changes in the number of judges. Figure A.7 presents the results from this specification in a graphical format. Positive integer labels on the x-axis report regression coefficients on the lagged explanatory variables whereas the negative integer labels correspond to the lead variables. Important to note is that existing workload and performance of courts is neither significantly or economically meaningfully correlated with the current or future judge staffing changes. Additionally, current and past changes in staffing impact disposal rates through increased resolution in the current as well as future years while the demand for litigation (number of new litigations) does not change significantly.

I also note significant effects on disposal rate using local projection DID estimation based on a sequence of first difference regression specifications following Dube et al. (2022) reported in Figure A.8. This strategy is particularly useful in settings similar to macro-finance, where shocks occur as impulses occurring over a short time period. While the staffing changes persist over the medium-run in the context examined in this paper, using this estimation strategy helps account for even short-run changes that could plausible generate persistent impact on court backlog reduction and other performance outcomes.

4D Local Firms' Production

To examine the downstream economic implications of local judicial staffing and capacity, I start with the reduced form effects on incumbent, formal sector firms located in the same geography as the jurisdiction of the district court. Specifically, I estimate the effects on profits, sales revenue, wage bills, and value of plant and machinery.

Figure 2 and Figure 3 depict the event study graphs following a net increase in the number of judges and a net decrease in the number of judges, respectively. Three key features of these graphs are: (a) a gradual increase (or decrease) in the outcome following staffing change, (b) effects visible in the long-term, and (c) statistically and economically insignificant prior period estimates. The gradual and long-run nature are consistent with the fact that these firms represent an average, formal sector firm in the district, not just those with legal cases in the court. These effects take time to appear as they are channeled through market mechanisms.

Table A.6 and Table A.7 present the results in a tabular format corresponding to each of the figures, respectively. Wage bill and profits increase by around 5% and 40%, respectively, over the long run following net judicial staffing increases. The effect on sales revenue is modest 1-2% over the period. Since the sample firms are large in terms of revenue, profitability, and employment at baseline, these effects are economically meaningful. The relatively large effect on profit is consistent with the fact that the profit numbers are much smaller relative to wage bill or sales revenue, and that the increase in profits are also likely to be driven by a reduction in other expenditures such as interest payments and other accounting expenses. Lastly, the effects on capital goods, including the value of plant and machinery, are not statistically significant even though the point estimates are large and in the same direction as other measures of productivity.

The effects of negative staffing changes generating vacancies are negative but smaller in magnitude. In the long run, wage bill and profits contract by 2% and 20% respectively. The negative effects on sales revenue is less noisy and steeper over time, 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. This relatively smaller effects following net decreases is consistent with the fact that the scale of the "treatment" is also smaller following net staffing decreases.

4E Robustness: Firm-level Outcomes

One important concern is whether the effects are an artifact of firm sample construction following the requirement of a balanced sample. That is, the effects could be driven by the changing composition of firms in the district even if the composition of firms in the sample remain fixed. I address this concern in three different ways. First, I examine the effect of staffing changes on new firm incorporations (firm entry) and total number of firms in the district. This itself is an important outcome and I discuss it in detail in the next subsection. In light of this, the results on the balanced sample of firms continue to hold and are likely an underestimate given that new firm entry and fewer exits (as the total number of firms in a district also marginally increase) around positive staffing events could increase competitive forces in the local production economy. Second, I estimate the effects using the full sample of firms, without restrictions (i.e. balance requirement; see Table A.8 and Table A.9). Third, I check if missingness of data is correlated with staffing changes and if so, how that would affect the interpretation of the key results. I find that the missing data is likely a consequence of improved judicial capacity, with fewer missing entries following net additions and greater missing entries following net decreases (importantly, with no pre-trends; see Table A.10 and Table A.11). This also implies that using unrestricted sample of firms is not a feasible strategy to estimate the causal effects, since missing data is not random.

Another concern is whether the effects are due to the fact that some of the sample firms may directly gain from improved judicial capacity due to their legal cases in the courts. I find that the effects persist even among firms with no legal case data in the sample courts in the entire study period and thus are suggestive of broader, local equilibrium effects (see Table A.12 and Table A.13).

Further, given the local nature of dispute resolution and importance of these services for market transactions, I check whether the effects are restricted to firms within the district and not experienced among incumbent firms in the neighboring districts as a placebo test (Table A.14 and Table A.15). Importantly, the point estimates are statistically and economically insignificant.

Lastly, I estimate the effects using the generalized event study and local projection DID (Dube et al. 2022) approaches, both of which show similar patterns of effects on firm productivity (Figure A.9 and Figure A.10).[18]

4F Plausible Broad-Based Impact

Two pieces of evidence suggest that the effect of judicial staffing changes are broad-based: (a) greater firm entry (new incorporations) with no evidence of increased exits (Cols 1-2 Table 3) following net judge increase, (b) suggestive evidence from night lights analysis, where nightlights intensity increases following positive staffing and decreases following negative staffing events (Cols 3 and 6 Table 3). The nightlight analysis, albeit noisy, 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 facts about the legal cases in frontline courts motivate examining credit access as an important mechanism for firm productivity: (a) banks are litigation intensive - over 75% of civil/commercial litigations in courts involve banks, and (b) banks are required to file debt non-payment cases in the corresponding courts to culminate the recovery process (for e.g., liquidate assets of the borrower). This suggests that well-functioning judiciary is important for banks' business and lending workflow.

[18]The results are robust to a battery of standard 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.16, Table A.17, Table A.18, and Table A.19, respectively). Inference is robust to clustering standard errors by state and event, in 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.20 and Table A.21).

I confirm this using the case-level data from my sample courts: (a) I observe that about 50% of all commercial banks in India have at least one ongoing litigation during the study period in these districts, and (b) in 80% of these, banks are the initiator of the complaint. Further, the value of assets under litigation involving debt recovery disputes are many orders of magnitude larger than other dispute types. Typically, such disputes are settled in favor of the lenders, where judges facilitate a settlement to enable partial or complete recovery (see Figure A.11 for descriptive statistics).[19]

5A Local Credit Supply

I use district-level credit summary data from the Reserve Bank of India to examine the effect of judicial staffing changes 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. The figure also shows lending by private sector banks, which are less likely to experience soft budget constraints unlike in the case of public sector banks that have government budgetary support.

Two take-aways from this analysis are: (a) total lending towards industrial needs increases following an increase in judicial staffing, with private sector banks playing an important role, and (b) effect following net decrease in the number of judges is relatively muted and noisy. The positive effects are consistent with the time horizon for short and medium-term loans such as those towards operating expenses rather than capital expansions. An increase in the resolutions of debt recovery cases also enable banks to recover stuck capital, which increases their liquidity by lowering provisions they need to make in their profit and loss statements for write-offs. This additional liquidity is likely recirculated as credit to industrial borrowers. The lack of negative effects is consistent with the fact there is no significant decline in case resolutions in courts affecting liquidity, ceteris paribus. That is, borrower default behavior does not respond to changes in the number of judges. This is a plausible assumption as individual or household borrowings, that form the largest bulk of banks' lending portfolio, are less likely to be tracking variations in the staffing levels in local courts.

5B Local Markets, Access to Credit, And Firms' Production Decisions

There are two key ingredients in a framework linking local judicial capacity with firm productivity. First relates to access to credit via local credit markets and repayment behavior (following Besley and Coate 1995; Banerjee and Duflo 2010). Second is about firms' optimization problem. Starting with the credit model, I assume that firms need external credit to finance operations, that has some

[19] Based on parsing judgements from a random subsample of cases involving banks, I found that over 83% of the credit related disputes have outcomes in favor of the banks. This was also confirmed based on unstructured interviews with retired and incumbent judges of district courts.

stochastic probability of success. A lender (e.g., bank) bases their lending decisions on whether repayment can be enforced through courts. The lender takes into account borrower firm's wealth towards collateral requirement or past borrowing behavior in order to lend. A debt contract is executed only if lender's expected return 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. Sub-game perfect Nash equilibrium (SPNE) through backward induction implies that the lender uses a wealth cut-off (or any other proxy for repayment capability) 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.

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 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.

Subsequently, firms would re-optimize their production decisions following credit market-level changes. In addition to the credit channel, improved courts could also directly benefit firms' production processes through lower transaction costs, for example, from lower monitoring and security costs in protecting assets, inventory, and raw material stock from thefts and embezzlement. 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.

Empirically, I note an expansion (contraction) in raw material expenditures, plausibly also reflecting lower monitoring costs in addition to an expansion in operations (see Panel B Figure 4). Further, I note an increase in firms' working capital and a decrease in interest expenditure immediately following staffing changes (Panel C Figure 4). Working capital reflects the extent of cash available to meet operating expenses.[20] These immediate effects on working capital and interest expenditure is consistent with the plausible role of liquidity in local credit markets.

[20]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.

5C Additional Empirical Tests

The conceptual framework in Appendix A.2 generates additional hypotheses that can be tested in the data, namely: (a) borrowers' (including firms) propensity to litigate as defendants as a function of their wealth, and (b) changes in lending to smaller borrowers (or those with limited past relationship with banks). I examine whether these outcomes - i.e. propensity to litigate by wealth size, and credit access by firm size change subsequent to judicial staffing changes.

Figure A.13 presents descriptive evidence of legal cases involving firms as defending litigants, which highlights the following key facts: (a) defendant firms have higher asset value compared to similarly leveraged non-litigant firm, and (b) asset value of high-leveraged defending firms is higher than other defending firms.[21] Panel A Figure 5 shows that smaller firms are more (less) likely to litigate when there are more (fewer) judges, consistent with the framework where borrower's propensity to litigate depends on their wealth-level passing a certain threshold, which is a function of local judicial capacity. Better capacity decreases whereas worse capacity increases this threshold.

Panel B Figure 5 presents the event study graphs of vacancy removal among the subset of smaller, less-leveraged firms. Leverage status along with firm size indicate: (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 bank credit. Consistent with the framework, such firms experience an increase in cheaper credit following net increases in the number of judges (i.e., both working capital increases and interest expenditure decreases).

5D Local Crime Rates

While credit market is an important channel to explain the link between judicial capacity improvements and an increase in firm-level productivity, it is certainly not the only one. Another important function that courts of law provide is law enforcement and improving public safety in the local area. One way to think of this cost in firms' production function is as additional monitoring costs incurred. With better local enforcement capacity, such expenses are lower. Empirically, I examine two types of reported crime by NCRB - serious crimes that include homicide, riots, crime causing significant bodily injuries, and less serious crimes (recorded as "other IPC crime", which include small-scale theft).

Table 4 shows reductions in both types of crimes following a net increase in the number of judges. A net decrease, on the other hand, generates a corresponding increase in less serious crimes but no significant effect on serious crime rates. With the caveat that I unable to distinguish whether these changes are due to reporting or true occurrence of crimes, these results suggest that local courts plausibly play an important role in protecting physical and financial property of local firms.

Decomposition of Firms' Profit I decompose firms' profits into that arising from production (sales), credit access (working capital), and local crime channels (monitoring costs) using a dis-

[21] The asset values for all sub-sample and heterogeneity analyses are measured from the year prior to the legal case sample period.

tributed lags model by incorporating lagged values of firm profits and firm fixed effects. Table A.22 presents a suggestive but important insight that interest expenditure has a large negative elasticity with respect to profit. Lowering of such expenditure has a large, significant association with profitability, even after accounting for district-year and industry-year dummies to account for time varying unobserved drivers of firm profits.

6 Benefits and Costs of Reducing Judge Vacancy

The analysis in this paper suggests that investing in frontline judicial staffing is important for improving local firm productivity and subsequently, overall economic development. Leveraging the fact that the firms in my sample are tax-paying firms, employing labor force with taxable income, this investment could generate large returns, both from the perspective of public budget surplus as well as increases in social returns. In Table 5, I present data, computations, and assumptions to generate a back-of-the-envelope benefit-cost ratio from investing in filling judge vacancies in district courts.

On the benefits side, I use the median values of profits and wage bills among the 6 sample firms per district to compute the increase in firm-level surplus and salaried income. Since both formal sector firms and their salaried workers pay corporate and income tax on their net income respectively, I apply the average tax rates on net increases in firm profit and wage bill, respectively. Corporate tax rates for registered domestic firms are specified in the Taxation Laws Amendment Ordinance (2019). I calculate the effective income tax rate on salaried workers as 7.3 percent, as a lower bound, after applying all possible exemptions and tax-slabs specified in the Union Budget, 2018-19. [22]

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. I compute the discounted net present value of the increase in profits, wage bills, the associated tax revenue, the corresponding expenditure on additional judges for 5 years following the increase in the number of judges. I assume the discount rate to be 5% in the base calculation and perform sensitivity analyses using lower and higher discount rates.

This computation shows that the benefits are orders of magnitude larger than the costs. For the public budget, the ratio implies revenues that are over 5 times larger than expenditure on average, whereas the social returns are over 30 times the cost. Even the most conservative estimates (with

[22] These assumptions are motivated by articles in the news media, with sources mentioned in Table 5. 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.

highest discount rate and the left-end of the confidence interval) suggest that the returns to investing in district judicial capacity is high and more than pays for itself.

7 Conclusion

To conclude, I show that well-functioning frontline judiciary is a core component of local state capacity. The current status-quo underscores the problem of large backlogs of legal disputes 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. This paper brings attention to the intersection of judicial institutions, state capacity, and financial sector development by using disaggregated legal case-level data. This insight is an important contribution to the literature that has hitherto focused on procedural laws or the introduction of specialized courts for resolving specific legal disputes by showing how the smallest unit of general courts of law are important for day-to-day market transactions and firms' production decisions.

District courts provide important legal services to the banking sector to enable efficient credit allocation and help protect property from ordinary thefts through law enforcement. This facilitates firm productivity through better functioning local credit market and lowering other transaction costs. This paper complements existing literature documenting the role of courts in enforcing bankruptcy laws as examined by Ponticelli and Alencar (2016) in the context of Brazil. Bankruptcy proceedings are the last step in the debt recovery process, when a borrower is unable to fulfill their outstanding debt obligations without restructuring or liquidation. Debt recovery cases in courts are more routine, and larger in magnitude relative to bankruptcy cases, perhaps due to incentives facing lawyers and over-optimism by litigating parties documented in Sadka et al. (2018).

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.

Acemoglu, Daron and Melissa Dell, "Productivity Differences between and within Countries," *American Economic Journal: Macroeconomics*, January 2010, *2* (1), 169–88.

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, "Land Reform, the Market for Protection, and the Origins of the Sicilian Mafia: Theory and Evidence," *Journal of Law, Economics, & Organization*, 2003, *19* (1), 218–244.

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.

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.

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.

Breza, Emily and Cynthia Kinnan, "Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis*," *The Quarterly Journal of Economics*, 05 2021, *136* (3), 1447–1497.

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.

Castellanos, Sara G, Diego Jiménez Hernández, Aprajit Mahajan, Eduardo Alcaraz Prous, and Enrique Seira, "Contract Terms, Employment Shocks, and Default in Credit Cards," Working Paper 24849, National Bureau of Economic Research July 2018.

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.

— , "The impact of the judiciary on entrepreneurship: Evaluation of Pakistan's "Access to Justice Programme"," *Journal of Public Economics*, 2009, *93* (1-2), 114–125.

— , "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.

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

Dube, Arindrajit, Daniele Girardi, and Alan M Taylor, "A Local Projections Approach to Difference-in-Differences Event Studies," *Working Paper*, 2022.

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.

Iyer, Lakshmi and Anandi Mani, "TRAVELING AGENTS: POLITICAL CHANGE AND BUREAUCRATIC TURNOVER IN INDIA," *The Review of Economics and Statistics*, 2012, *94* (3), 723–739.

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

Khan, Adnan Q., Asim I. Khwaja, and Benjamin A. Olken, " Tax Farming Redux: Experimental Evidence on Performance Pay for Tax Collectors *," *The Quarterly Journal of Economics*, 10 2015, *131* (1), 219–271.

— **, Asim Ijaz Khwaja, and Benjamin A. Olken**, "Making Moves Matter: Experimental Evidence on Incentivizing Bureaucrats through Performance-Based Postings," *American Economic Review*, January 2019, *109* (1), 237–70.

Khwaja, Asim Ijaz and Atif Mian, "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market," *American Economic Review*, September 2008, *98* (4), 1413–42.

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.

Laeven, Luc and Christopher Woodruff, "The Quality of the Legal System, Firm Ownership, and Firm Size," *The Review of Economics and Statistics*, 2007, *89* (4), 601–614.

Lichand, Guilherme and Rodrigo R. Soares, "Access to Justice and Entrepreneurship: Evidence from Brazil's Special Civil Tribunals," *The Journal of Law & Economics*, 2014, *57* (2), 459–499.

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.

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.

Olken, Benjamin A. and Rohini Pande, "Corruption in Developing Countries," *Annual Review of Economics*, 2012, *4* (1), 479–509.

Paravisini, Daniel, "Local Bank Financial Constraints and Firm Access to External Finance," *The Journal of Finance*, 2008, *63* (5), 2161–2193.

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.

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

Rigol, Natalia and Benjamin N. Roth, "Loan Officers Impede Graduation from Microfinance: Strategic Disclosure in a Large Microfinance Institution," October 2021.

Sadka, Joyce, Enrique Seira, and Christopher Woodruff, "Information and Bargaining through Agents: Experimental Evidence from Mexico's Labor Courts," Technical Report w25137, National Bureau of Economic Research October 2018.

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.

Schnabl, Philipp, "The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market," *The Journal of Finance*, 2012, *67* (3), 897–932.

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.

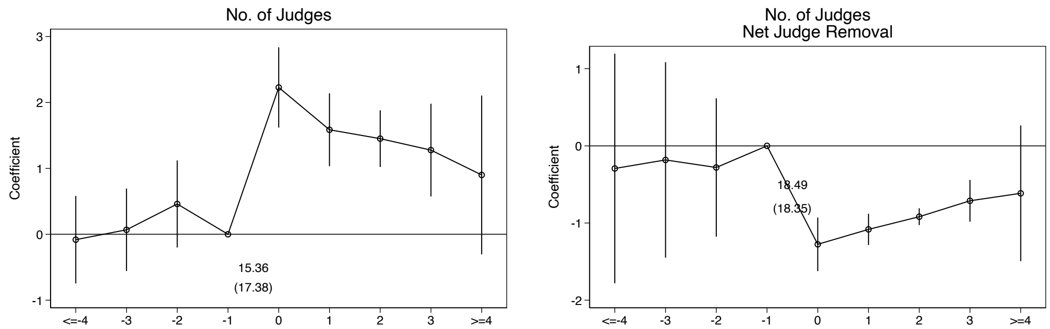
von Lilienfeld-Toal, Ulf, Dilip Mookherjee, and Sujata Visaria, "THE DISTRIBUTIVE IMPACT OF REFORMS IN CREDIT ENFORCEMENT: EVIDENCE FROM INDIAN DEBT RECOVERY TRIBUNALS," *Econometrica*, 2012, *80* (2), 497–558.

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.

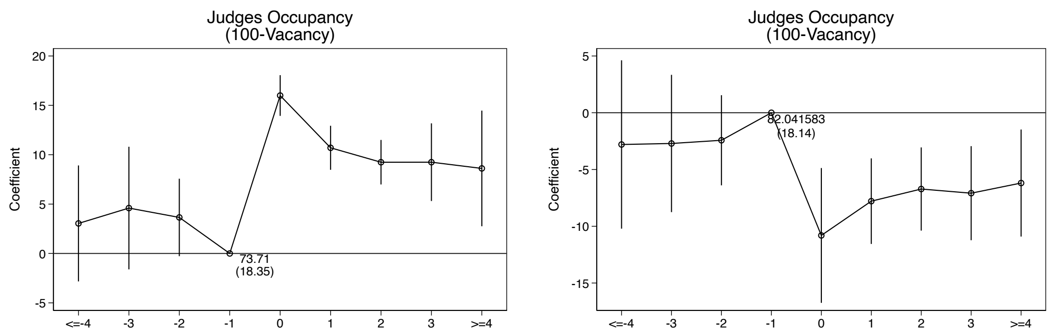
8 Figures

Figure 1: Removal and Creation of Vacancy and Court Performance

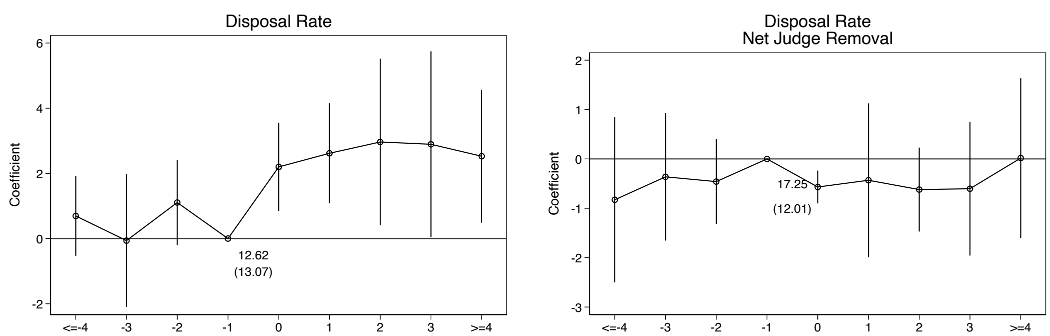
Panel A: Judge Headcount



Panel B: Inverse Vacancy Rate

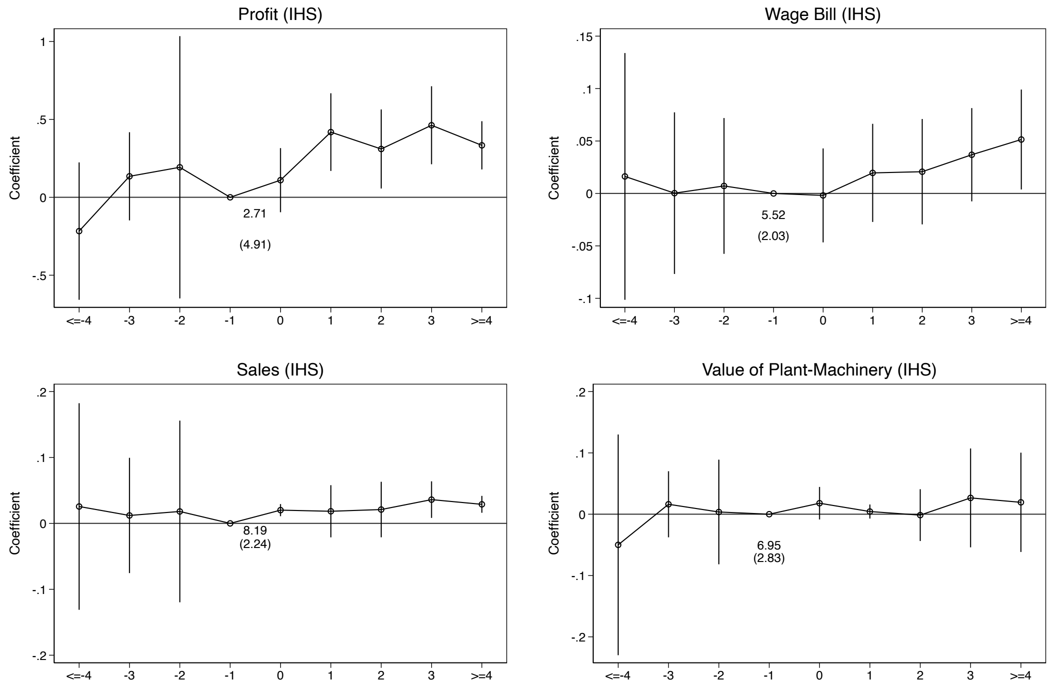


Panel C: Court-Level Disposal Rate



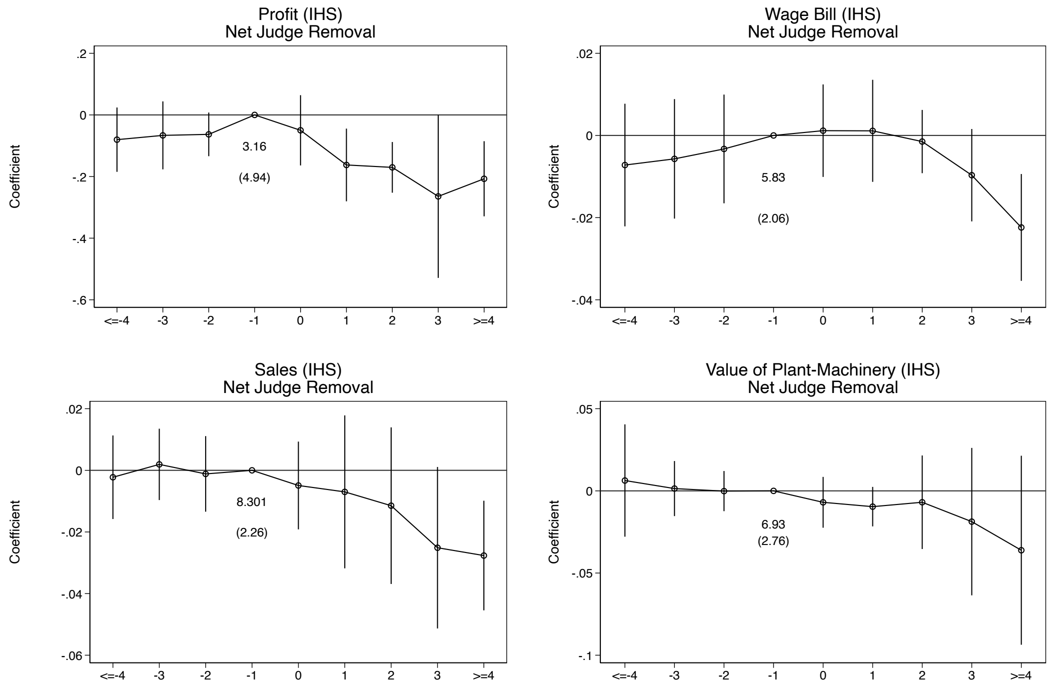
Notes: The figures plot the event study interaction coefficients for positive and negative staffing changes from estimating Equation 1 using total number of judges (Panel A), inverse vacancy rates (Panel B) and disposal rate (expressed in percentage terms in Panel C) as dependent variables, respectively. 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. The table equivalent of these graphs is Table A.2.

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. Using log transformation also yields similar results. The sample comprises of a balanced panel of incumbent firms in the district that report their annual balance sheet information over the study period, enabling the use of firm fixed effect in the specification. The first row presents the coefficients with profits and wage bills as the dependent variables. The dependent variables in second row are sales revenue and the value of capital goods (plant/machinery), 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 an event and standard errors are clustered by district and event. Error bars present 95% confidence interval. The table equivalent of these graphs is Table A.6.

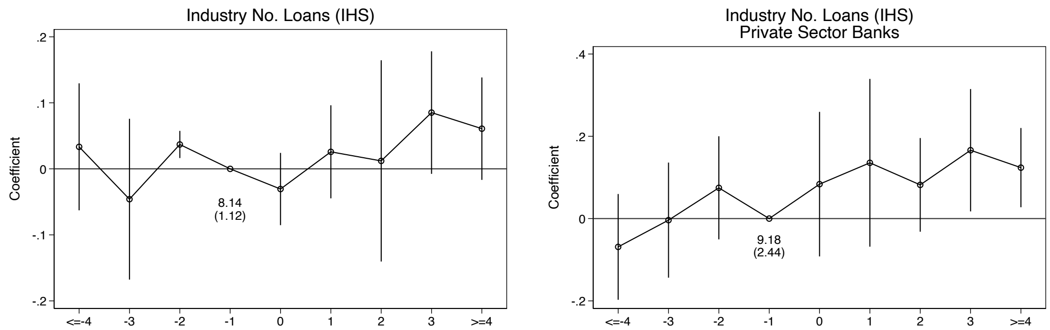
Figure 3: Local Firms' Production: Creation of Vacancy



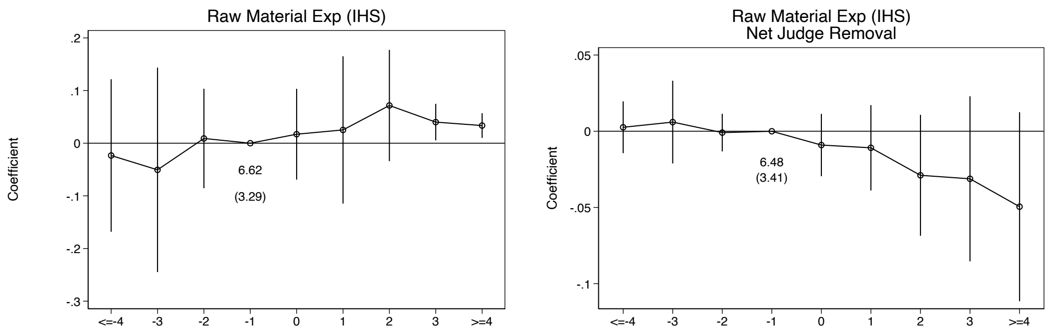
Notes: The figures above plot the event studies coefficients on negative staffing change event-time interaction dummies from estimating Equation 1 for firm-level variables. The outcome variables are transformed using inverse hyperbolic sine function to account for 0s and negative values observed in the balance-sheet data. Using log transformation also yields similar results. The sample comprises of a balanced panel of incumbent firms in the district that report their annual balance sheet information over the study period, enabling the use of firm fixed effect in the specification. The first row presents the coefficients with profits and wage bills as the dependent variables. The dependent variables in second row are sales revenue and the value of capital goods (plant/machinery), 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 an event and standard errors are clustered by district and event. Error bars present 95% confidence interval. The table equivalent of these graphs is Table A.7.

Figure 4: Credit Outcomes

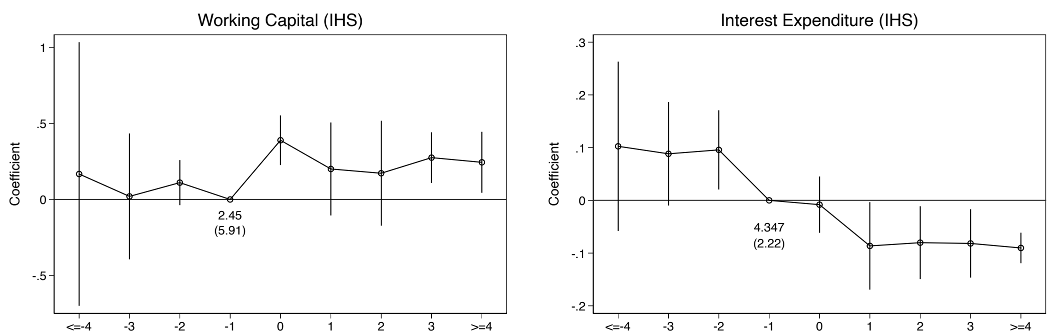
Panel A: District-Level Lending



Panel B: Firm-level Raw Material Expenditure - All Sample Firms



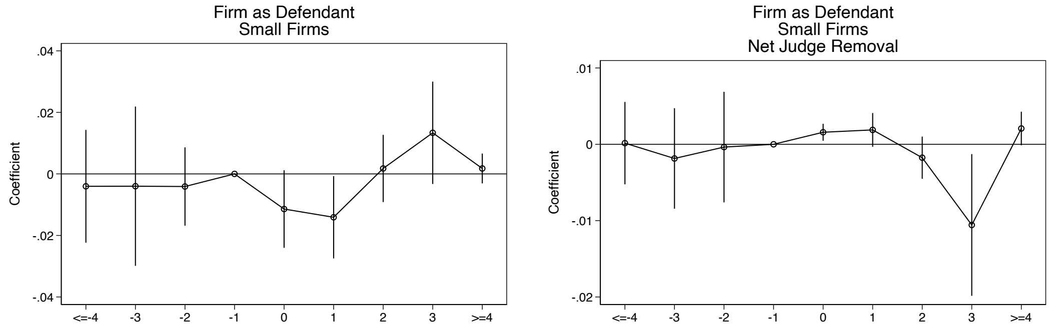
Panel C: Firm-level Working Capital and Interest Expenditure - All Sample Firms



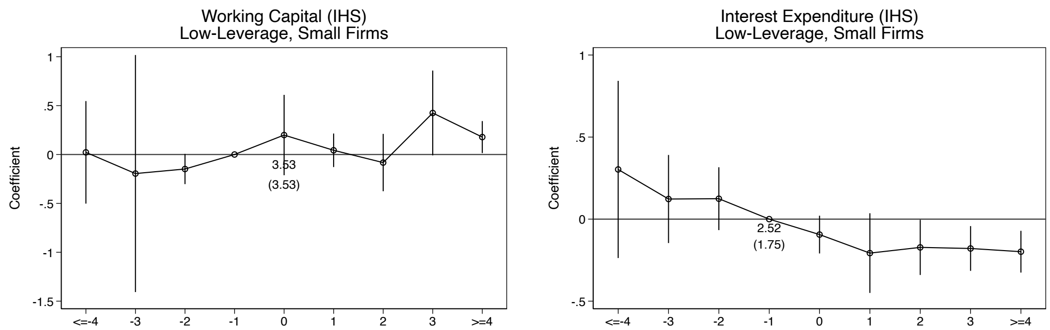
Notes: Panel A presents effects on overall lending by all banks branches as well as branches of private sector banks, respectively, within a district to industrial borrowers. Panel B documents the effect of both judge vacancy removal and creation on raw material expenditure. Panel C presents effects of judge vacancy removal on working capital and interest expenditure for all firms. Error bars present 95% confidence interval.

Figure 5: Credit Mechanism

Panel A: Litigation Probability Among Smaller Firms



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



Notes: Panel A presents event study graphs using a dummy dependent variable encoding whether a firm is found filing new litigation in a specific district court in a given calendar year. Panel C presents effects of judge vacancy removal on working capital and interest expenditure for the subset of small-sized less-leveraged firms, respectively. Error bars present 95% confidence interval.

9 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

Notes: Panel A summarizes the court-level variables computed from trial-level disaggregated data. Panel B summarizes district-level bank lending to industries. Panel C summarizes 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: Balance Table: A Long-Differenced Estimation of Judge Staffing Changes

	(1)	(2)	(3)	(4)
	Δ Judges	Δ Judges	Δ Vacancy	Δ Vacancy
Δ Pop	-0.597	-0.564	0.387	0.353
	(0.742)	(0.688)	(0.604)	(0.578)
Δ # HH	0.349	0.377	-0.282	-0.309
	(0.422)	(0.523)	(0.313)	(0.365)
Δ SC Pop	-0.0138	-0.00937	-0.00447	-0.0108
	(0.0647)	(0.0759)	(0.0467)	(0.0546)
Δ Lit Pop	0.140	0.0706	-0.0647	0.00732
	(0.225)	(0.140)	(0.190)	(0.156)
Δ Urban Pop	-0.0482	-0.0550	0.0494	0.0569
	(0.0543)	(0.0545)	(0.0469)	(0.0471)
Δ All Emp	-0.0184	-0.0203	0.00872	0.0108
	(0.0377)	(0.0363)	(0.0299)	(0.0285)
Δ Manuf Emp	0.0126	0.0142	-0.00562	-0.00726
	(0.0299)	(0.0285)	(0.0240)	(0.0226)
Δ Candidates		0.0176		-0.0206
		(0.0182)		(0.0170)
Δ Elec Turnout		0.157		-0.157
		(0.416)		(0.324)
Δ Winner Vote Share		0.130		-0.162
		(0.386)		(0.244)
Observations	194	194	194	194
State FE	X	X	X	X
Joint P-value	0.890		0.810	
Joint P-value (electoral)		0.324		0.194

Notes: This table uses a long difference specification, regressing long-differenced judicial staffing measures - the number of judges as well as judge vacancy rates - on lagged long-differenced district-level measures from population and economic census including population, demographic composition, urbanization, employment including manufacturing employment, and electoral outcomes. All the variables are measured in terms of percentage changes from the baseline period. A more typical approach to generating balance table using pair-wise regressions between baseline outcomes and judicial staffing changes, as followed in RCTs, also do not yield any statistical or economically meaningful correlation coefficients on the staffing variable.

Table 3: District-level Firm Incorporations, Total Number of Firms, and Nightlights

	(1) Vacancy Removal New Incorp.	(2) Vacancy Removal Total Firms	(3) Avg. Nightlights (IHS)	(4) New Incorp.	(5) Vacancy Creation Total Firms	(6) Vacancy Creation Avg. Nightlights (IHS)
Event x <=-4	-1.274	-8.789	-0.105	0.0650	-0.167	0.0315
	(1.009)	(7.129)	(0.0751)	(0.168)	(2.483)	(0.0322)
Event x -3	-0.212	-4.672	-0.0570	0.0671	-0.231	0.0201
	(0.366)	(2.838)	(0.0491)	(0.139)	(0.599)	(0.0213)
Event x -2	-0.168	-1.555	0.00240	0.144	0.0383	-0.0136
	(0.201)	(1.827)	(0.00753)	(0.201)	(0.650)	(0.0288)
Event x 0	0.286	1.549	0.00893	-0.0289	-0.702	-0.00139
	(0.0709)	(1.659)	(0.0165)	(0.0695)	(1.145)	(0.0166)
Event x 1	0.286	3.387	0.0234	-0.0184	-0.857	-0.0203
	(0.117)	(1.875)	(0.0275)	(0.0309)	(1.438)	(0.0207)
Event x 2	0.520	6.808	0.0353	-0.0840	-2.370	-0.0127
	(0.0856)	(4.003)	(0.0392)	(0.116)	(1.961)	(0.0178)
Event x 3	0.466	7.635	0.0369	0.0482	-1.705	-0.00840
	(0.142)	(4.751)	(0.0386)	(0.0551)	(1.704)	(0.0169)
Event x >=4	0.644	9.972	0.0584	-0.0711	-2.483	-0.0382
	(0.196)	(6.544)	(0.0559)	(0.0996)	(2.944)	(0.0399)
Observations	4806	7497	6993	4806	7497	6993
No. Units	1.7	37.74	192	1.7	37.74	192

Notes: This table presents the estimates from Equation 1 using new firm incorporation and total number of firms in a district in a given year, including those not in the main analysis balanced panel. For nightlights reported in Columns 3 and 6, 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. Standard errors are clustered by district and event. I do not report statistical significance stars in line with journal submission guidelines.

Table 4: Local Recorded Crime and Judge Vacancy Changes

	Vacancy	Removal	Vacancy	Creation
	(1) Serious IPC Crime (IHS)	(2) Other IPC Crime (IHS)	(3) Serious IPC Crime (IHS)	(4) Other IPC 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). Serious IPC Crime include crimes that do no require a court order for the police to complete their investigation. Other IPC 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. I do not report statistical significance stars in line with journal submission guidelines.

Table 5: 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
Annual Per Judge Salary + Other costs	3.33	Million INR	Second National Judicial Pay Commission
Benefit-Cost (Tax Revenue) ($\delta = 0.05$)	6.64 [1.21]	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social) ($\delta = 0.05$)	35.12 [6.3]	Ratio	Calculation Bootstrapped SE
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: 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. Figure A.15 shows the distribution of the benefit-cost ratio following the bootstrapping procedure.

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] 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.

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.

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 need an additional $K_B = K - K_M$ from the lender to start the project, where K_M is the amount they raise from the market, with market return ϕ. 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 payoff is 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

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

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

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

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

The timing of the game where the lender and borrower decide on their strategies are 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.

$$
\begin{aligned}
\frac{\partial R}{\partial \gamma} &= \frac{\overbrace{\frac{\partial C_L(\gamma)}{\partial \gamma}}^{\text{-ve}} \overbrace{(1 - G(\tilde{W}) - C_B g(\tilde{W}))}^{+\text{ve}}}{((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B} \\
&\quad - \frac{(1 - G(\tilde{W}))C_L(\gamma) - K_B}{(((1 - G(\tilde{W}))\Gamma + G(\tilde{W}))K_B)^2} \left(\overbrace{g(\tilde{W}) \frac{\partial C_B}{\partial \gamma} (K_B - \Gamma)}^{\approx 0} \right) \\
\implies \frac{\partial R}{\partial \gamma} &< 0 \\
\frac{\partial W^*}{\partial \gamma} &= \frac{\overbrace{(1 - F(\tilde{W}))\frac{\partial C_L}{\partial \gamma} - C_L f(\tilde{W})\frac{\partial C_B}{\partial \gamma}}^{\text{-ve}}}{((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta} - \frac{(1 - F(\tilde{W}))C_L(\gamma) - K_B}{(((1 - F(\tilde{W}))\Gamma + F(\tilde{W}))\delta)^2} \underbrace{f(\tilde{W})\frac{\partial C_B}{\partial \gamma}(\delta - \Gamma)}_{\approx 0} \\
\implies \frac{\partial W^*}{\partial \gamma} &< 0
\end{aligned}
$$

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 in the input market. The firm's problem is to maximize their profits as follows:

$$
\text{Max}_{X_1,X_2}\big(\Pi = pQ(X_1, X_2) - w_1X_1 - w_2X_2 - m_i(\gamma)\big) \tag{7}
$$

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

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. $K = K_M + K_B$, 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:

$$\mathcal{L} = pQ(X_1, X_2) - w_1 X_1 - w_2 X_2 - m_i(\gamma) + \lambda\big(K_i - w_1 X_1 - w_2 X_2 - m_i(\gamma)\big)$$

FOC:

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

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

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

To examine how the optimal production choices vary with exogenous variation in the institutional quality parameter, γ, I use Implicit Function Theorem where X_1, X_2, λ are endogenous variables and γ 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:

$$Det[J] = 2pw_1w_2 \underbrace{Q_{x_1x_2}}_{\text{+ve}} - p(w_2^2 \underbrace{Q_{x_1x_1}}_{\text{-ve}} + w_1^2 \underbrace{Q_{x_2x_2}}_{\text{-ve}}) > 0$$

$$\frac{\partial X_1}{\partial \gamma} = -\frac{Det[J_{x_1}]}{Det[J]} = -\frac{p\,\overbrace{(\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma})}^{+ve}(w_1 \overbrace{Q_{x_2x_2}}^{\text{-ve}} - w_2 \overbrace{Q_{x_1x_2}}^{\text{+ve}})}{Det[J]} > 0$$

$$\frac{\partial X_2}{\partial \gamma} = -\frac{Det[J_{x_2}]}{Det[J]} = -\frac{p\,\overbrace{(\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma})}^{+ve}(w_2 \overbrace{Q_{x_1x_1}}^{\text{-ve}} - w_1 \overbrace{Q_{x_2x_1}}^{\text{+ve}})}{Det[J]} > 0$$

$$\frac{\partial \lambda}{\partial \gamma} = -\frac{Det[J_\lambda]}{Det[J]} = -\frac{p^2\,\overbrace{(\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma})}^{+ve}\overbrace{(Q_{x_1x_1}Q_{x_2x_2} - Q_{x_2x_1}Q_{x_1x_2})}^{\text{depends on functional form}}}{Det[J]} =?$$

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.

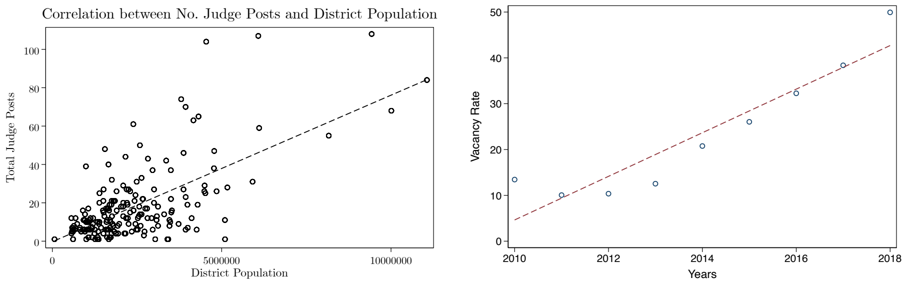
2. For marginal small firms, $i = S$ and $W \approx W^* - \epsilon$, the marginal benefit $K_B - \frac{\partial m_S}{\partial\gamma}$ is due to both availability of borrowing from banks K_B as well as a reduction in monitoring costs. I assume that the monitoring costs for small firms do not decrease 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 $(\underbrace{\frac{\partial K_S}{\partial\gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial\gamma}}_{\approx 0}) \approx 0$.

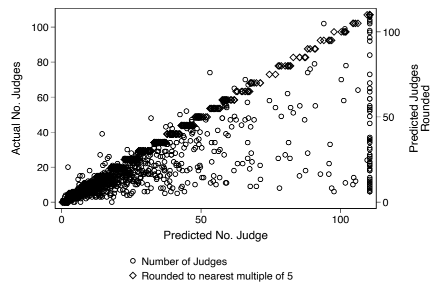
A.3 Appendix: Figures

Figure A.1: Judge Posts, Vacancy, and District Population

Panel A: Court-size, vacancy, and district population

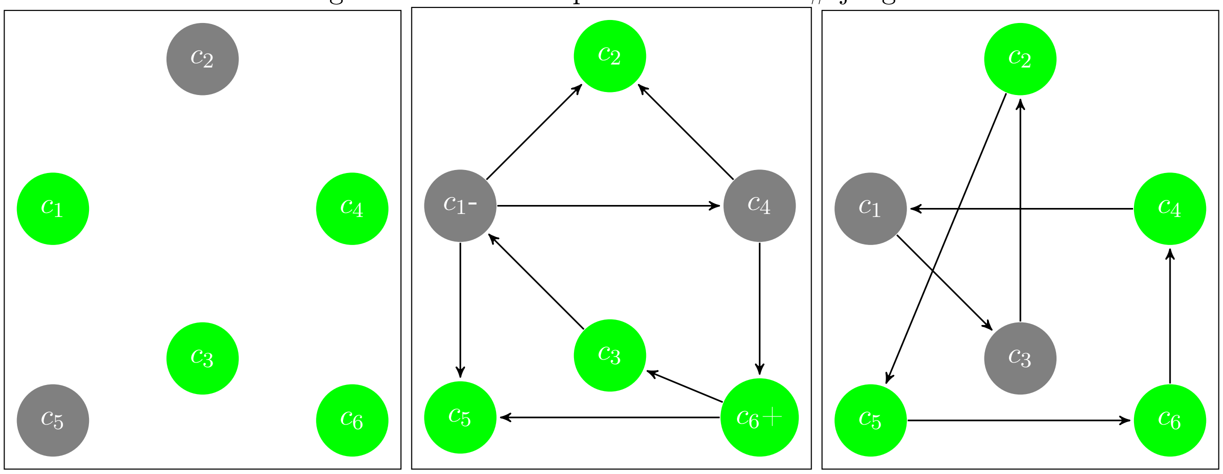


Panel B: Actual Number of Judges vs. Law Commission Recommendation



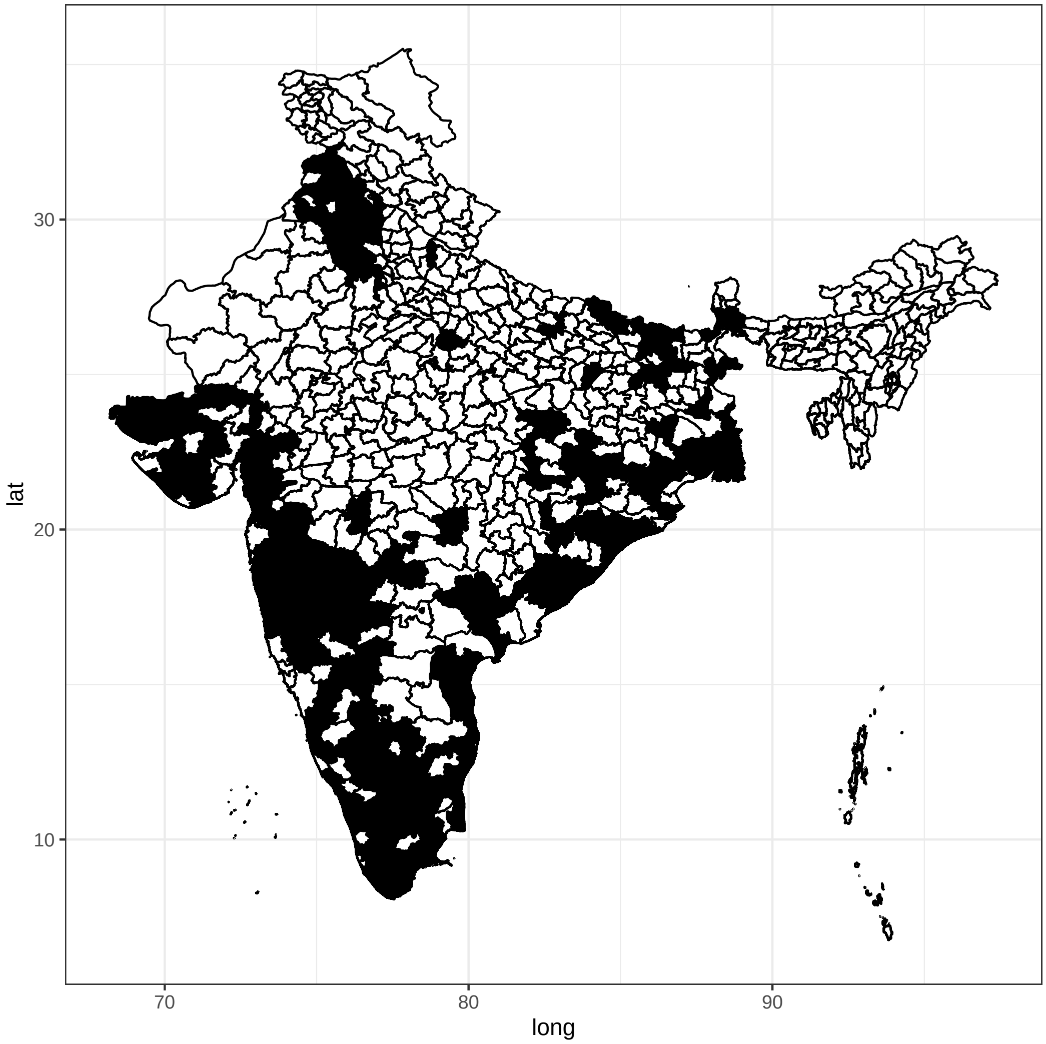
Notes: Y axis presents total number of judge posts across the sample courts. X-axis is the district population as measured in 2011 census. In the bottom panel, I plot the observed number of judges in a district court-year on the left y-axis, predicted number of judges based on the Law Commission Report 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.2: An example of variation in # judges



Notes: This graphic represents a stylized example of net judge staffing changes over time. Panel 1 presents t=0, Panel 2 - t=1, and Panel 3 - t=2. A node refers to a district court. Green node implies no judge vacancy and gray node implies some judge vacancy. At the end of t=0 and t=1, there are staffing changes arising from recruitments, retirements, and rotations, with rotations represented by directed arrows in Panels 2 and 3. The direction of the arrows in Panels 2 and 3 indicate judge rotation, from origin to destination courts. The + and − inside the nodes indicate addition of a newly recruited judge and retirement, respectively. The node colors in Panels 2 and 3 presents the resulting implications of staffing changes on judge vacancies in the sample courts in t=1 and t=2, respectively. At t=1, C2 and C5 no longer have any vacancy whereas C1 and C4 experience vacancy as a result of these dynamics. C3 and C6 remain at full occupancy at both t=0 and t=1. At t=2, C3 experiences a vacancy whereas C4 is back at full staffing levels. All the other courts experience no net change between t=1 and t=2.

Figure A.3: Sample district courts



Notes: 7 of 14 states in the sample include over two-thirds of their districts. Gujarat, Punjab, and Tamil Nadu are among the top industrialized states and have over 80% of their districts in the study sample.

Figure A.4: Construction of sample of firms

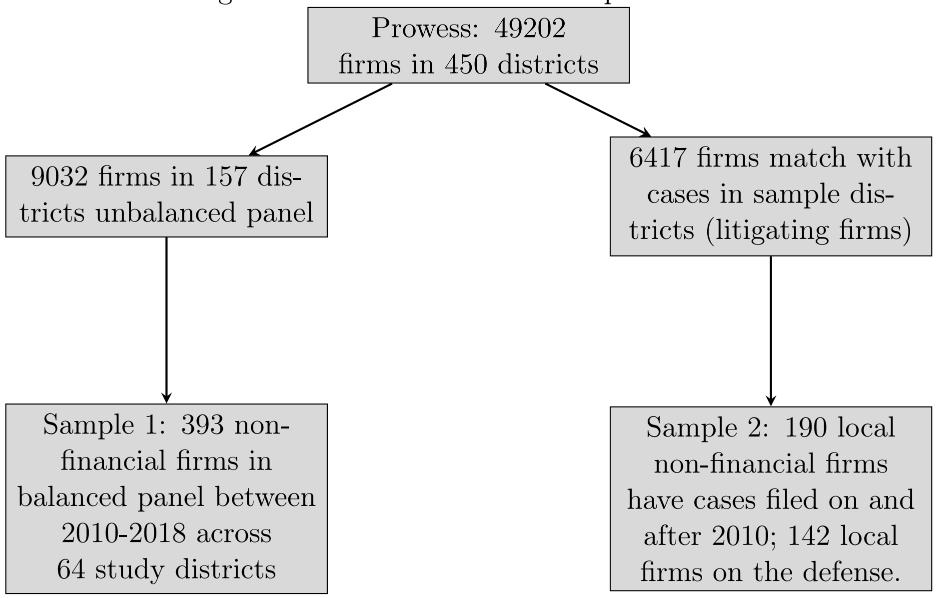
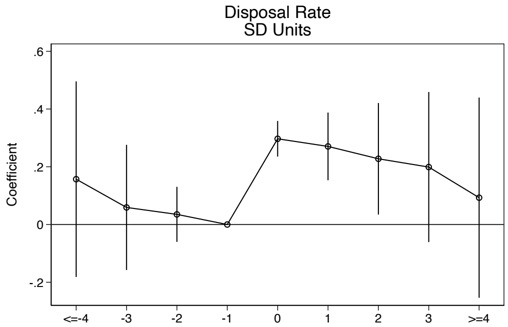
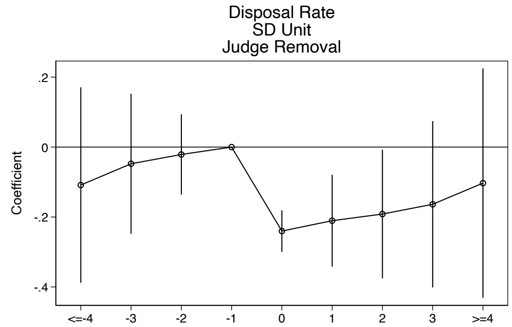


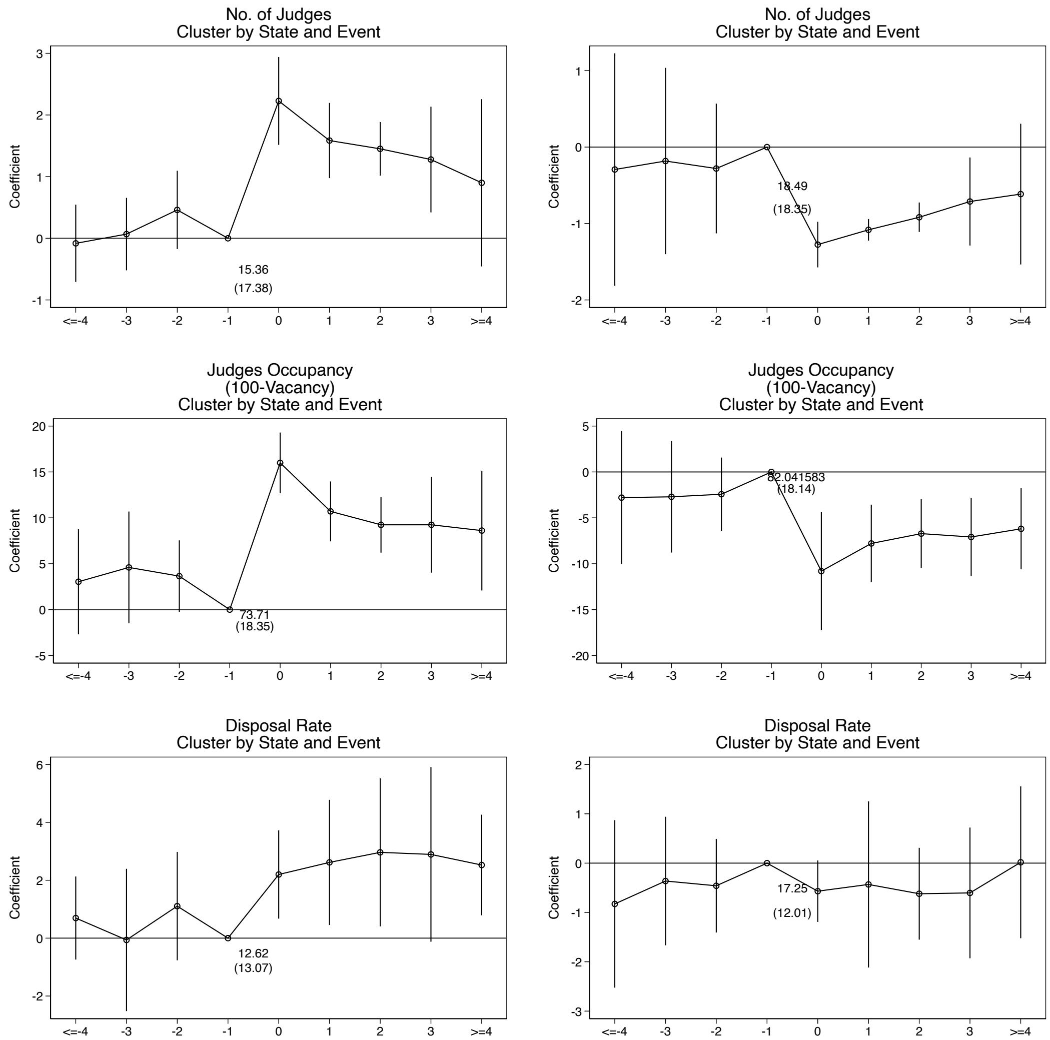
Figure A.5: Multiple Event Study Estimator: Simulation





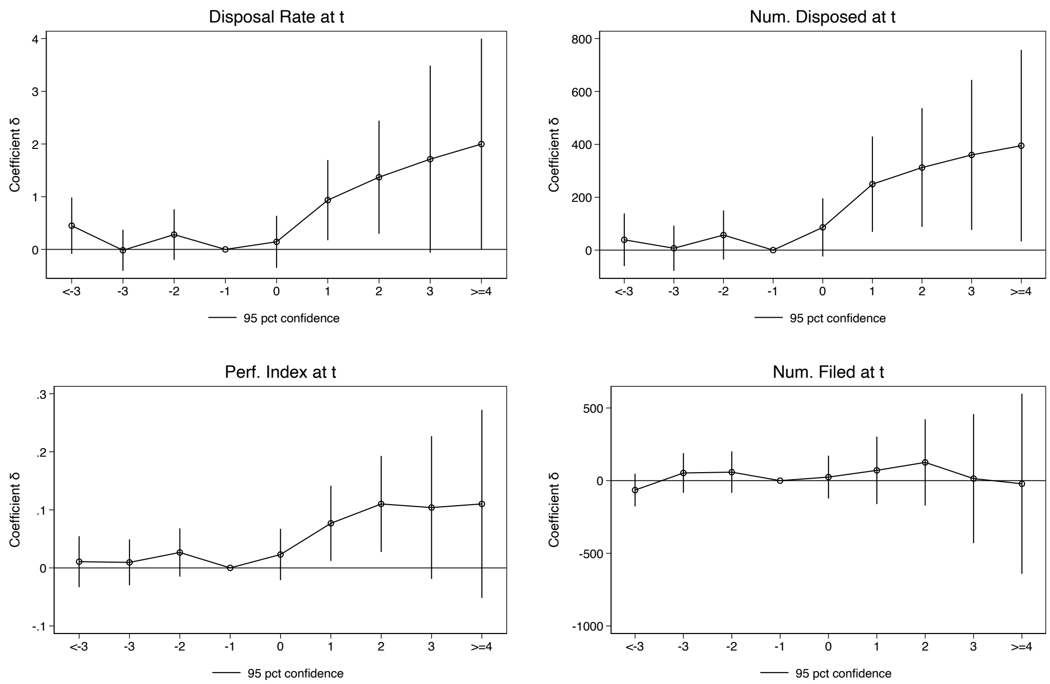
Notes: The above graphs present estimation of the treatment effects using the stacked event study estimator for multiple events using simulated data. The DGP of disposal rate is coded as a function of positive or negative event shocks of equal magnitude - 0.3 standard deviations in effect size - with error term distributed as a gamma function, mimicking data. Each district court is randomized to have 2 positive and 3 negative shocks to the number of judges over a span of 9 years. The error term for the number of judges is drawn from a uniform distribution.

Figure A.6: Court Outcomes: Inference Robustness



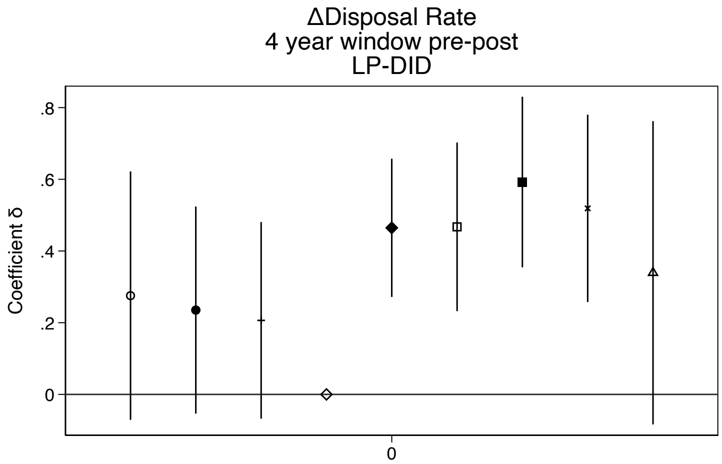
Notes: The figures plot the event study interaction coefficients from estimating Equation 1. Standard errors are clustered by state (instead of district) and event. Error bars present 95% confidence interval.

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. The value labels on the x-axis needs to be interpreted differently from those in standard event study figures - positive integers refer to the regression coefficient on lagged explanatory variable by period indicated by the integer and negative integers refer to the coefficients on lead variables. For example, regression coefficient corresponding to 1 in the figures is the coefficient on $\Delta x_{i,t-1}$ and -1 corresponds to $\Delta x_{i,t+1}$ in Equation 2. The coefficients on the lead variables indicate whether the number of judges is itself determined by the existing workload in the courts. As noted in these figures, none of the different court performance indicators either significantly or economically meaningfully correlate with the next period staffing levels. 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: Local Projection DID: Court Performance

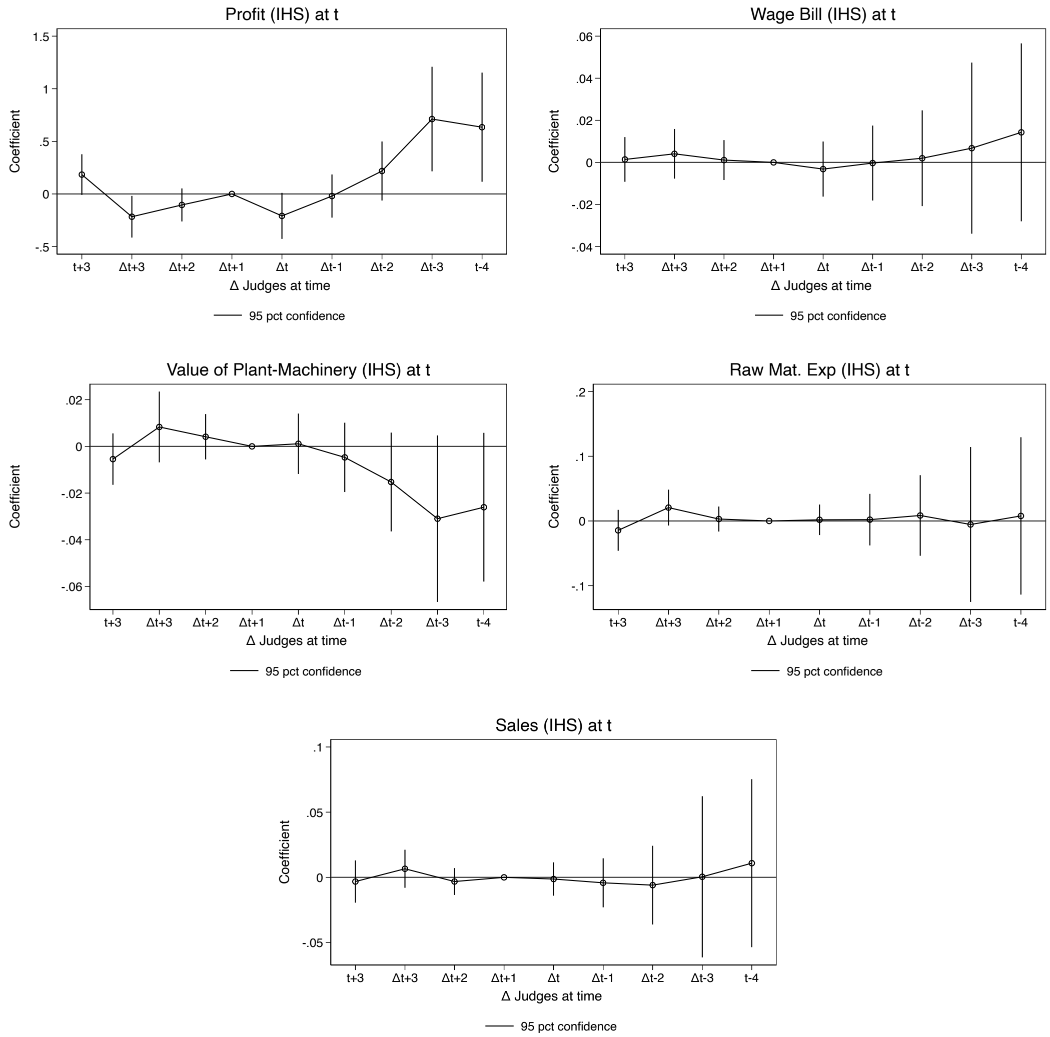


Notes: Following Dube et al. (2022), the local projection DID specification accounts for empirical challenges arising from impulse response functions generated by judicial staffing changes that occur many times and in opposing directions within the study period, similar to events in finance. Each coefficient in the graphs above represent a separate specification as follows with $h = -4, -3, ..., 3, 4$, i representing the unit of observation - firm or a district, and d referring to the corresponding district-court:

$$y_{i,t+k} - y_{i,t-1} = \beta_k \Delta NumJudges_{d,t} + \alpha_d + \delta_t + \epsilon_{i,t}$$

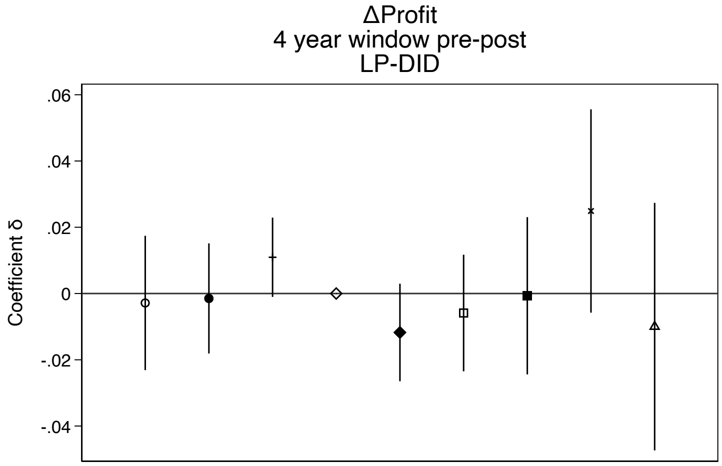
where Δ is the first difference operator.

Figure A.9: 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.10: Local Projection DID: Firm Productivity

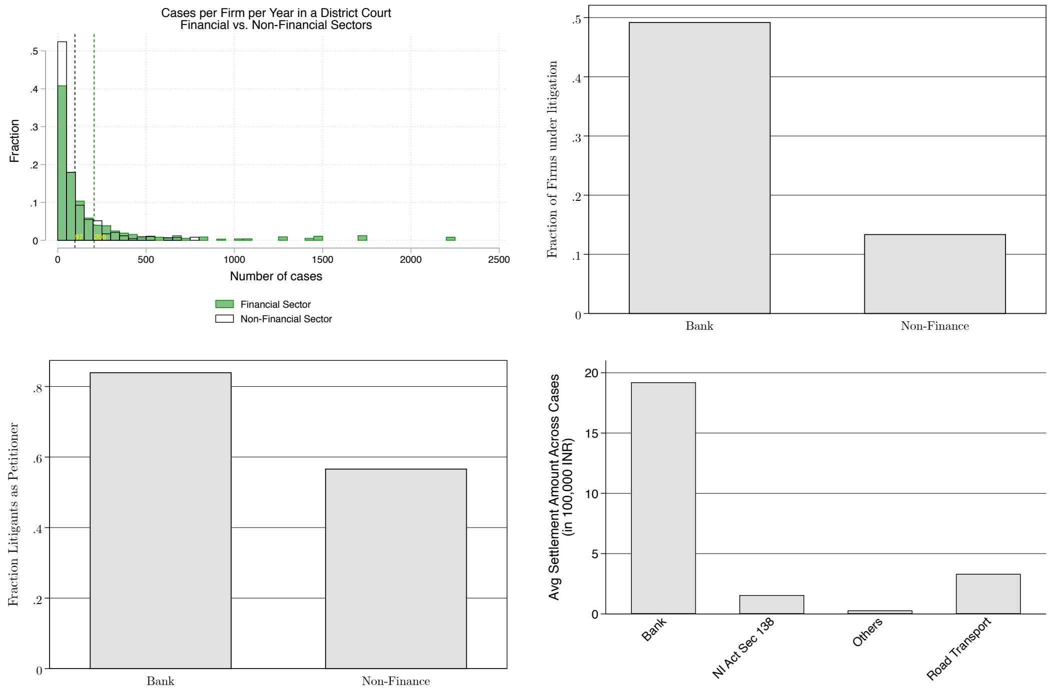


Notes: Following Dube et al. (2022), the local projection DID specification accounts for empirical challenges arising from impulse response functions generated by judicial staffing changes that occur many times and in opposing directions within the study period, similar to events in finance. Each coefficient in the graphs above represent a separate specification as follows with $h = -4, -3, ..., 3, 4$, i representing the unit of observation - firm or a district, and d referring to the corresponding district-court:

$$y_{i,t+k} - y_{i,t-1} = \beta_k \Delta NumJudges_{d,t} + \alpha_d + \delta_t + \epsilon_{i,t}$$

where Δ is the first difference operator.

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



Notes: Top-left figure presents the intensity of firm-related cases in district courts per firm, categorized as belonging to the financial sector or not. 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

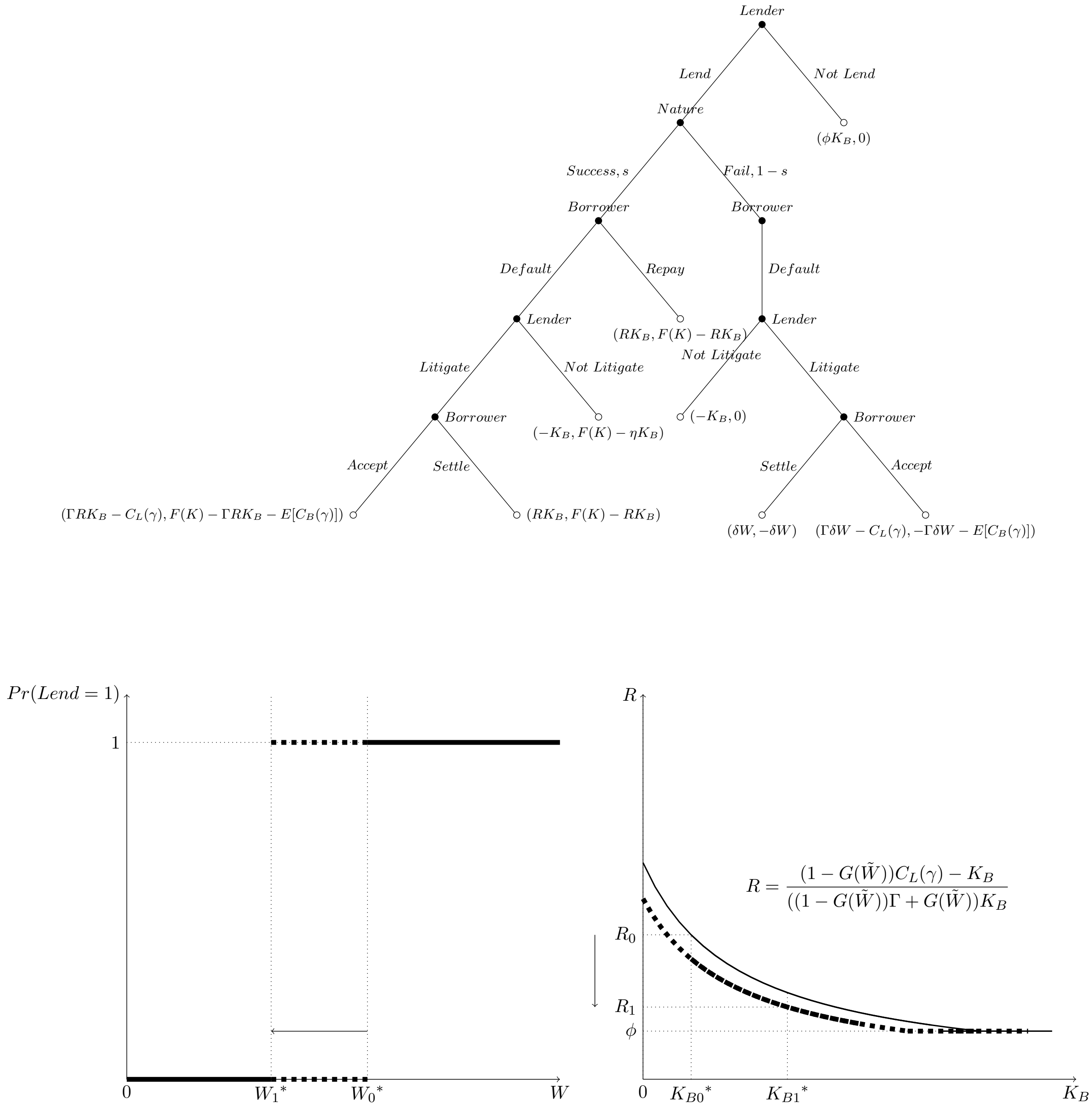
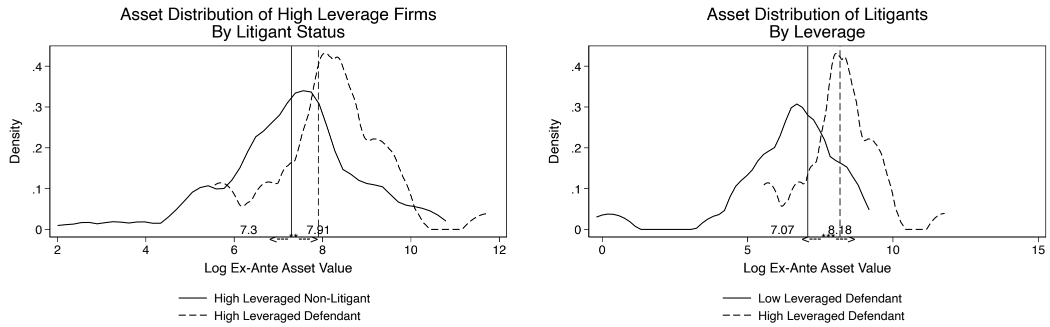


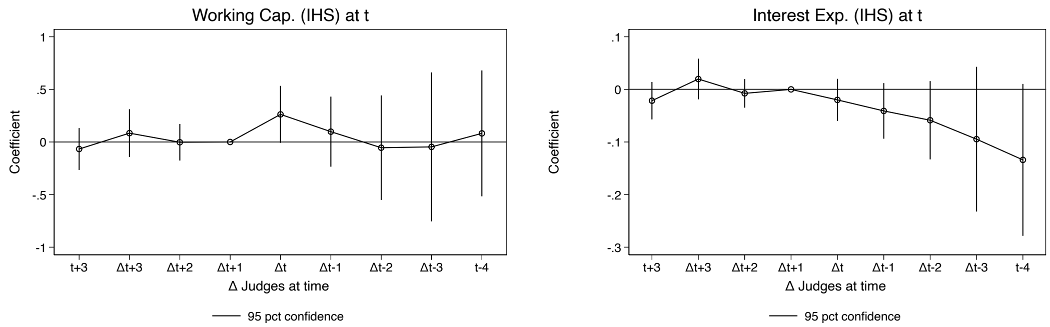
Figure A.13: Litigation Behavior



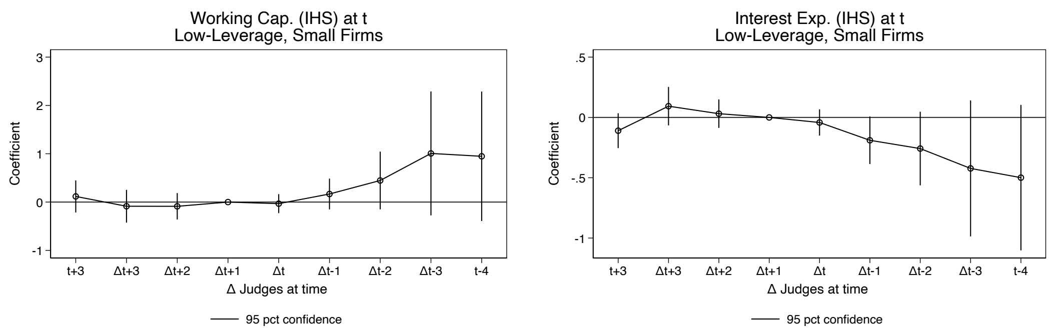
Notes: Panel A presents the kernel densities of local non-financial firms' ex-ante total asset value by: (a) litigation status among high leverage firms (left), and (b) leverage status among the defending firms (right). The lines represent the average asset values with statistical significance of this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

Figure A.14: Firms' Credit Outcomes: Continuous Explanatory Variable

Panel A: Firm-level Working Capital and Interest Expenditure - All Sample Firms

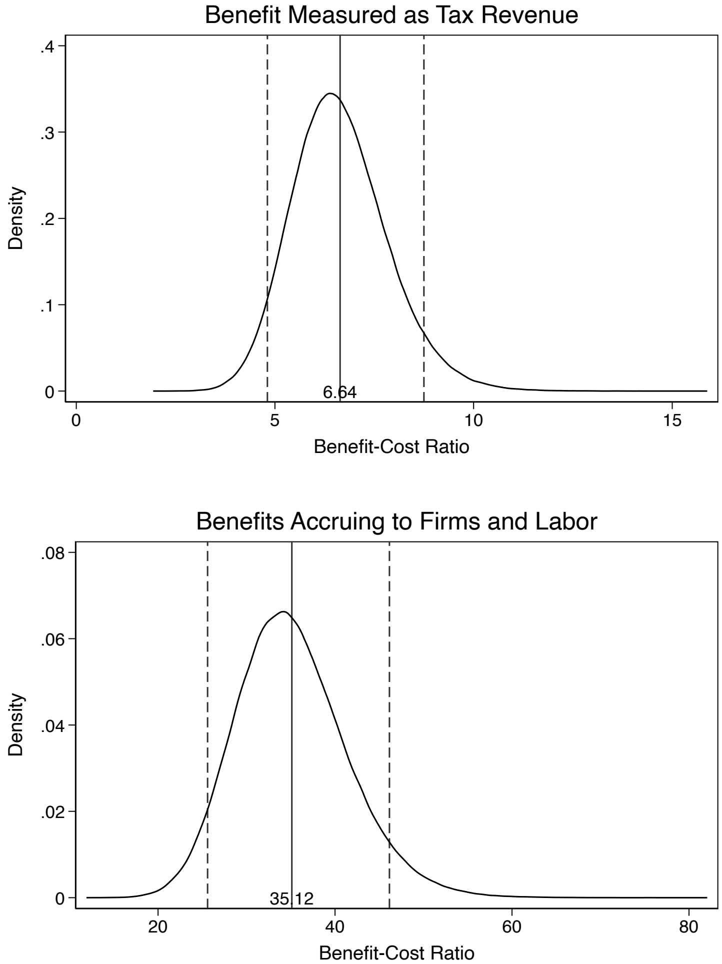


Panel B: Subsample of Low-Leverage, Small Sized Firms



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: 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.

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: Court Outcomes and Judge Vacancy Changes

	Vacancy	Removal			Vacancy	Creation
	(1)	(2)	(3)	(4)	(5)	(6)
	No. of Judges	100 - Vacancy Rate	Disposal Rate	No. of Judges	100 - Vacancy Rate	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 A.3: 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.4: 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.5: 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.6: 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 A.7: 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 A.8: Vacancy Removal and Unbalanced Firm-Level Data

	(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	-0.0359	-0.0457	-0.0406	-0.0185	-0.195	0.0594	0.00212
	(0.0122)	(0.00681)	(0.0339)	(0.00299)	(0.0166)	(0.0602)	(0.0267)
Pos x -3	-0.00492	-0.0237	-0.0164	0.0297	-0.0860	0.0570	-0.0207
	(0.00847)	(0.00575)	(0.0267)	(0.00422)	(0.0292)	(0.0728)	(0.0118)
Pos x -2	-0.0143	-0.00698	-0.0270	0.000962	-0.00186	0.0000186	0.00546
	(0.00842)	(0.0105)	(0.0177)	(0.0124)	(0.0875)	(0.0358)	(0.00662)
Pos x 0	0.0128	0.000795	-0.0120	0.00255	-0.0453	0.0166	-0.00727
	(0.00912)	(0.00375)	(0.00719)	(0.0125)	(0.0351)	(0.0368)	(0.0130)
Pos x 1	0.0141	-0.0102	-0.000444	0.0126	-0.0450	0.00876	-0.0157
	(0.00438)	(0.0106)	(0.00782)	(0.00877)	(0.0200)	(0.0331)	(0.0108)
Pos x 2	0.0175	-0.00371	-0.000445	0.0120	0.0153	0.0335	-0.0101
	(0.00269)	(0.00536)	(0.00758)	(0.00413)	(0.0161)	(0.0156)	(0.00471)
Pos x 3	0.0127	-0.00824	-0.0167	0.00950	-0.0449	0.0357	-0.0169
	(0.00253)	(0.0114)	(0.00922)	(0.00791)	(0.0204)	(0.0231)	(0.00504)
Pos x >=4	0.0120	-0.0106	-0.0226	0.000800	-0.0652	0.0332	-0.0298
	(0.00335)	(0.0149)	(0.0265)	(0.00824)	(0.00853)	(0.0168)	(0.00433)
Observations	201696	180969	129551	201093	218988	236671	171867
No. Firms	6689	5746	4341	6726	6981	7489	5909
No. Districts	149	148	140	150	150	152	147

Standard errors in parentheses

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. Standard errors are clustered by district and event.

Table A.9: Vacancy Creation and Unbalanced Firm-Level Data

	(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	0.00474	0.0134	0.0108	0.00469	0.0303	-0.00271	0.0137
	(0.00245)	(0.00662)	(0.00829)	(0.00144)	(0.00831)	(0.00279)	(0.00254)
Neg x -3	0.00157	0.00857	0.00999	-0.000129	0.00846	0.00915	0.0122
	(0.00307)	(0.00503)	(0.00994)	(0.00506)	(0.0110)	(0.0116)	(0.00175)
Neg x -2	0.00399	0.00417	0.0102	0.00196	-0.00443	0.00649	0.00388
	(0.00254)	(0.00392)	(0.00392)	(0.00192)	(0.0155)	(0.0107)	(0.00159)
Neg x 0	-0.00419	-0.00349	0.00258	-0.00188	-0.00632	-0.00667	-0.00110
	(0.00386)	(0.00244)	(0.00158)	(0.00134)	(0.00579)	(0.00468)	(0.00185)
Neg x 1	-0.00555	-0.00820	-0.00282	-0.00572	-0.0298	0.00629	-0.00486
	(0.00282)	(0.00369)	(0.00227)	(0.00189)	(0.0195)	(0.0108)	(0.00187)
Neg x 2	-0.00963	-0.0128	-0.00284	-0.00732	-0.0573	-0.00801	-0.00723
	(0.00130)	(0.00229)	(0.00377)	(0.00197)	(0.0275)	(0.0195)	(0.00402)
Neg x 3	-0.0117	-0.0189	-0.00525	-0.00897	-0.0386	-0.0214	-0.00917
	(0.00202)	(0.00340)	(0.00294)	(0.00435)	(0.0193)	(0.00913)	(0.00272)
Neg x >=4	-0.0147	-0.0245	-0.0106	-0.00878	-0.0480	-0.00563	-0.0144
	(0.00234)	(0.00356)	(0.00852)	(0.00594)	(0.0128)	(0.00678)	(0.00224)
Observations	201696	180969	129551	201093	218988	236671	171867
No. Firms	6689	5746	4341	6726	6981	7489	5909
No. Districts	149	148	140	150	150	152	147

Standard errors in parentheses

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. Standard errors are clustered by district and event.

Table A.10: 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.11: 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.12: 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.13: 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.14: 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.15: 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.16: 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.17: 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.18: 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.19: Dropping Largest Districts: 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	-0.0141	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.20: 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.21: 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.22: Decomposition - Firm Profits

	(1)	(2)	(3)	(4)
Sales	1.635	1.637	1.405	1.242
	(0.331)	(0.332)	(0.263)	(0.307)
Working Cap	0.115	0.114	0.120	0.107
	(0.0275)	(0.0278)	(0.0305)	(0.0355)
Interest Exp	-0.855	-0.856	-0.756	-0.997
	(0.199)	(0.200)	(0.193)	(0.189)
Lesser Crime	-0.131			
	(0.123)			
All Crime		-0.104		
		(0.463)		
Profit t-1	0.0214	0.0210	-0.00181	-0.00443
	(0.0212)	(0.0212)	(0.0206)	(0.0212)
Profit t-2	0.0161	0.0165	0.00260	-0.00359
	(0.0121)	(0.0122)	(0.0127)	(0.0174)
Observations	2708	2708	2503	2114
No. Firms	369	369	341	299
Firm FE	X	X	X	X
Year Interactions	State-Year	State-Year	District-Year	District-Year, Industry-Year

Notes: This table presents a firm fixed effect regression of asinh-transformed variables - profit (dep var) on sales revenue, working capital, interest expenditure, local crime (depending on other district-time controls) and lagged profit variables. Following firm-level profit maximizing problem, profit should be positively correlated with sales revenue with an elasticity close to 1 as well as the extent of working capital to finance operating expenses, whereas negatively correlated with the cost of borrowing (reflected in interest expenditure) and other costs induced by local crime. Columns 1 and 2 control for state-year dummies to non-parametrically account for macro-economic changes at the state-level in addition to firm fixed effect. Columns 3 and 4 introduce district-year and additionally, industry-year dummies respectively. Since crime variables vary only at the district-year level, these are absorbed by the district-year dummies. The purpose of this table is to suggest that financing-related costs have larger elasticities with respect to firm profits compared to local crime.