Frontline Courts As State Capacity: Micro-Evidence from India

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Courts facilitate dispute resolution, making them a key component of state capacity. Using administrative rules that generate exogenous variation in the timing of creation and resolution of judge shortages in district courts in India, I show that each additional judge resolves 200 cases, lowering the extent of litigation backlog. In a context with many pending debt recovery trials, adding judges improves credit circulation, and increases profits and wage bills of local formal sector firms. I conservatively estimate that investing in judicial staffing generates a benefit-cost ratio exceeding 3. (*JEL* O16, O43, K41, G21)

Courts play a central role in enforcing contracts and property rights, which supports the development of the formal financial sector, investment, and economic growth (La Porta et al. 1998; Djankov et al. 2003). Long lags in trial resolution can increase uncertainty and transaction costs that impede effective contracting and weaken *de facto* rights (Johnson et al. 2002). While this is well supported in theory (North 1986), there is little empirical evidence using disaggregated data on the day-to-day functioning of courts. In this paper, I exploit the universe of trial-level data between 2010 and 2018 from a quarter of sub-national (district) courts in India to examine the effect of relaxing judicial capacity constraints on local economic development.

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District courts in India had over 11 million trials pending for more than 3 years as of 2019, implying 10 times more backlog per capita relative to similar courts in the United States. A key constraint is staffing of courts. 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 further after taking into account the extent of vacancies. In addition to affecting overall trust in market transactions (Nunn 2007), poor capacity of courts can also constrain factors of production, stuck under litigation, from being put to productive use. This situation is not only exclusive to India and other developing economies but also common among the judiciary in many OECD countries (Coviello et al. 2015).[1]

In this paper, I exploit administrative rules on judge reassignments that generate sharp discontinuities in the number of judges in district courts around these events, significantly affecting courts' capacities to resolve the backlog of litigation. I use a stacked event study design that accounts for treatment effect heterogeneity across districts and over time (Sant'Anna and Zhao 2020, Sun and Abraham 2021) and verify that there are no significant trends in the prior period as a support for the parallel trends assumption.[2]

I employ this research design using court-level variables that I generate from 6 million disaggregated litigation records from a sample of 195 district courts between 2010 and 2018. I use timestamps in the data to construct judges' workflow and calculate the number of judges, the number of cases filed and resolved, and the rate of backlog resolution (disposal rate) in the sample courts in each calendar year. I merge this court-level dataset with a balanced panel data on non-financial sector firms using their registered office location to examine the effects of judicial staffing changes on firm profits and factor use. A majority of such firms in India are single plant firms (Hsieh and Olken 2014); therefore, the location of registered office is also the location of production. Further, firms primarily borrow locally - for example, from the local branches of banks.[3] Thus, performance of the corresponding district court is likely

[1]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.

[2]I examine the robustness of the reduced form results through an alternate approach using the number of judges as a continuous-valued policy variable in a generalized event study design

[3]While such branches can be a part of large public or private-sector banks spanning national or

to be important in the context of debt contract enforcement and subsequent credit circulation. I also merge district-level annual bank lending outcomes with this dataset to help shed light on these mechanisms.

I report three main results from this analysis. First, I find a significant impact on court-level litigation backlog resolution (disposal rate) depending on the direction of staffing changes. A positive change increases the number of resolutions by 200 trials per judge added, increasing the disposal rate by 20 percent (2-3 percentage points) each year over the next few years. A negative change worsens trial resolutions, generating additional backlogs.

Second, I note a sharp increase in local firms' working capital and an increase in district-level aggregate lending by banks to industrial borrowers in the years following positive changes. I develop a conceptual framework that builds on standard lending models by introducing variation in the quality of contract enforcement by local 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 lower interest expenditure across all sample firms, and also among smaller firms with low ex-ante leverage.

Third, profits and the wage bills of local firms increase following positive changes in judicial staffing (decrease following negative changes). This suggests that an expansion of cheaper credit is important for the scale of firms' operations, especially in developing economies like India where firms are both credit constrained and credit rationed (Banerjee and Duflo 2014). Quantitatively, I find that the average wage bill and the average profit increase by 5% and 40%, respectively. Decomposing the long-run reduced form effect on firm profits, I find that the increase in working capital and the reduction in interest expenditure together explain over 80% of the increase in profits. Finally, these wage and profit effects are also seen among non-litigating local firms, suggesting a broad-based impact.

These findings highlight the substantial economic cost imposed by persistent judge vacancies in the Indian judiciary. A back of the envelope calculation of the benefit-cost ratio of reducing vacancy shows large returns. Using the causal estimates of staffing changes, I compute the benefit-cost ratio both from the perspective of public

international markets, the amount of credit for circulation is typically determined based on quotas with targets set for each branch. Therefore, recovered capital from debt-recovery litigations serve as additional liquidity available for recirculation locally. I discuss the context of banking in India in detail in Section 2B.

finance as well as social return. I measure social return only accruing to sample firms (through corporate profit) and their employees (through wages), which is likely to be an underestimate considering that an improvement in judicial capacity could generate many other benefits not examined by this paper. The calculation suggests that investing in judicial staffing generates over 3 times tax revenue relative to its cost considering even the most conservative estimate (the average indicates over 5 times return on investment). The social return is orders of magnitude higher.

This paper contributes to three strands of the literature. First, this shows that alleviating judicial staffing constraints can spur local economic development by facilitating an expansion of formal sector economic activity. In this regard, this paper builds on the works by Djankov et al. 2003; Chemin 2009; Visaria 2009; Chemin 2012; Ponticelli and Alencar 2016; Amirapu 2017; Kondylis and Stein 2018; Boehm and Oberfield 2020. The literature hitherto has either taken an aggregate approach - exploiting cross-sectional variations in court efficiency measures, or focused narrowly on a small number of courts, reflecting a lack of micro-data at scale. Using large-scale disaggregated data, I show that courts experience varying degrees of staffing shortages over time that affect their capacity to resolve ongoing litigation, generating a substantial consequence on social welfare. These estimates are likely a lower bound since I do not consider longer-term efficiency gains through channels such as: firm entry and exit, spillovers on the informal sector, and effects on household consumption.[4]

Second, this paper highlights the importance of well-functioning courts for facilitating credit markets. A large literature has documented the significance of institutional finance for firm and economic growth, which is particularly salient in the context of developing economies where firms and individuals are credit constrained (Rajan and Zingales 1998; Burgess and Pande 2005; Banerjee and Duflo 2014). This paper shows that courts play a key role in unlocking capital tied-up in litigations and enable banks to recirculate cheaper credit. Additional research is required to understand whether this effect can also be interpreted as lowering capital misallocation. If lenders recirculate credit to potentially defaulting borrowers (Khwaja and Mian 2005; Cole 2009; von Lilienfeld-Toal et al. 2012; Giné and Kanz 2017) as refinancing to prevent actual

[4]Further, this complements a vast criminal justice literature from the US and other high income countries that show mixed social welfare implication of judicial capacity. Yang (2016) shows that judge vacancy in the United States increases trial dismissals by prosecutors and Dobbie et al. (2018); Bhuller et al. (2019); Norris et al. (2020) find mixed effects of incarceration on social welfare by exploiting variation in judge leniency.

default, then this would require complementary policies regulating lenders. However, the effects on interest expenditure and firms' production outcomes, on average, suggest that banks likely reallocate freed-up capital from debt recoveries to high return economic activity.

Finally, the results in this paper underscore the need to adequately staff key public institutions in order to enhance state capacity in low and middle income countries. A growing body of literature has noted a significant relationship between reducing staffing constraints and improving public service delivery in sectors ranging from education (Muralidharan and Sundararaman 2013), public works (Dasgupta and Kapur 2020), and early childhood development (Ganimian et al. 2021).[5] This also complements literature that examines the economic costs of staff absence in the public sector (Duflo et al. 2012; Dhaliwal and Hanna 2017). By focusing on a much understudied sector - the sub-national judiciary, this paper estimates the marginal value of public fund (Hendren and Sprung-Keyser 2020) of at least 3 from reducing judge vacancies.

The rest of the paper is organized as follows. Section 1 discusses the context and assignment of judges to courts. Section 2 presents the data sources, and discusses the court and economic outcome variables. Section 3 details the empirical strategy for causal identification, with the first stage summarized in Section 4. Section 5 presents a conceptual framework on access to credit as an important mechanism that I empirically test, documenting the results on local firm production in Section 6. Section 7 provides a discussion on the key findings along with a benefit-cost analysis. Section 8 concludes.

1 Context

World Justice Project Rule of Law Index ranks India in the bottom half of 128 countries in civil and criminal justice (ranks 98 and 78, respectively, as per World Justice Project 2021). Further, countries in the bottom half of the ranking are mainly low and middle income countries suggesting a strong correlation between rule of law and 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.

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

The judiciary in India is a three tier unitary system in contrast to the federal structure of the executive and the legislature. In this paper, I examine the functioning of courts at the district-level, which are often the first interface of the judicial system. Specifically, I study the District and Sessions Court (hereinafter called district court), which is typically the court of first instance for disputes involving contracts and firms. There is one district court per administrative district, which also serves as the court of appeal for judgements from sub-district courts within its jurisdiction.[6]

Due to separation of powers, the judiciary in India is responsible for setting policies for its functioning including recruitment of judges and management of courts whereas the budgetary power rests with the state-level executive. So, any reform that the judiciary wants to adopt can only be implemented with budgetary support from the executive. However, 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 Capacity Constraints

The number of judges relative to the country's population is perhaps one of the most critical constraints. On average, there are 20 authorized judge posts per million. In contrast, there are close to 100 judges per million in the United States (Institute for the Advancement of the American Legal System 2021) and close to 200 per million in the European Union (European Union 2021 average over 2017-2019). This ratio is further reduced when we account for the extent of vacancies in these posts.

The total number of judge posts in a district is determined jointly by the respective state high court and the state-level executive based on the underlying population, whereas personnel policies such as judge tenure and assignment are under the purview of the high courts alone. While there is no clear rule on how the number of judge posts are revised over time, periodic reports by the Law Commission of India, an executive body under the central government Ministry of Law and Justice (particularly, The Law Commission of India (2014) report No.245), point out that there is no specific

[6]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.

approach hitherto and is relatively ad hoc. Typically, the numbers are determined at the time of setting up a court's physical infrastructure, which happens once every few decades (mainly at the time of district formation) rather than vary at a shorter time scale. Figure A.1 (Top Panel) shows a strong, albeit imperfect correlation between district population and the number of judge posts.

Further, about a quarter of judge posts in district courts are vacant, which have persisted or worsened over the years (see Bottom Panel 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.

District judges are senior law officials, who are promoted from sub-district courts after reaching seniority. A few are directly hired from the state bar council, and a few through competitive exams. They typically serve 10-15 years before retiring, unless promoted to the state high court, if at all. These judges serve a short tenure in any given court - 2-3 years (see Top Panel, Figure A.2), and are frequently rotated. The state high courts determine judge assignment and rotations between district courts. Each year, a high court committee on district judge assignments examines the list of judges completing their tenure in their current location. The committee then assigns these judges to different district court locations, ensuring no repetition over their tenure. Further, judges are never assigned their home district or districts where they have had any legal experience (for example, as a lawyer).

The specific assignment process is based on a seniority-first serial dictatorship mechanism, subject to the specific constraints listed above. A judge coming up for a reassignment is asked to list 3-4 rank-ordered district court locations for their next posting. The high court committee collates these lists and carries out the assignment algorithm each cycle. First, the senior-most judge is assigned their top ranked location. Next, the second senior-most judge is assigned their top-ranked location as long as it does not conflict with the more senior judge, and so on. In case of conflict, the assignment moves down the ranking order of the more junior judge. Finally, newly recruited judges are assigned randomly to a court with vacancy, also subject to the constraints above.[7]

[7] There is a lot of similarity in these processes across states with only minor differences. The main point being that these policies are decided centrally, based on written rules, and not decided by any individual high court judge or district courts.

High courts rarely override the above assignment rule in order to manage the number of vacancies across district courts in the state. The Law Commission of India (2014) Report No. 245 expresses concern about the high number of district judge vacancies and recommends an algorithm to determine the required number of judges to reduce backlogs. This algorithm is based on past annual case filing and average judge productivity (resolution rate). However, applying this rule to the data shows that this recommendation is rarely followed (Bottom Panel, Figure A.2).[8]

An unintended consequence of these policies and systemic constraints is that the number of judges in a district court vary in an ad hoc fashion over time. Given chronic vacancies and delays in recruitment, these policies generate as good as random variation in the *timing* of creation and filling up of vacancies, and perhaps even the extent of vacancy, within a district court. This is central to my identification strategy, which I discuss in detail in Section 3 below.

2 Data

2A Court-level Variables: Explanatory Variables

I assemble the universe of 6 million public trial records from the E-Courts database (Supreme Court of India 2018), spanning all litigation filed or pending for resolution between 2010 and 2018, from a sample of 195 district courts (see **??**). These districts were selected to ensure an overlap with the location of registered formal sector firms in predominantly non-metropolitan industrial districts and is representative of other similar districts in India. Each record details the trial meta-data as well as lists hearing dates with the corresponding trial stage.[9]

Observing number of judges: The trial data also records the courtroom number and the judge post where a case has been assigned. Since the data represents the universe of trials between 2010 and 2018, I am able to identify whether a specific judge post is vacant based on annual workflow observed for that post. To illustrate,

[8]The correlation between observed number of judges and the predicted number of judges based on the algorithm is purely mechanical due to serial correlation in the number of judges within a court over time.

[9]E-courts is a public facing e-governance program covering the Indian judiciary. While the setting up of infrastructure for the computerization of case records started in 2007, the public-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.

courtrooms in a district court are numbered 1, 2, 3,... and the judge posts are labeled Principal District Judge (PDJ), Additional District Judge (ADJ) 1, ADJ 2, etc. Workflow in a given calendar year corresponding to a specific courtroom and judge post is recorded as a trial resolution, outcome of a hearing, interim orders, or filing of a new trial. Therefore, I encode the specific judge post as present if I observe non-zero workflow in a given year and as vacant, otherwise.[10] With this encoding, I generate the number of judges in a district court for each year in my study period, which is consistent with the data reported in the Law Commission Reports.

Changes in staffing from judge additions and removals: The number of judges vary within a district court over time. I mark a year as a positive judicial staffing event if the number of judges is greater than that of the preceding year and as a negative event if the number is less than that of the preceding year. Years with no addition or removal are those with the same number of judges as the preceding year. This strategy only examines changes in court-level judge staffing in aggregate and cannot distinguish individual judge addition from new assignments or instances of removal from outgoing judge or retirement.

Constructing annual court performance variables: I construct court-level annual workflow panel data from individual trial records. I define and construct the key performance variable - rate of backlog resolution (henceforth referred to as disposal rate), as the percentage of total workload resolved in a year. The numerator in this ratio is the number of cases resolved in a year whereas the denominator is the sum of cases that are newly filed and those pending for resolution as of that year. This measure is strongly correlated with other possible measures of court performance (see Table A.1 for pairwise correlations between the different measures). For robustness, I construct an index as the first principal component across all these measures using Principal Component Analysis.[11]

[10] For some states, the position is coded as "VACANT" in case of vacancy in the data but this is not consistent across all districts in the sample as well as over the study period. Some case meta-data also contains judge name, but again, this is not consistently recorded across all districts as well as over time. Therefore, I am unable to exploit rich judge-level characteristics using this data.

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

2B Firm-level Variables: Outcome Variables

Population of Interest: Matching firms by their registered office location presents the relevant legal jurisdiction for the set of non-financial firms that form the population of interest, as also followed in von Lilienfeld-Toal et al. (2012). For such firms, registered office location is also the corporate headquarters and the location of production since a large share of firms in India are single-plant firms (Hsieh and Olken 2014). Registered office location is also the relevant court jurisdiction for potential litigations against a firm, as per the Code of Civil Procedure, 1908.[12] Further, I only consider firms incorporated before 2010 - the beginning of the study period, and those that continue to exist until 2018 - the end of the study period, in order to prevent any confounding due to firm entry and exit.

On the other hand, financial firms like banks can be engaged in litigation even outside their home district. In fact, banks have to file debt recovery disputes in the district court of their borrower. Qualitative interviews with managers and legal counsels of large banks suggest that 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 is also followed in the case of firms where lending is through bank branches located in the same district as the firms' registered office location.[13] Further, these branches have quotas and targets for lending every year, with additional quotas for specific economic sectors (for example, small and medium enterprises) set by the central bank. The details of lending, repayments, and write-offs due to unpaid debt, all are accounted in the "profit and loss statements" (balance sheets) at the branch-level, whose officials face incentives tied to these. Therefore, judicial capacity of courts in the same location as borrowers matter for banks for enforcing debt contracts.

Firm-level data: I use CMIE-Prowess dataset covering 49202 firms to measure

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

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

annual firm-level outcomes. The data are collated from annual reports, stock exchange reports, and regulator reports for the universe of all listed companies ($\approx$ 5000 listed on Bombay and National Stock Exchanges) and a sample of unlisted public and private companies representing formal, registered firms. Since the organized sector accounts for $\approx$ 40% of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), this dataset captures a large share of value addition in the economy. Firm-specific outcomes include production (sales revenue, wage bills, value of capital goods, and raw material expenditure), accounting (profit and loss), and borrowing (working capital and interest expenditure) variables. Detailed identifying information in the dataset, including firm name and registered office location, enables me to match them with the court-level dataset.

Banking data: For banking outcomes, I use aggregate district-level lending statistics across all commercial banks as provided by the Reserve Bank of India (RBI). This includes total number of loans, and total outstanding loan amount, disaggregated by sector and type of bank.

Sample construction: Of the 49202 firms, 13298 firms are registered within the jurisdiction of 161 of the 195 sample district courts. Remaining 34 district courts result in no match. While 4739 non-financial firms were incorporated before 2010, only 393 remain in the balanced panel spanning 64 districts with the court data and thus form the main sample for analysis.

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

Next, I fuzzy-merge these firms with the trial dataset using firm names and manually verify the resulting matches. About 190 of these firms have one or more trials during the study period. Further among these, 142 firms appear as defendants, consistent with the assumption that home district courts are the relevant institution. Appendix Figure A.3 describes the firm sample construction process in detail.

2C Summary Statistics

Panel A of Table A.2 presents summary statistics for the court variables. On average, there are 18 judge posts per district court, with 23 percent vacancy. There are 1.62 instances of positive staffing change with 2 judges added, and 3.6 instances of negative

change with 3 judges removed per district court over the sample period. Average disposal rate is 14 percent with standard deviation 12, that is, 14% of total workload is resolved in a given year. In other words, it would take nearly seven years to clear all backlog if there were no new litigation. The timestamps on individual trials resolved within the study period indicate an average trial duration of 420 days (SD 570 days). A key difference between disposal rate and the average trial duration is that the former includes the universe of all trials within the study period whereas the latter only includes duration for trials that were resolved within this period. Therefore, disposal rate avoids selection concerns in its construction process.

Panels B and C describe credit market and local firm-level outcomes. On average, banks make 9138 loans per year with about USD 4.2 million (INR 310 million) in circulation (outstanding amount) to the industrial sector within the sample districts. The summary on annual firm-level financials indicate that these are large firms, with USD 181 million (INR 1.35 billion) in average sales revenue and USD 10 million (INR 740 million) in average profits. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

3 Research Design

As detailed in Section 1, judge staffing level in a court changes frequently due to addition and removal of judges resulting from their 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 capacity improvements and negative changes for the effect of capacity declines.

3A Stacked Difference in Differences Event Study

With a one time, albeit staggered, change in district court's number of judges, the causal effect parameter could be estimated using recent dynamic difference in difference estimators that correctly account for dynamic treatment effects and treatment effect heterogeneity across groups and cohorts (Sant'Anna and Zhao 2020, Sun and Abraham

2021). However, in the context of this paper, district courts experience multiple staffing changes, and in opposing directions, over the study period. My preferred empirical strategy takes into account this multiplicity of events, occurring in different years across district courts, by stacking separate datasets generated for each district-event. The dataset for an event e within a district d is centered around one period prior to the event with relative yearly event-time bins, including binned end points (clubbing all the years in the dataset outside this effect window). I append all such district-by-event datasets to generate a stacked dataset for analysis, with each event indexed by an event number (this strategy follows Deshpande and Li 2019 that uses event studies around the closing of social security offices and Cengiz et al. 2019 that examines the effect of multiple minimum wage revisions on employment distribution, both in the context of the United States).[14]

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

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

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

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

[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.

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. I test for the presence of any pre-period differential trends by examining $\beta^{+}_{j} = 0, \beta^{-}_{j} = 0; \forall j < 0$.

I restrict the effect window to 4 years prior and post with binned endpoints. This completely includes the full tenure of judges in a court. The coefficients within this window are also estimable without loss of precision given the limitations of my data. For inference, I use two-way cluster robust standard errors for estimated event-time coefficients, clustering by both district and event (Bertrand et al. 2004, Abadie et al. 2017).[15]

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

3B Alternate Identification Strategy

I use the number of judges as continuous-valued "treatment" in a generalized event study framework. As before, the identifying assumption is less stringent than assuming that the number of judges in any given year is random, but relies on "parallel" trends between districts with one more judge than others. Though using this approach will not produce comparable estimates of the causal effect parameter from the stacked event study approach above, it serves two purposes: (a) provides a qualitative test for whether the estimated parameters from the stacked event study approach is of the

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

right sign, and (b) provides coefficients that can be interpreted as changes in outcome arising from a unit change in the number of judges in a court.

I implement the generalized event-study design following Schmidheiny and Siegloch (2020) and Freyaldenhoven et al. (2021) as follows:

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

where Δ is the first difference operator and the effect window spans 4 years in the lead and 4 years in the lag. $judge_{dt}$ is the number of judges in a court d in year t. As before, y_{it} is the outcome of either local firm or district court, and 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. $judge_{d,t-4}$ and $1 - judge_{d,t+3}$ serve as the endpoints. For inference, I cluster standard errors by district.

Causal identification with this approach requires the following slightly stronger assumptions than my preferred empirical strategy: (a) parallel trends between treated and control districts as before, but (b) homogenous treatment effects across cohorts and groups.

4 First Stage

In this section, I discuss the reduced form results of judge staffing changes on court's performance with respect to resolution of litigation backlog. I start by showing the discontinuity in the staffing levels in Section 4A, followed by discussing the effects on court-level disposal rate in Section 4B.

4A Exogenous Timing of Staffing Changes

Panel A Figure 1 presents the regression coefficients on the interacted terms from Equation 1 using positive change dummy, showing that net addition of judges to courts generates a sharp increase in the number of judges immediately. On average, these events increase the number of judges by ≈ 2 over a baseline level of 15 judges, increasing the staffing level by over 13%. However, due to short tenure and reassignments in a context of chronic vacancies, the effect wanes over time. A negative change reduces

the number of judges in a court by a similar magnitude (Figure A.4).

The sharp discontinuity in the number of judges rather than a smooth change following positive staffing change suggests that chronic vacancies and policies on judge reassignments generate exogenous variation in the timing of court-level judicial staffing. While I fail to reject the null hypothesis for individual point estimates in the prior period, they are jointly significant with p-value 0.05. This would have been concerning if not for the sharp discontinuity in event-time. Moreover, these are not significant around the timing of negative changes.

Column 1 of Table 1 presents the estimates on positive change interactions in a tabular format and Columns 1-3 of Table A.3 by subsets of districts based on their population. The discontinuity can be seen across the different subsamples. Since the total number of judge posts in a court is a function of the corresponding district population, the net increase in the number of judges is marginally larger in more populous districts relative to other districts.

The staffing discontinuities are present even after dropping industrial states and metropolitan districts (Table A.4), suggesting that the judiciary closely follows its policies on tenure and frequent reassignment irrespective of the district characteristics (i.e., districts in non-industrial states or smaller, more rural districts are no more or less likely than others to experience staffing changes). Finally, the estimates continue to be significant when I cluster the standard errors by state and event (as opposed to district and event in the preferred specification), to account for any spatial correlation between district courts arising mechanically from reassignment of judges from one district to another (Figure A.5).

4B Reduced Form Effects on Court Performance

The sharp change in the total number of judges following positive (or negative) change has a substantive effect on the corresponding court's trial disposal rate as defined in Section 2. Panel B Figure 1 plots the regression coefficients on the event-time bins interacted with positive change dummy as per Equation 1. Disposal rate increases by ≈ 2 percentage points over a baseline of 12.62 percentage points, indicating an increase proportional to the increase in the number of judges. Each additional judge resolves 200 additional trials in a context where the average annual court-level caseload is $\approx$

20000 trials.[16] Negative changes worsen court disposal rate by generating additional backlogs each year (Figure A.4).

Columns 2-5 of Table 1 present the event study estimates of disposal rate as well as other court-level outcomes in a tabular format. These are - number of trials filed (Column 3), number of trials resolved (Column 4) and an index (Column 5) combining all other court-level performance measures. Estimation using the index as an outcome suggests an effect size of 0.2 standard deviation units.

These events generate similar magnitude of effects on court performance measures across various subsamples of courts, shown in Table A.3. Further, the results are robust to dropping top industrial states or metropolitan districts (Table A.4). Finally, the post-period estimates continue to be statistically significant even with clustering by state and event to account for spatial correlation between districts (Figure A.5).

Similar to the number of judges, court performance variables also exhibit a discontinuity in event-time. This clear break in trend suggests a causal relationship between changes in staffing and the judicial capacity of district courts in resolving litigation backlogs.

The generalized event study approach exploiting the number of judges as the continuous treatment variable following Equation 2 shows similar patterns of effects (Figure A.6), where consistently higher lagged number of judges translates into better disposal rates and overall court performance, with very little crowding out due to changes in demand for litigation (new litigations filed). This approach also demonstrates no significant correlation between prior period staffing levels and the current period court-level measures, further supporting the causal interpretation.

4C Patterns of Litigation Involving Firms

Matching firms to the trial records in the sample courts generates the sample of litigating firms, and identifies plaintiffs (petitioners) and defendant (respondent) firms. While these firms can be registered elsewhere, the code of civil procedure specifies the location of filing dispute, which is typically the location of the defendant. As discussed in Section 2B, a large majority of the litigating local non financial firms appear as defendants in the corresponding district court. On the other hand, close to 50%

[16] I also confirm these numbers by estimating the specification using number of resolved trials as the dependent variable. I focus on disposal rate as the key measure as it measures backlog resolution in terms of percentage reduction in the number of active trials.

of all commercial banks in India have at least one ongoing litigation in the sample courts and over 80% of the litigating banks appear as plaintiff (Figure A.8). What this suggests is that courts play an important in debt contract enforcements, since banks routinely have to file debt recovery disputes in the court of the borrower.[17]

5 Conceptual Framework

Role of Courts: Courts are state institutions and their functioning can vary spatially as well as temporally. The extent of staffing of courts and overall judicial/legal environment determine courts' enforcement ability. I consider the role of courts in the functioning of credit markets where enforceable debt contracts are central to the lending business.

Debt contracts: I follow a standard model of debt contract where the lender (e.g. bank) bases their lending decisions on whether repayment can be enforced through courts. Borrowers need external credit to finance investment in new or existing projects, that has some stochastic probability of success. The lender takes into account borrower wealth towards collateral requirement. Lending takes place only if lender's expected return from lending is greater than the market return. Upon completion of the contract period, the borrower either repays or evades, which is costly. Evasion leads to default, which initiates debt recovery process and subsequently, litigation. This recovery process incurs a cost to both lender and borrower, as a decreasing function of court's effectiveness in the resolution process. That is, better and faster resolution implies lower litigation related costs, ceteris paribus. Availability of judges, therefore, have a direct and important bearing on the functioning of courts.

Some borrowers may choose to litigate if their payoff is higher under litigation. Other borrowers may choose to settle with the lender and avoid continuing the litigation process. A sub-game perfect Nash equilibrium (SPNE) through backward induction suggests that the lender uses a wealth cut-off in order 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

[17]Parsing judgements from a random subsample of litigations involving banks indicates that about two-thirds pertain to credit default and about a fifth pertain to inheritance/property related disputes where the bank is involved through housing mortgage. Over 83% of the credit related disputes have outcomes in favor of the bank. This occurs either by undergoing full trial and obtaining a judgement in their favor or by reaching a settlement with the defaulting borrower, leading to its dismissal.

detail in Appendix A.2.

Production behavior: As banks lower interest rates and lend to smaller firms, firms re-optimize their production decisions. In addition to better access to credit, improved courts could also directly benefit their production processes through lower transaction costs, for example, with input vendors or through lower hold-up in labor disputes. While the effect on borrowing vary by firm size, the average effect on input use, production and profit is expected to increase for all.

Empirical tests Specifically, following the framework, I test for the following hypotheses in relation to an improvement in judicial capacity:

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

H2: Due to improved debt contract enforcement, interest rate decreases for all levels of borrowing. Lenders also lend to smaller borrowers.

H3: Firm sales and input use increase with judicial capacity.

H4: Firm profits increase with judicial capacity. For marginal firms, the effect on profit depends on the trade-off between increased input costs and benefits from reduction in other transaction and monitoring costs.

6 Reduced Form Effects on Economic Outcomes

In this Section 6A, I discuss key stylized facts about firms involved in litigation as a respondent (defendant) in light of the conceptual framework above. Next, I present reduced form effects on credit outcomes, both at the firm-level and market-level (district) in Section 6B. Finally, I explain the results on firm-level production outcomes in Section 6C, focusing on profits, sales revenue, wage bills, value of plant and machinery, and raw material expenditures.

6A Stylized Facts on Firms' Litigation Behavior

Figure A.9 shows the distribution of trials involving firms as defending litigants, which highlights the following key facts: (a) debt-related trials are many times more than other contract enforcement litigations,[18] (b) highly leveraged firms (i.e., those with

[18]The value of settlement is also orders of magnitude higher for debt relative to other contract enforcement or in tort cases such as road accidents (see Figure A.8).

ex-ante debt-equity ratio greater than 1) form a greater share of defendants, and (c) defendant firms have higher ex-ante asset value. This supports the proposition from the economic framework above that firms that frequently borrow and default on repayments end up being pursued by creditors through debt recovery litigation in courts. Further, larger defaulting firms participate in the litigation process rather than settle before going to court.

6B Credit Outcomes

The framework above suggests that access to cheaper credit is potentially important to firms to expand production since they are typically credit constrained. This is particularly true in the context of weak institutions and low-levels of financial market development. I begin with examining firms' access to credit by examining the reduced form effects of judicial staffing changes on firms' working capital and interest expenditure.[19] Next, I discuss the results on district-level lending by banks to industrial borrowers. All economic outcome variables are transformed using inverse hyperbolic sine (arcsine) function to account for 0s and negative values, and to help interpret the coefficients in terms of percentage changes.[20]

Access to Credit Panel A Figure 2 and Columns 1-2 of Table 2 show sharp discontinuities in firms' working capital (which jumps up) and interest expenditure (which jumps down) following positive staffing changes. Panel B Figure 2 and Columns 3-4 of Table 2 present the coefficients on the interaction terms for the subsample of smaller, less-leveraged firms. Leverage status along with firm size indicates: (a) fulfillment of firms' demand for debt by firm size, i.e. low leverage status among smaller firms suggests unmet debt needs, and (b) past access to formal credit. Consistent with the framework, cheaper credit is available to all firms, including smaller firms. This enables even those with lower borrowing in the past (plausibly due to their size and ability to meet collateral requirements) to expand their working capital subsequent to

[19]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.

[20]Translating coefficients into elasticities could be problematic using inverse hyperbolic sine transformation for small values or if a large fraction of values are zeros (Bellemare and Wichman 2020). However, in this context, the numbers are sufficiently large that either log or arcsine transformations yield similar results. For example, less than 2% of the working capital or profit values are 0.

an improvement in local judicial capacity.

Results from the generalized event study specification are also consistent with these findings (see Figure A.10). On the other hand, negative judicial staffing changes have no significant effect on working capital on average, whereas interest expenditure increases among small, less-leveraged firms although the coefficients are not statistically significant (Figure A.11).[21]

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

Panel C Figure 2 presents the event study graphs using total number of loans to industrial borrowers (left) and total outstanding amount from these loans (right) as the outcome variables. Positive changes increase the number of loans but does not significantly increase outstanding amount (money in circulation that includes both newly lent credit as well as credit due for repayment) from such loans. Columns 5 and 6 of Table 2 tabulate the coefficients on the event-time interaction bins. Heterogeneity by banking sector suggests these effects are mainly driven by private sector banks rather than public sector banks, where private banks increase both the number of loans and experience repayment.[22] Finally, negative changes lead to lower total lending and higher outstanding payments (Figure A.11).

There are two plausible reasons why creditors respond to changes in the number of judges in the corresponding district court. First, there is some persistence in the increase in judicial capacity (i.e., backlog resolution) following judge addition. This is also a relevant time horizon for short and medium-term loans (for e.g., loans for operating expenses rather than capital expansions), and therefore suggests an increase in short-term lending behavior. Second, timely resolution of debt trials enable banks to recover stuck capital, which increases their liquidity (by lowering provisions they need

[21]The results on interest expenditure across all firms does not conclusively indicate any specific pattern following negative judicial staffing changes: there is an evident declining trend in the prior period, and the negative coefficients in the post period are small and statistically insignificant.

[22]The incentive structure in public sector banks and soft budget constraints add further layers of complexity, in addition to the ability of local judicial institutions in enforcing debt contracts. See Table A.5 for lending results by banking sector.

to make in their profit and loss statements for any debt write-offs). This additional liquidity is likely recirculated as fresh credit as seen in the form of immediate increase in firms' working capital.

6C Local Firms' Production

The sample of firms comprises of all incumbent firms in the district that report their balance sheet data over the study period. This generates a balanced panel of firms that helps account for: (a) potential endogenous entry and exit of firms, and (b) endogenously missing annual financial data. Further, the specification includes firm fixed effect that absorbs all time invariant firm-level potential confounds.

The event study estimation shows a sizable effect following judicial staffing changes in the corresponding district court as shown in Figure 3 and Table 3 for positive changes. Wage bills increase gradually following net judge addition, increasing by 5% over the long-term relative to the baseline. Profits increase by over 40% relatively sooner. On the other hand, other input expenditures - value of plant and machinery (capital goods) and on raw material - and sales revenue show a modest increase and some of these are not statistically significant. Since profit is calculated from an accounting perspective, a part of the increase could be from sources other than production, such as lower expenditure on credit. The confidence intervals are also large, suggesting a large amount of heterogeneity.

These effects are also observed among non-litigating firms in the sample (Figure A.12). Further, the results are robust across many different 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.6 and Table A.7). 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.8). Finally, results from the generalized event study specification in Equation 2 using variation in the number of judges depict similar patterns of results (Figure A.13).

On the other hand, negative staffing changes have a much stronger negative effect, with significant decline not only in wage bill and profit, but also in sales revenue, raw material expenditure and the value of capital goods (Figure A.14).

One concern is that firms could be litigating in other courts not in the sample. Or that functioning of courts other than their corresponding district courts also matter and could bias the estimates if there are strong spatial correlations between courts. First, as discussed before, firms are more likely to be sued in their district court as per procedural law. Second, even if other district courts matter , the estimates presented here would likely be: (a) unbiased if there are no significant correlations between the key court-level variables in home district court and those of other courts in the same state, (b) a lower bound if these are negatively correlated with each other due to the nature of judge reassignment where judge addition to one court would mechanically be linked to a reduction in another.[23]

Decomposition of Firms' Profit Lastly, I decompose the reduced form effect on firms' profits discussed earlier into share arising from credit access, i.e., through changes in working capital and interest expenditure. In order to overcome the potential endogeneity problem in directly using current period working capital or interest expenditure to estimate their elasticities with respect to firm profits, I use a generalized event study design using leads and lags of these mediating variables similar to the specification in Equation 2.

Table 4 presents the results from this exercise. Columns 1 and 2 show that firm profits only respond to contemporaneous or lagged values of the mediating variables, and there is little evidence of significant trends in the prior period (the coefficient estimates on the leads are statistically and economically insignificant). Figure A.15 depicts the corresponding event study graphs. Applying the estimated elasticities to the reduced form effects of judge addition on working capital and interest expenditure, I calculate the increase in profits from credit mechanism. In percentage terms, these amount to 50.74% and 33.73%, respectively, explaining over 80% of the increase in firms' profits.[24]

[23]Staffing of courts in other states are in-principle uncorrelated with staffing in home district court since each states implements its own rotation system. Lack of any correlation between courts within the same state or a negative correlation helps put a direction on any potential bias arising from the rotation system. For there to be a positive correlation, home court and all other courts should experience judge increases/decrease at the same time. However, in the absence of expansions in the total number of judges within any state in this period, the bias term will likely be always negative due to the rotations.

[24]For increase in profits in period $t \geq 4$, I apply the estimated elasticities on working capital and interest expenditure to their respective reduced form estimates of net judge addition from $t = 0$ through $t \geq 4$, and sum it across these periods. I obtain the reported shares by dividing the increase

6D Alternate Explanations

Improved judicial staffing could also effect firms' production outcomes through channels other than credit access. For example, better enforcement environment could improve labor-industry relation and facilitate structural transformation. Additionally, it can improve supply-chain networks through better enforcement of trade contracts. However, as seen in Figure A.9, disputes other than debt recovery form a relatively small share of litigations involving firms as a respondent.

Further, better courts could improve the general law and order situation in the district. Lower crime could boost productive activities including industrial production. While this may be true, this does not rule out the importance of the credit channel. I find lower overall crime mainly driven by crimes lower in severity, which is likely to spur a whole gamut of productive activities including increased lending by banks (see Table A.9).

7 Discussion

7A On Debt Recovery Litigation

The results indicate that the shocks to local court capacities result in credit market adjustments and changes in local firm production. Courts play an important role in facilitating local credit market, plausibly through the recovery of capital tied-up in litigations.

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

in profit from either of the two variables by the overall increase in profit from net judge addition in $t >= 4$.

addresses an important concern in the state capacity literature - that of persistent vacancies in the public sector, in contrast to the introduction of additional agencies addressing public services.

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

7B Benefit-cost analysis

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

In Table A.10, I present the assumptions and the calculated benefit-cost ratio using these estimates. On the benefits side, I use the median values of profits and wage bills among an average of 6 sample firms per district to compute the increase in firm-level surplus and salaried income. Since both formal sector firms and salaried individuals pay corporate and income tax on their net income respectively, I also compute the benefit-cost ratio from the perspective of state revenue and expenditure generated at the district-level. I use the corporate tax rate for registered domestic firms in India as specified in the Taxation Laws Amendment Ordinance (2019). I calculate the effective income tax rate on salaried individuals as 7.3 percent based on applying the exemptions

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

and tax-slabs specified in the Union Budget, 2018-19.[26]

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

On the benefit side, I compute the discounted net present value of the increase in profits (benefit accruing to firms), wage bills (benefit accruing to the salaried labor force in the district), and the associated tax revenue for each year in the post period using the estimates and tax rates as detailed in Table A.10. I assume the discount rate to be 5% in the base calculation and perform sensitivity analyses using lower and higher discount rates (Table A.11).

Figure 4 shows the distribution of the computed benefit-cost ratios, both from the perspective of tax revenue generated for the state as well as social surplus, along with the 90% confidence intervals. To generate these distributions, I use 1000,000 random draws of the coefficient estimates from a normal distribution with mean equal to the estimated coefficients and standard deviation equal to the standard errors of the coefficients (as per the Central Limit Theorem). This basic computation shows that the benefits are orders of magnitude larger than the costs. For the state, the ratio implies revenues that are over 5 times higher than the expenditure on additional judges on average, whereas the social returns are even higher, implying a return over 30 times the cost. Even the most conservative estimates (with higher discount rate) suggest that the returns to investing in district judicial capacity is high and more than pays for itself.

8 Conclusion

To conclude, I show that well-functioning frontline judiciary is important for credit circulation and local firm productivity using disaggregated data and exogenous variation

[26]These assumptions are motivated by articles in the news media, with sources mentioned in Table A.10. 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.

in the timing of staffing changes in district courts in India. The current status-quo on the speed of trial resolution is abysmally low in a context where, on average, about a quarter of the judge posts are vacant. Therefore, reducing vacancy by adding more judges is a highly cost-effective intervention, suggesting over 3 times return to public expenditure.

This paper shows that regular courts play an important role in facilitating credit access, which complements their role in enforcing bankruptcy process or supply-chain trade contracts as shown in existing literature. This is concordant with the observation that debt recovery trials form the largest share of litigation facing firms. Lenders initiate litigation against defaulting borrowers as a necessary first step before taking collateral into possession or initiating bankruptcy proceedings. Consequently, firms are able to increase their working capital through cheaper loans. In a context where firms are credit constrained, access to cheaper capital helps expand production and profits.

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 institutional environment. For example, examining how functioning of district courts interact with the quality of laws protecting creditor rights can potentially shed light on the mechanisms behind capital misallocation.

References

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

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

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

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

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

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

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

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

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

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

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

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

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

Cole, Shawn, "Fixing Market Failures or Fixing Elections? Agricultural Credit in India," *American Economic Journal: Applied Economics*, January 2009, *1* (1), 219–50.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

of Denver Institute for the Advancement of the American Legal System, University, "FAQs Judges in the United States," 2021.

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

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

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

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

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

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

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

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

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.

Union, EU European, "Eurostat," 2021.

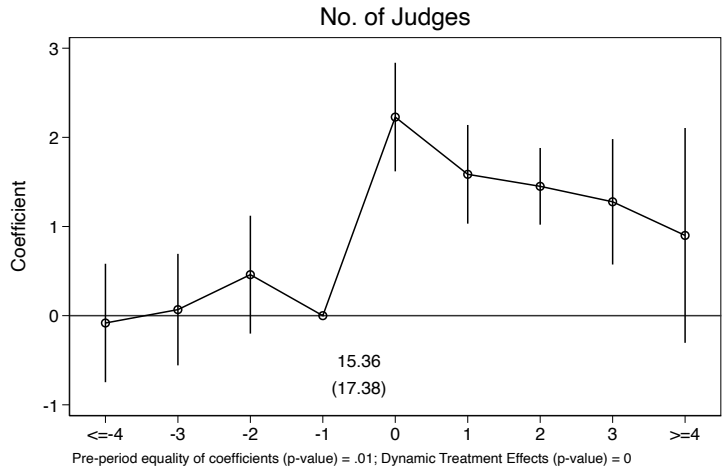
Visaria, Sujata, "Legal reform and loan repayment: The microeconomic impact of debt recovery tribunals in India," *American Economic Journal: Applied Economics*, 2009, *1* (3), 59–81.

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

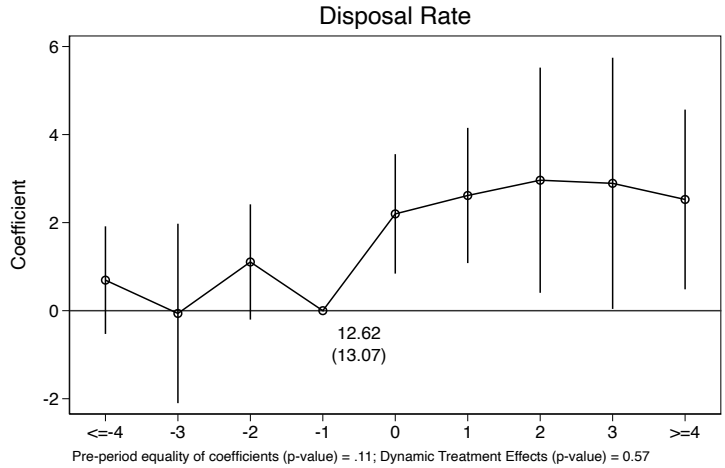
Yang, Crystal S., "Resource Constraints and the Criminal Justice System: Evidence from Judicial Vacancies," *American Economic Journal: Economic Policy*, November 2016, *8* (4), 289–332.

9 Figures

Figure 1: Positive Judicial Staffing and Court Performance
Panel A: Total Number of Judges



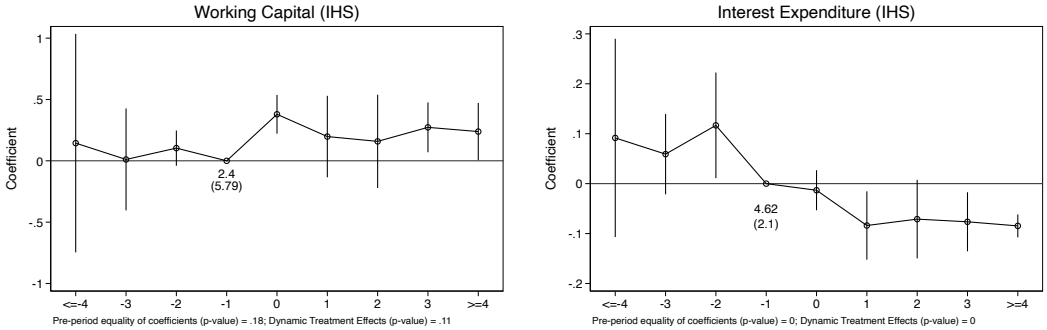
Panel B: Court-Level Disposal Rate



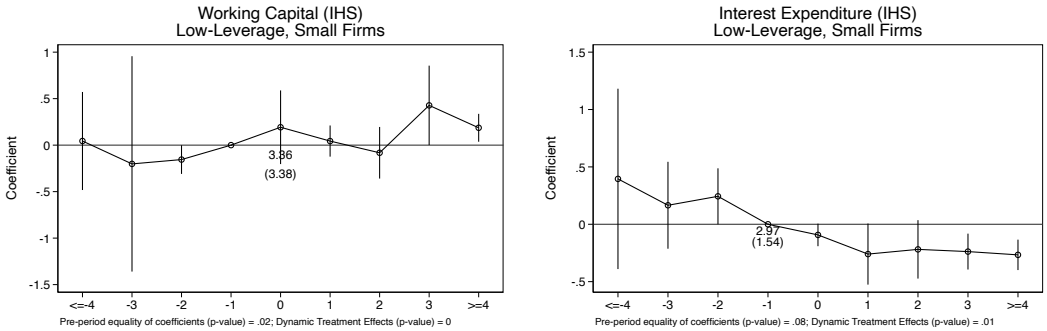
Notes: The figures plot the event study interaction coefficients for positive staffing changes from estimating Equation 1 using total number of judges (Panel A) and disposal rate (expressed in percentage terms in Panel B) as dependent variables, respectively. In all the figures, the end-points take into 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. Results from clustering by state - to account for any serial correlation between districts - are reported in the appendix Figure A.5

Figure 2: Credit Outcomes: Effect of Net Judge Addition

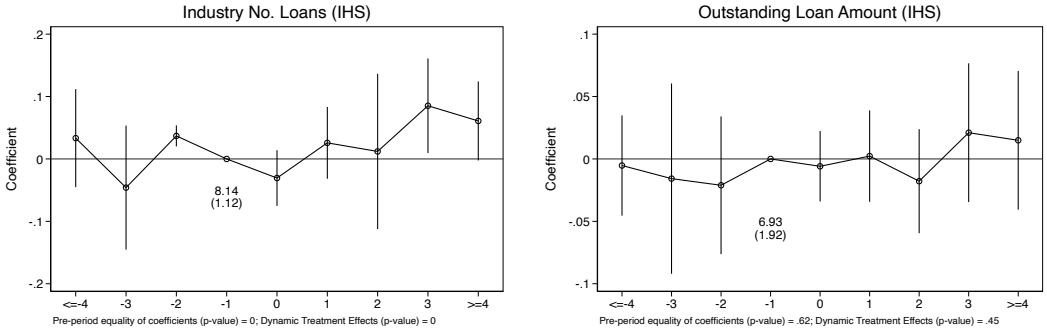
Panel A: Firm-level Working Capital and Interest Expenditure - All Sample Firms



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

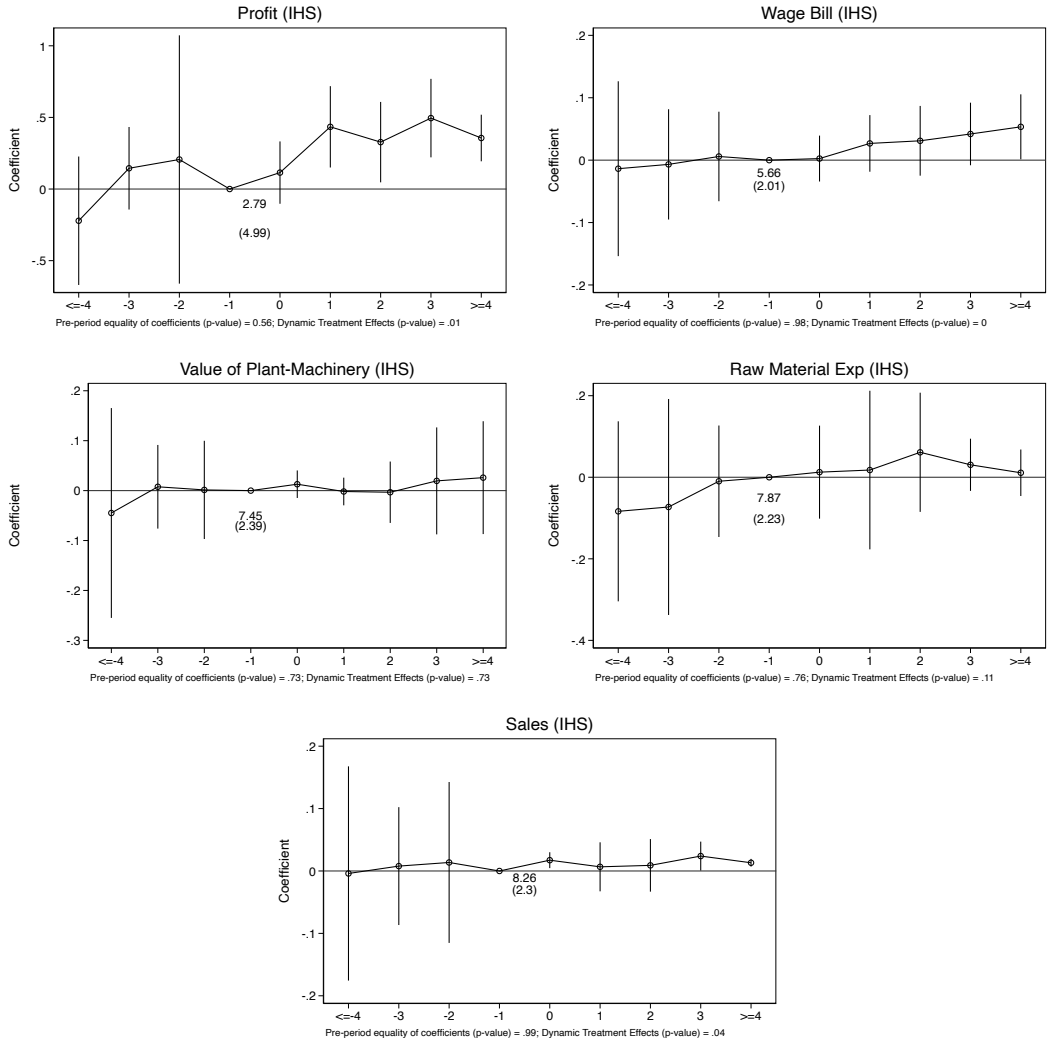


Panel C: Aggregate District-Level Bank-Lending



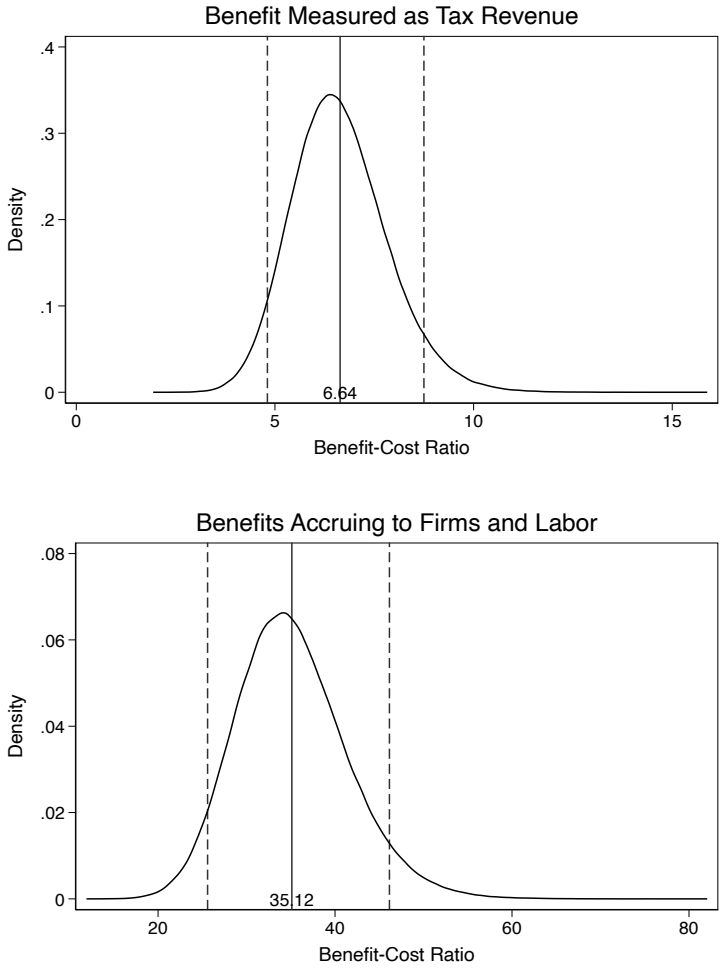
Notes: Panel A presents effects on working capital and interest expenditure for all firms and Panel B for the subset of small-sized less-leveraged firms. Panel C presents the results on district-level bank lending outcomes, with the regressions weighted by the number of active bank cases before the start of the study period. Error bars in Panel C present 90% confidence interval and rest present 95% confidence interval.

Figure 3: Local Firms' Production: Effect of Net Judge Addition



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

Figure 4: Benefit-Cost Ratio



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

10 Tables

Table 1: Court Outcomes: Net Judge Addition Stacked Event Study

	(1) No. of Judges	(2) Disposal Rate	(3) No. Filed	(4) No. Disposed	(5) Court Index
Pos x <=-4	-0.0821	0.694	276.2	463.2	0.196
	(0.307)	(0.566)	(144.0)	(69.26)	(0.0381)
Pos x -3	0.0678	-0.0628	80.08	200.8	0.0929
	(0.289)	(0.943)	(91.29)	(97.65)	(0.0719)
Pos x -2	0.460	1.106	172.0	175.6	0.0799
	(0.306)	(0.606)	(61.38)	(171.9)	(0.0334)
Pos x 0	2.228	2.199	171.3	362.8	0.163
	(0.282)	(0.628)	(134.7)	(141.8)	(0.0695)
Pos x 1	1.585	2.617	160.7	256.3	0.156
	(0.256)	(0.711)	(291.7)	(273.8)	(0.0775)
Pos x 2	1.451	2.964	421.7	442.3	0.234
	(0.199)	(1.184)	(322.5)	(299.6)	(0.0991)
Pos x 3	1.277	2.893	379.4	412.3	0.170
	(0.326)	(1.320)	(326.0)	(477.9)	(0.123)
Pos x >=4	0.900	2.526	395.4	289.0	0.116
	(0.558)	(0.945)	(302.7)	(254.8)	(0.0327)
Observations	9162	9162	9055	8347	8247
No. Districts	195	195	195	182	181

Standard errors in parentheses

Notes: This table presents the estimates from Equation 1 using court-level outcomes, equivalent to Figure 1. Columns 3-5 presents additional court-level variables including the demand for litigation (cases filed) in Column 3, number of trials resolved in Column 4, and an index computed as the first principal component from Principal Component Analysis of all possible court-level performance variables in Column 5. All court-level specifications include district fixed effect. Standard errors are clustered by district and event.

Table 2: Credit Outcomes: Net Judge Addition Stacked Event Study

	(1) Working Cap. (IHS) All Sample	(2) Interest Exp (IHS) All Sample	(3) Working Cap. (IHS) Low Lev. Small	(4) Interest Exp (IHS) Low Lev. Small	(5) Indus. Loans (IHS) District-Level	(6) Outstanding (IHS) District-Level
Pos x <=-4	0.144	0.0916	0.0445	0.396	0.0334	-0.00527
	(0.405)	(0.0902)	(0.239)	(0.357)	(0.0437)	(0.0224)
Pos x -3	0.0110	0.0591	-0.202	0.166	-0.0460	-0.0158
	(0.189)	(0.0366)	(0.526)	(0.172)	(0.0553)	(0.0424)
Pos x -2	0.104	0.117	-0.155	0.244	0.0369	-0.0211
	(0.0653)	(0.0481)	(0.0701)	(0.111)	(0.00935)	(0.0307)
Pos x 0	0.379	-0.0132	0.192	-0.0928	-0.0306	-0.00589
	(0.0717)	(0.0182)	(0.180)	(0.0446)	(0.0249)	(0.0157)
Pos x 1	0.198	-0.0839	0.0438	-0.260	0.0258	0.00227
	(0.151)	(0.0311)	(0.0761)	(0.121)	(0.0320)	(0.0204)
Pos x 2	0.158	-0.0711	-0.0821	-0.219	0.0121	-0.0178
	(0.173)	(0.0357)	(0.126)	(0.116)	(0.0693)	(0.0232)
Pos x 3	0.273	-0.0764	0.428	-0.238	0.0852	0.0210
	(0.0922)	(0.0269)	(0.194)	(0.0710)	(0.0422)	(0.0309)
Pos x >=4	0.238	-0.0847	0.186	-0.267	0.0609	0.0149
	(0.106)	(0.0104)	(0.0681)	(0.0602)	(0.0353)	(0.0309)
Observations	22744	20305	6210	4619	5670	5670
No. Firms	393	374	105	90	NA	NA
No. Districts	64	63	30	29	110	110

Standard errors in parentheses

Notes: This table presents the estimates from Equation 1 using credit outcomes - across all sample firms (Columns 1-2), for the subset of less-leveraged small firms (Columns 3-4), and at the market/district-level using bank lending outcomes (Columns 5-6), equivalent to Figure 2. All firm-level specifications include firm fixed effect and district-level specifications include district fixed effect. The specifications in Columns 5-6 include number of bank-related trials at the start of the study period as weights. Standard errors are clustered by district and event.

Table 3: Local Firms' Outcomes: Net Judge Addition Stacked Event Study

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)
Pos x <=-4	-0.0137	-0.0448	-0.0835	-0.00398	-0.221
	(0.0636)	(0.0955)	(0.100)	(0.0780)	(0.204)
Pos x -3	-0.00676	0.00767	-0.0729	0.00783	0.145
	(0.0401)	(0.0381)	(0.120)	(0.0429)	(0.131)
Pos x -2	0.00589	0.00140	-0.00978	0.0136	0.206
	(0.0326)	(0.0447)	(0.0621)	(0.0586)	(0.394)
Pos x 0	0.00255	0.0128	0.0125	0.0173	0.115
	(0.0167)	(0.0125)	(0.0518)	(0.00577)	(0.0988)
Pos x 1	0.0268	-0.00178	0.0177	0.00667	0.434
	(0.0206)	(0.0126)	(0.0883)	(0.0178)	(0.129)
Pos x 2	0.0310	-0.00328	0.0612	0.00900	0.327
	(0.0254)	(0.0279)	(0.0664)	(0.0191)	(0.127)
Pos x 3	0.0419	0.0195	0.0306	0.0239	0.495
	(0.0228)	(0.0487)	(0.0291)	(0.0105)	(0.124)
Pos x >=4	0.0534	0.0260	0.0110	0.0132	0.356
	(0.0236)	(0.0513)	(0.0259)	(0.00280)	(0.0739)
Observations	22004	20982	17592	22206	22522
No. Firms	389	374	323	391	391
No. Districts	64	64	63	64	64

Standard errors in parentheses

Notes: This table presents the estimates from Equation 1 using firm-level outcomes, equivalent to Figure 3. Using logarithmic transformation instead of arcsine yields similar estimates. The need for a balanced panel in order to ensure no endogenous missing values of firm-level outcomes results in an overlap with 64 out of the 195 districts in the litigation micro-data. All firm-level specifications include firm fixed effect. Standard errors are clustered by district and event.

Table 4: Decomposition - Firm Profits

	Credit Working Cap (IHS) (1)	Variables Interest Exp (IHS) (2)
t+3	0.0167	0.0208
	(0.0265)	(0.124)
Δt+3	-0.0193	0.0198
	(0.0257)	(0.0924)
Δt+2	-0.0217	-0.00426
	(0.0140)	(0.0596)
Δt	0.162	-0.417
	(0.0360)	(0.243)
Δt-1	0.165	-0.389
	(0.0403)	(0.234)
Δt-2	0.137	-0.379
	(0.0345)	(0.232)
Δt-3	0.128	-0.335
	(0.0417)	(0.223)
t-4	0.126	-0.347
	(0.0575)	(0.235)
Percent Δ Profit	50.74	33.73
Observations	3048	1325
No. Firms	391	322
No. Districts	64	55

Standard errors in parentheses

Notes: The column names in this table refer to mediating variables whose leads and lags are noted as row headers. The dependent variable is arcsine firm profits. I employ a distributed lag specification as in Equation 2, modified as follows

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

where i denotes the firm, d district, s state, and t calendar year. $Credit$ variables include working capital and interest expenditure, indicated as column headers in the above table. The coefficients are normalized relative to the explanatory variable from period $t+1$. I scale the positive change reduced form effects on working capital and interest expenditure in the post period by the above event study estimates from Columns 1 and 2 to obtain change in profit through the credit channel. Further dividing these with the reduced form effect on profit generates the estimates in the last row, depicting the percent change in profit due to credit. The event study graphs corresponding to the table above are in Figure A.15.

Appendix for "COURTS REDUX: MICRO-EVIDENCE FROM INDIA" For Online Publication Only

A.1 Data Appendix

A.1.A. Outcome variables

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

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

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

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

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

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

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

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

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

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

A.1.B. Matching firms with trial data

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

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

2. Create a set of unique firms appearing in above dataset. I note that same firm could appear as a litigant in more than one district. Procedural laws pertaining to civil and criminal procedures determine where a specific litigation can be filed based on the issue under litigation.

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

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

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

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

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

A.2 A model of credit market with enforcement costs

A.2.A. Credit Market

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

At the start, borrower needs to invest, K, in a project which returns $f(K)$. Their exogenous wealth endowment is W. They needs an additional $K_B = K - K_M$ from the lender to start the project, where K_M is the amount they raises from the market. Borrower repays RK_B at the end of the contract period, where $R = 1 + r > 1$ incorporates the interest rate r. The project succeeds with probability s, upon which the borrower decides to repay or evade. Evasion is costly as the borrower incurs an evasion cost ηK_B leading to a payoff $f(K) - \eta K_B$. The lender loses the entire principal, $-K_B$. Repayment results in $f(K) - RK_B$ as payoff to the borrower and the lender earns RK_B. On the other hand, the borrower automatically defaults if her project fails, in which case the lender can choose to litigate to monetize borrower's assets to recover their loan. This game is depicted in Figure A.7. Litigation is costly and lender incurs a cost, $C_L(\gamma) > 0, \frac{\partial C_L}{\partial \gamma} < 0$, as a function of judicial capacity, γ. The borrower can also choose to litigate with costs, $C_B(\gamma) > 0, \frac{\partial C_B}{\partial \gamma} < 0$, or settle out of court. Once the lender chooses to litigate and borrower accepts, lender wins with a very high probability. The intuition behind the relationship behind enforcement costs and judicial capacity can be explained by the fact that the litigants need to spend on travel, logistics, and lawyer fees over the duration of the trial, which is longer when

the judicial capacity is lower.[2]

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

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

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

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

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

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

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

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

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

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

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

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

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

The timing of the game where the lender and borrower decide on their strategies are depicted as an extensive form game in Figure A.7.

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.7.

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

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

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

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

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

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

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

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

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

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

A.2.B. Firm Production

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

$$\text{Max}_{X_1, X_2} \big(\Pi = pQ(X_1, X_2) - w_1 X_1 - w_2 X_2 - \phi m_i(\gamma) \big) \tag{7}$$

$$s.t \; w_1 X_1 + w_2 X_2 + \phi m(\gamma) \leq K_i(\gamma) \; i \in \{S, L\}$$

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

and the overall interest rate on bank lending, $R(\gamma, .)$ drops.

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

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

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

Constrained Optimization:

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

FOC:

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

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

$$\frac{\partial \mathcal{L}}{\partial \lambda} = K_i - w_1X_1 - w_2X_2 - m_i(\gamma) = 0$$

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

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

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

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

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

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

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:

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

$$\frac{\partial \Pi^*}{\partial \gamma} = \underbrace{(pQ_{x_1} - w_1)}_{\text{This is } w_1\lambda}\frac{\partial X_1^*}{\partial \gamma} + \underbrace{(pQ_{x_2} - w_2)}_{\text{This is } w_2\lambda}\frac{\partial X_2^*}{\partial \gamma} - \underbrace{\frac{\partial m_i}{\partial \gamma}}_{\text{-ve}} > 0$$

$$\frac{\partial g^*}{\partial \gamma} = \underbrace{(\frac{\partial K_i}{\partial \gamma} - \frac{\partial m_i}{\partial \gamma})}_{\text{marginal benefit}} - \underbrace{\Big(w_1\frac{\partial X_1^*}{\partial \gamma} + w_2\frac{\partial X_2^*}{\partial \gamma}\Big)}_{\text{marginal cost}}$$

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

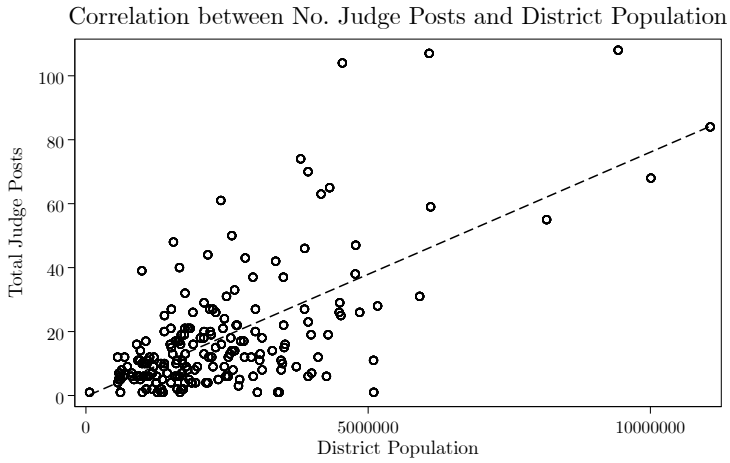
1. For large firms, $i = L$, the marginal benefit $0 - \frac{\partial m_L}{\partial \gamma}$ is mainly due to reduction in monitoring costs since there is no change in their borrowing from banks. If this reduction in monitoring costs is greater than the marginal increase in input costs, then profits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

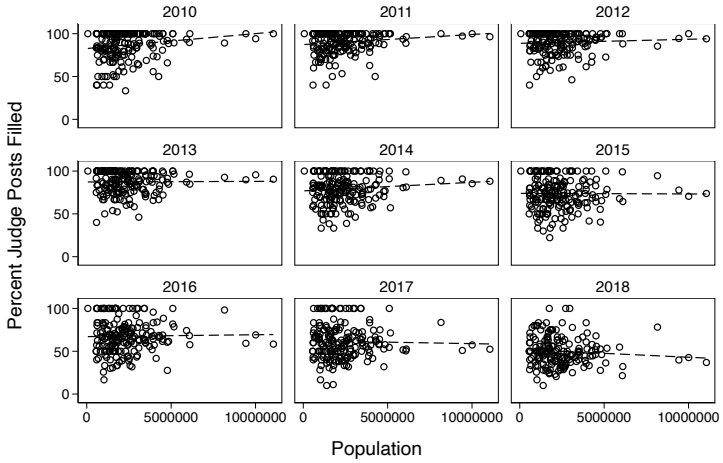
3. For inframarginal small firms, $i = S$ and $W << W^*$, neither their optimal inputs nor their profits change since $(\underbrace{\frac{\partial K_S}{\partial \gamma}}_{=0} - \underbrace{\frac{\partial m_S}{\partial \gamma}}_{\approx 0}) \approx 0$.

A.3 Appendix: Figures

Figure A.1: Total Number of Judge Posts and District Population
Panel A: Court-size and district population

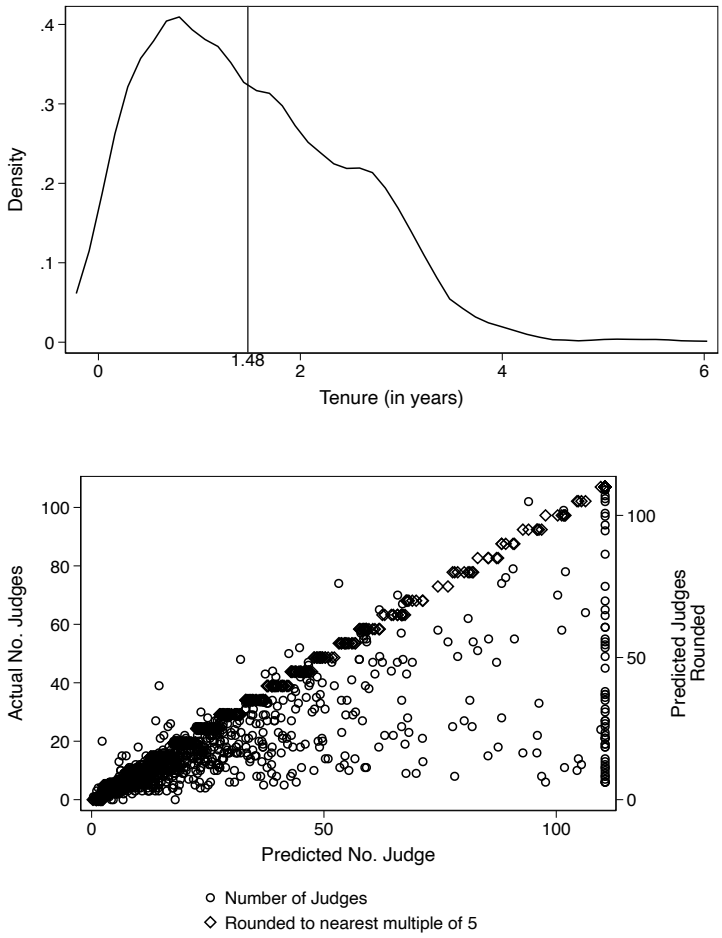


Panel B: Vacancy-rates over time and district population



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

Figure A.2: Judge tenure and assignment



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

Figure A.3: Construction of firm sample

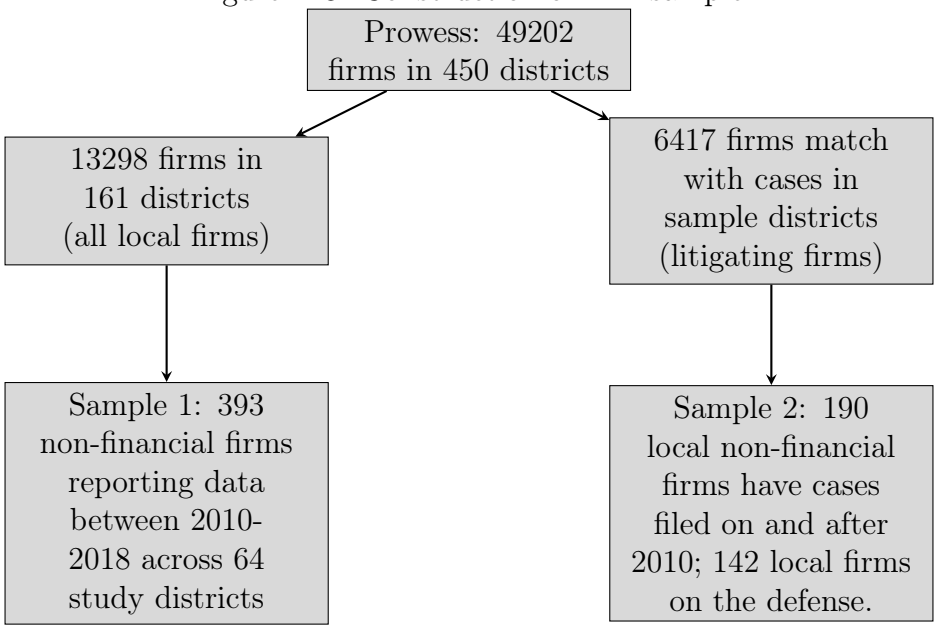
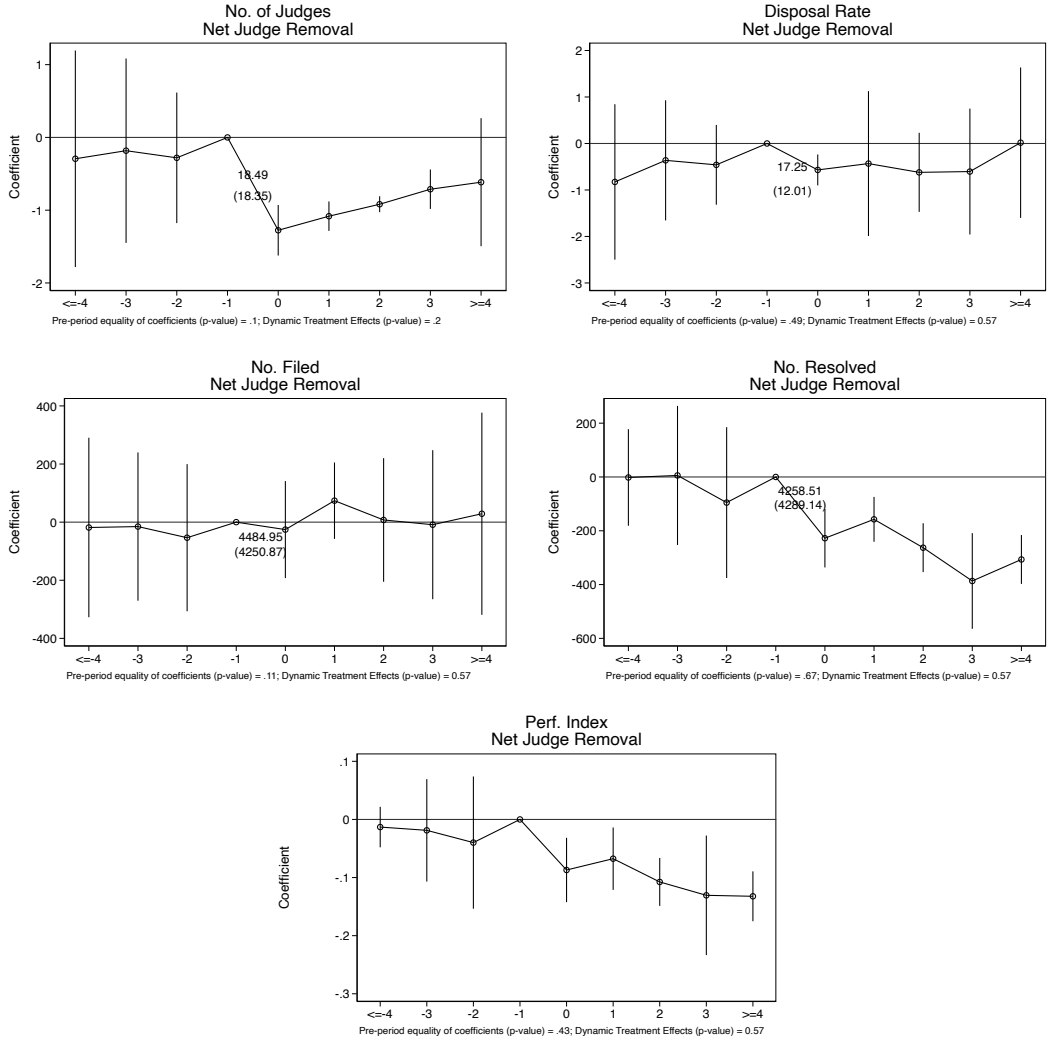
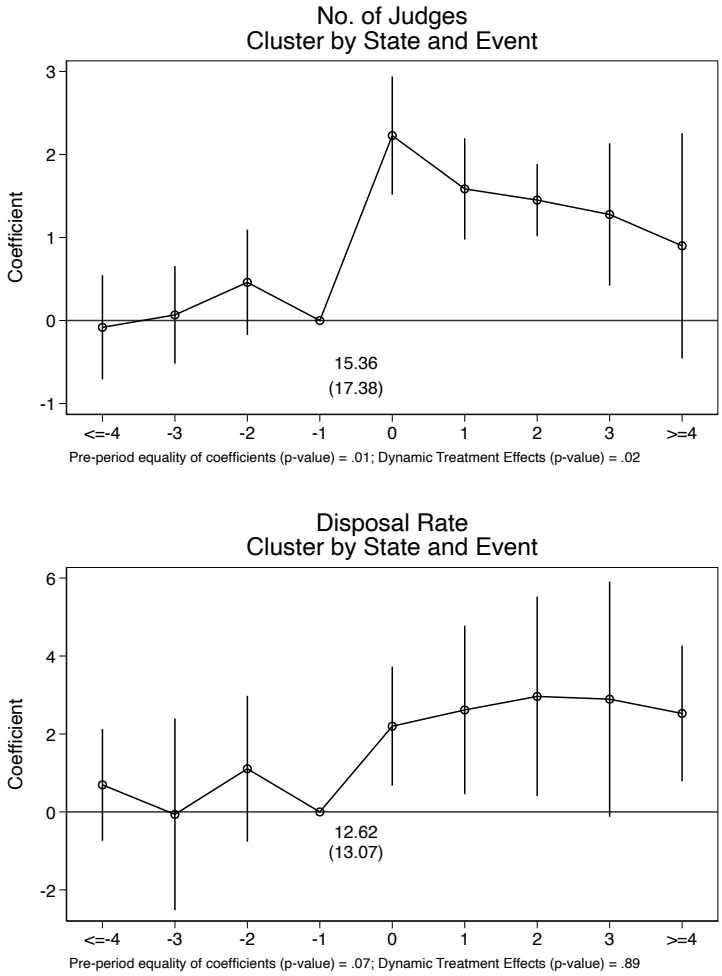


Figure A.4: Court-level Outcomes: Net Judge Removals



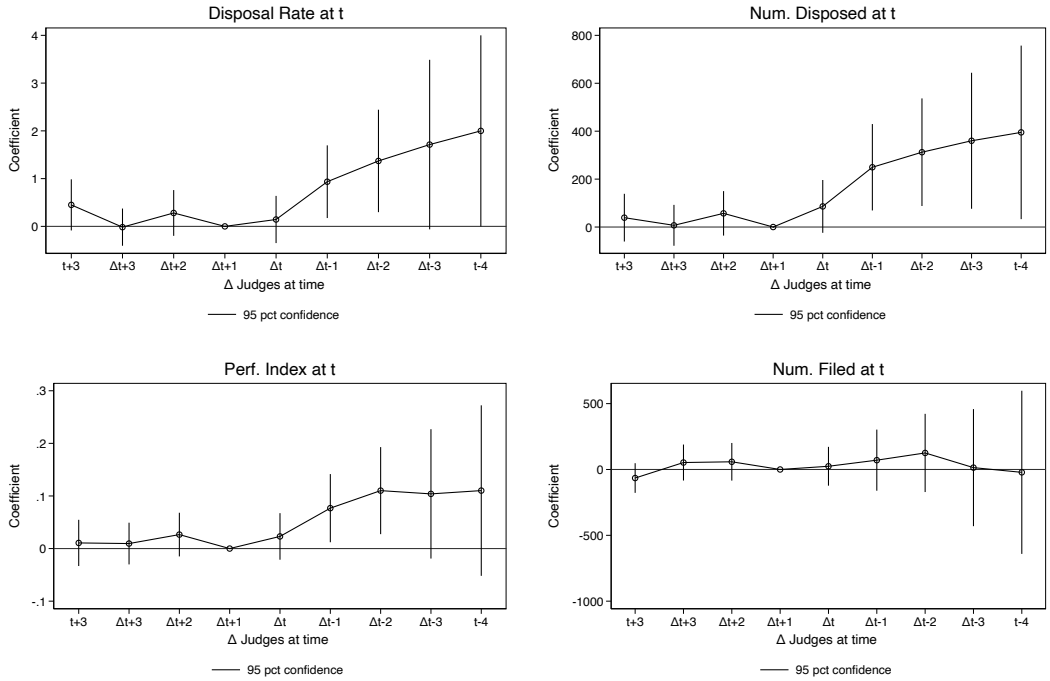
Notes: The figures in the first row plot the event study interaction coefficients for negative staffing changes from estimating Equation 1. In all the figures, the end-points take into account all future and past observable events in the data. The coefficients are all normalized to the period prior to the event. Standard errors are clustered by district and event. Error bars present 95% confidence interval.

Figure A.5: Court Outcomes: Inference Robustness



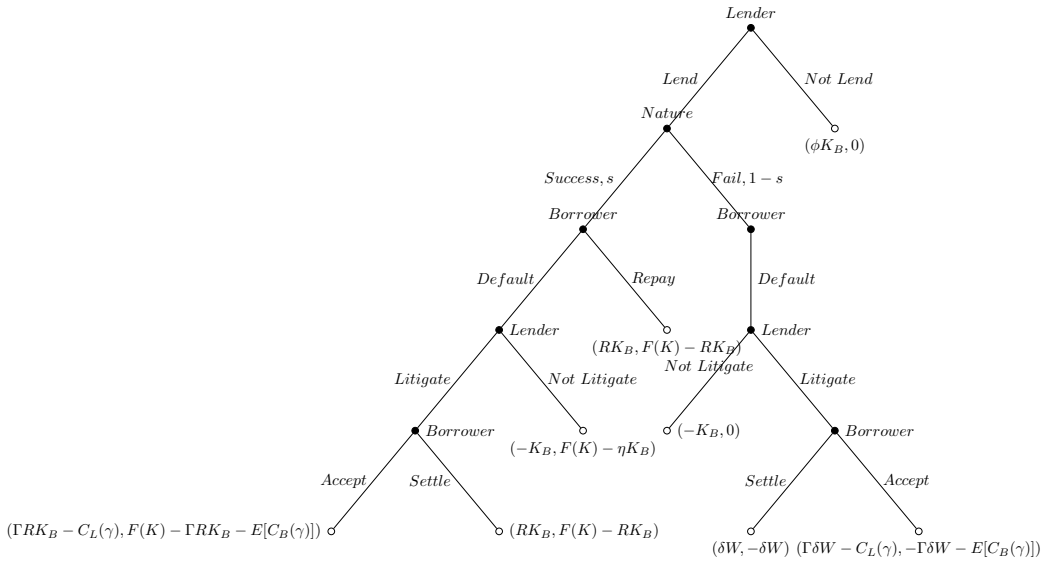
Notes: The figures plot the event study interaction coefficients for positive changes from estimating Equation 1. Standard errors are clustered by state (instead of district) and event. Error bars present 95% confidence interval.

Figure A.6: 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. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

Figure A.7: Model: Credit and Litigation



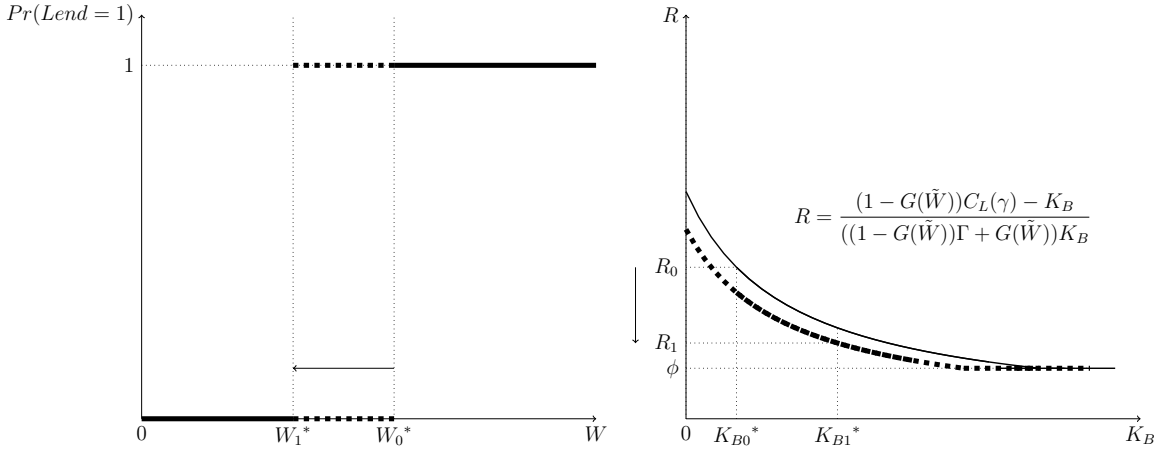
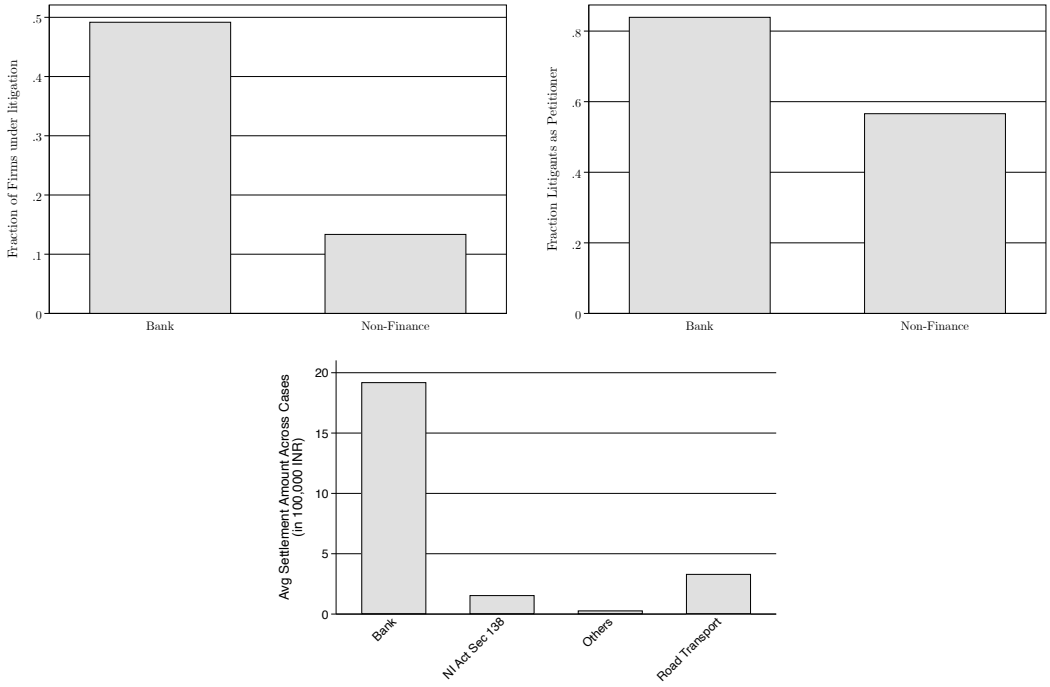


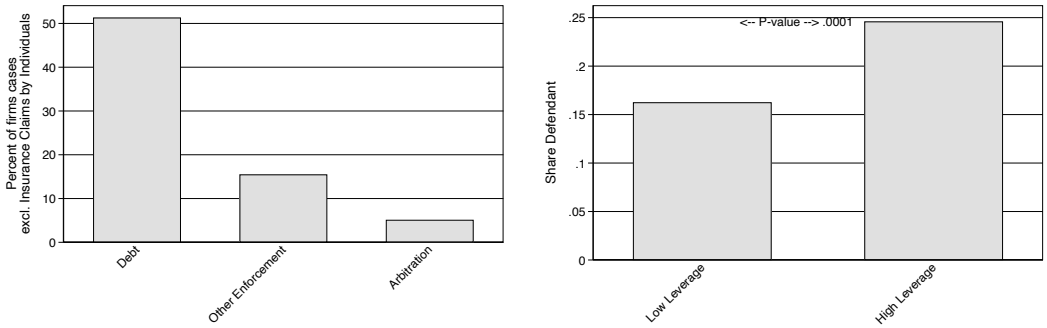
Figure A.8: Debt Litigations and Settlement Amounts



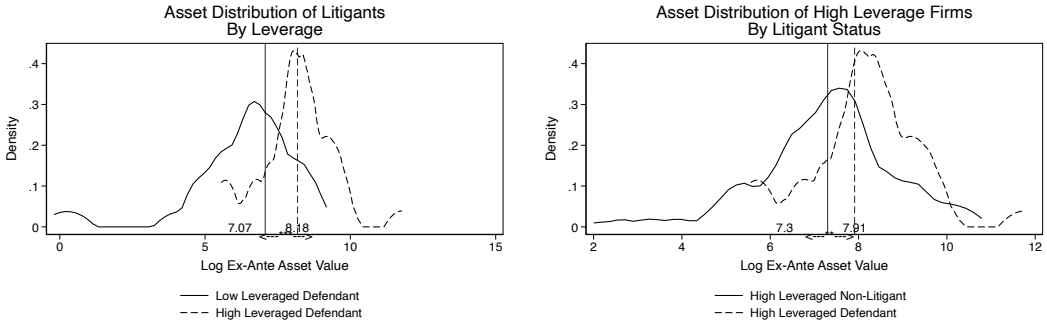
Notes: Top-left panel presents fraction of all firms in Prowess data belonging to either banking sector or non-finance sector (for e.g., manufacturing, services, trade and transportation, etc.) with at least one trial in the trial-level dataset. Top-right panel presents the fraction of these litigating 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.9: Litigation Behavior

Panel A: Firms' Cases in Courts



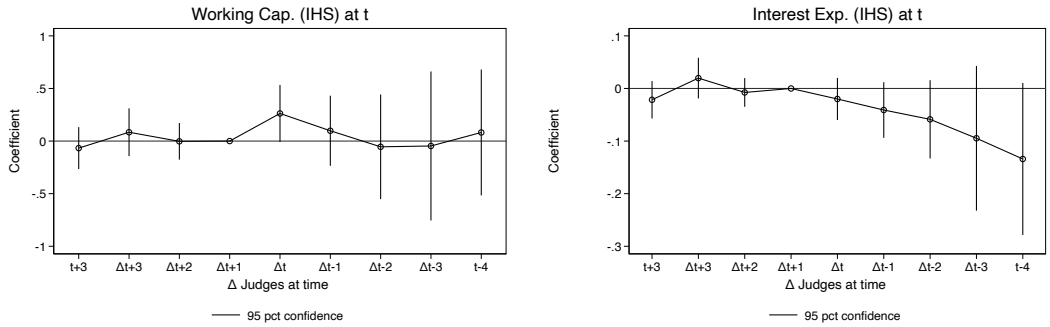
Panel B: Wealth Distribution



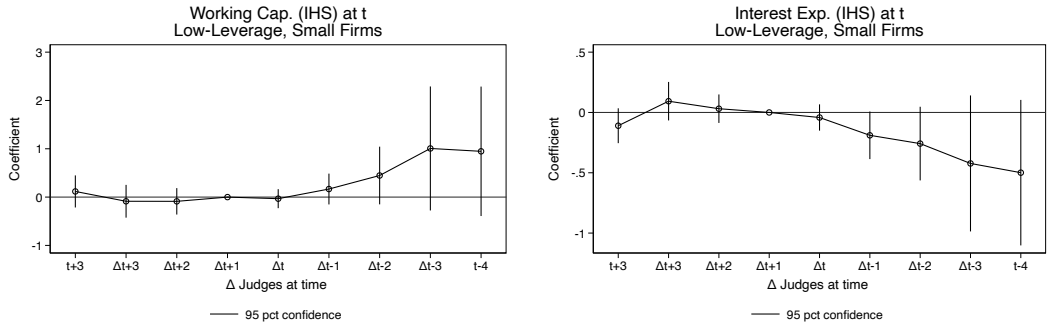
Notes: Panel A presents the share of trials involving non-financial firms by dispute type (left) and leverage (right). Trials involving financial sector firms, including banks, are excluded. Panel B presents the kernel densities of local non-financial firms' ex-ante total asset value by: (a) leverage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

Figure A.10: Credit Outcomes: Continuous Explanatory Variable

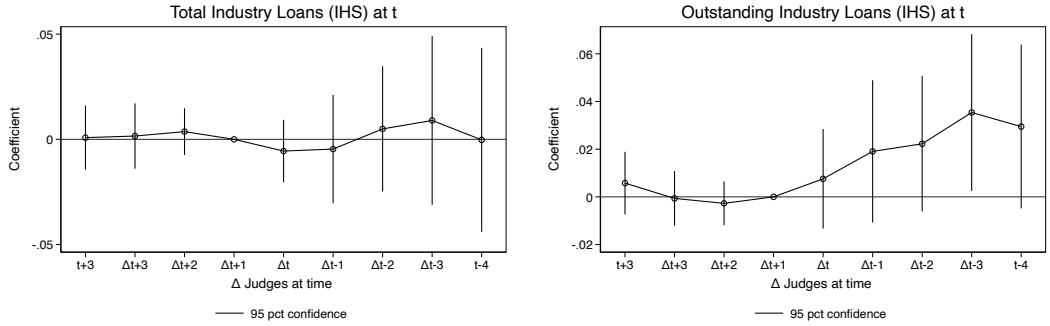
Panel A: Firm-level Working Capital and Interest Expenditure - All Sample Firms



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

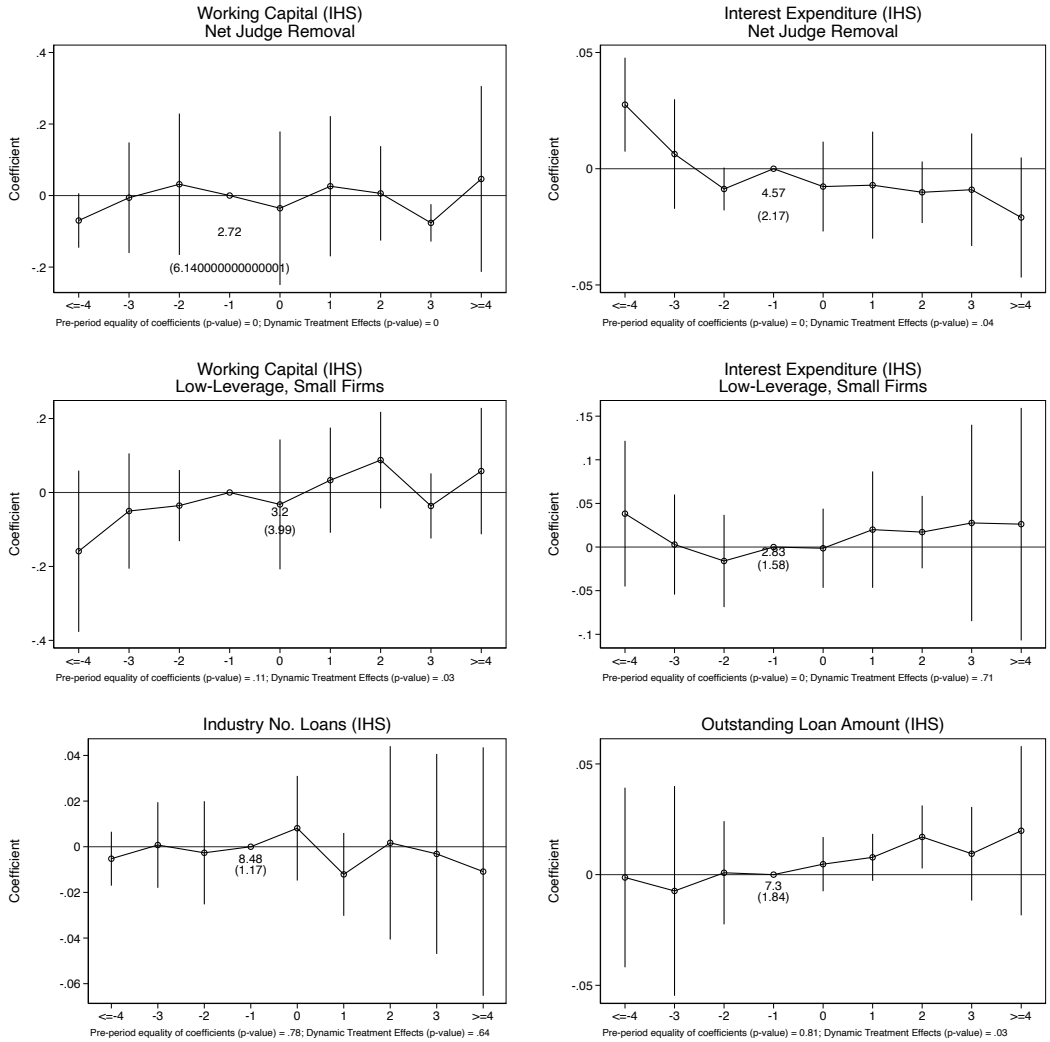


Panel C: Aggregate District-Level Bank-Lending



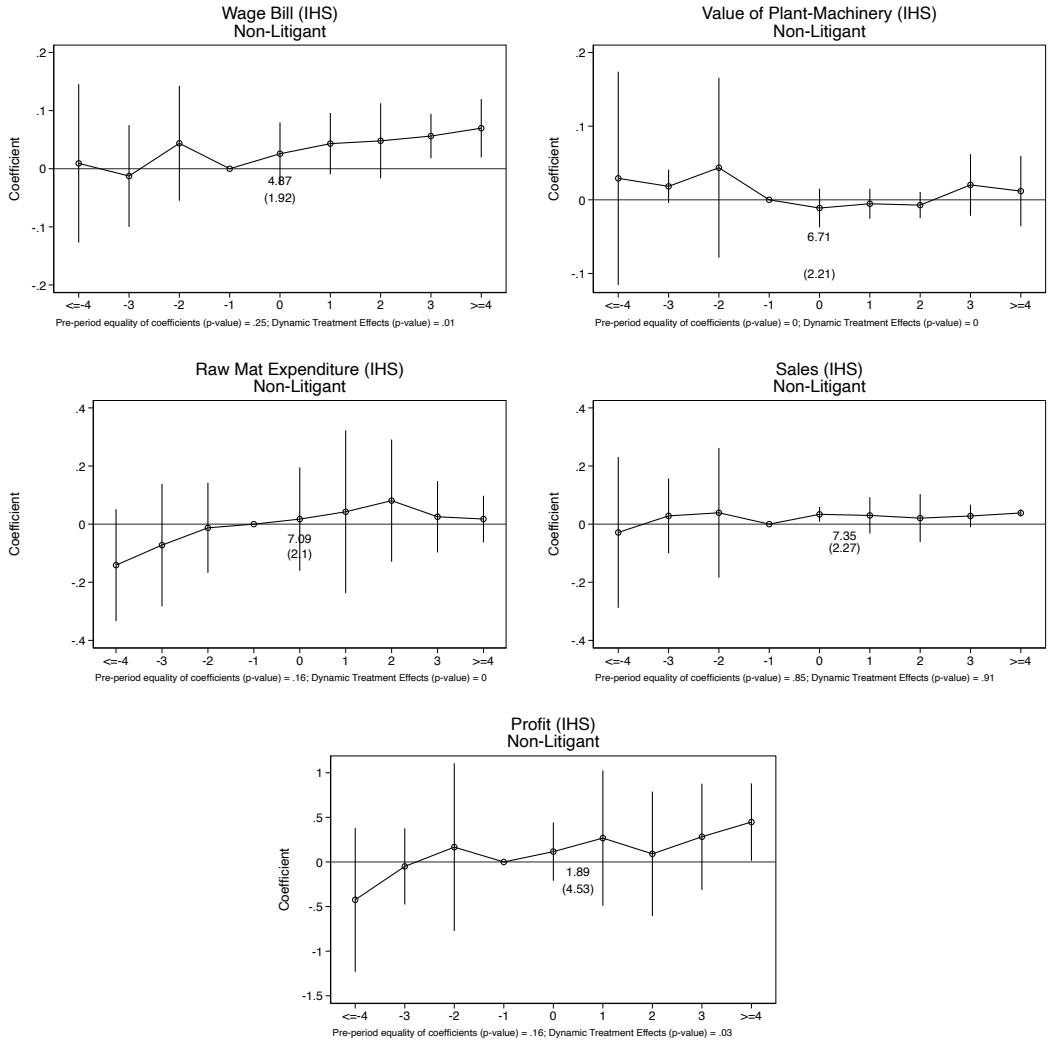
Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the outcome is measured at t as in Equation 2. Panel B presents the coefficients using outcomes on the subsample of low-leverage, small-sized firms. Each estimate includes 95% confidence interval.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

Figure A.11: Credit Outcomes: Net Judge Removals



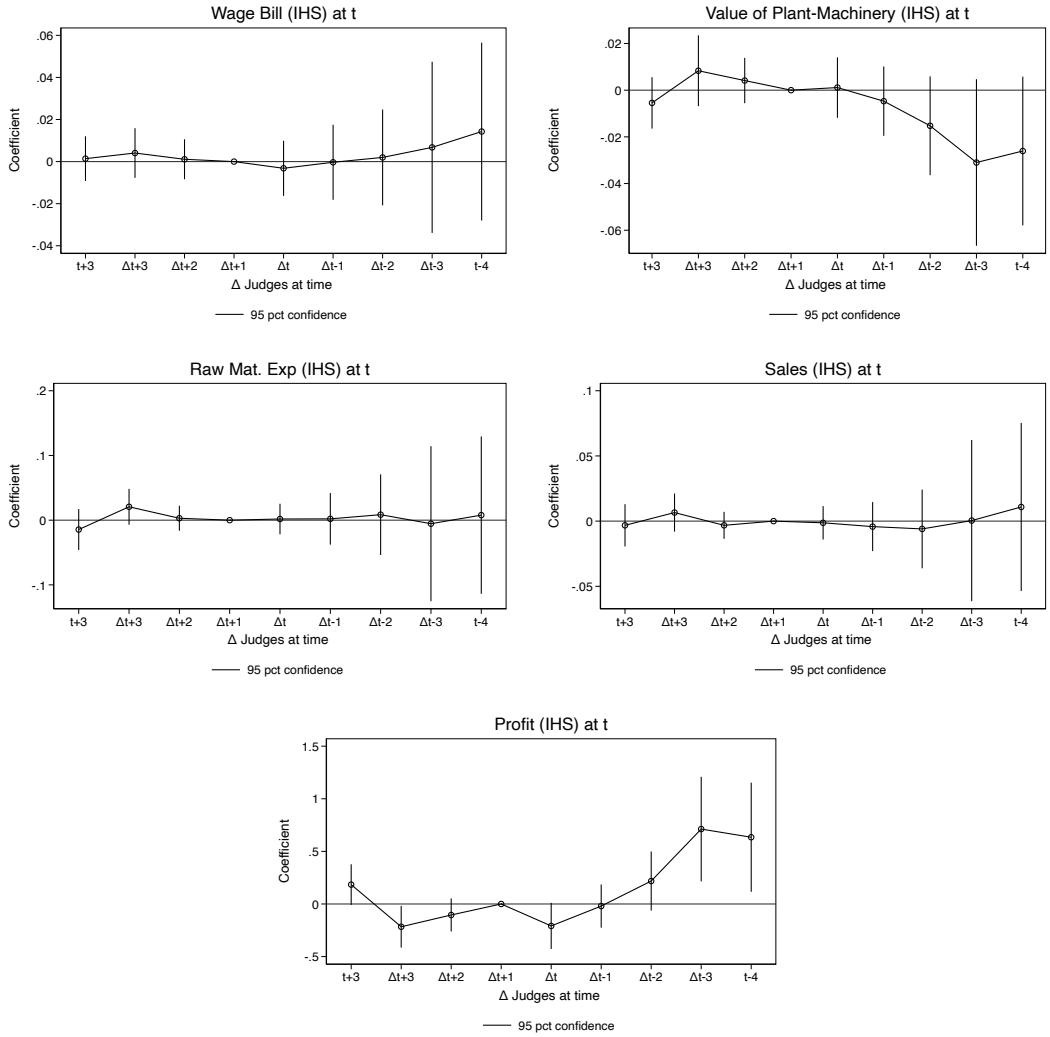
Notes: These graphs reproduce the reduced form graphs from Figure 2 but with negative staffing change interactions rather than the positive staffing interactions from Equation 1. Each estimate includes 95% confidence interval for firm-level outcomes and 90% confidence interval for district-level banking outcomes. Standard errors are clustered by district and event.

Figure A.12: Subset of Non-Litigating Firms



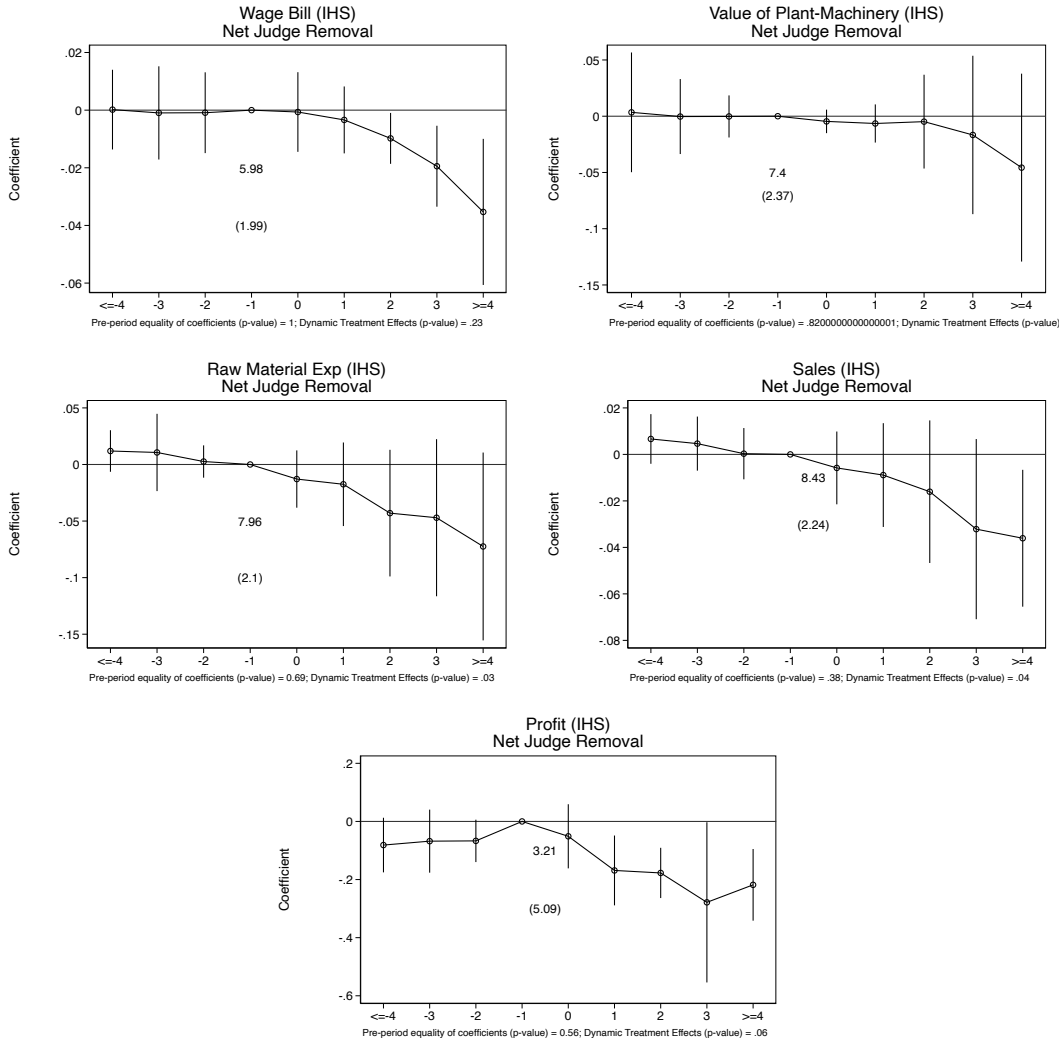
Notes: These graphs reproduce the reduced form graphs from Figure 3 but only on the subsample of non-litigating firms. Each estimate includes 95% confidence interval. Standard errors are clustered by district and event.

Figure A.13: Firm-Level Outcomes: Continuous Explanatory Variable



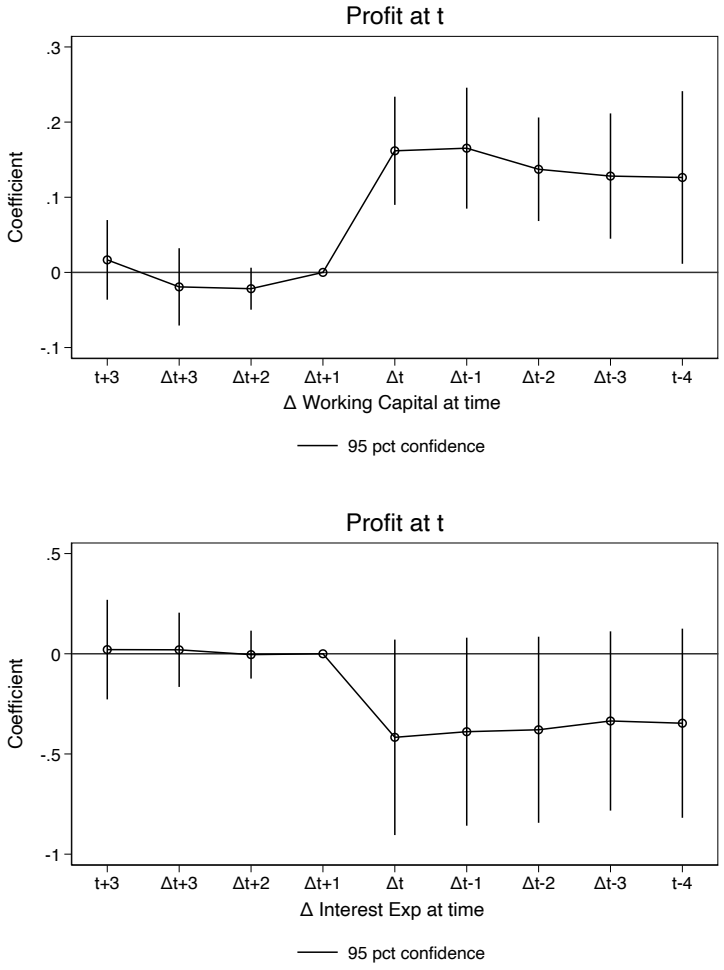
Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the firm-level outcome is measured at t as in Equation 2. Each estimate includes 95% confidence interval. Standard errors are clustered by district.

Figure A.14: Firm-Level Outcomes: Net Judge Removals



Notes: These graphs reproduce the reduced form graphs from Figure 3 but with negative change dummy interactions rather than positive change interaction dummies. Each estimate includes 95% confidence interval. Standard errors are clustered by district and event.

Figure A.15: Access to Capital and Firm Profit



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

A.4 Appendix: Tables

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

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

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

Table A.2: 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 Variables						
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: Firm Variables						
Wage Bill (in real terms, million INR)	391	3440	844.32	1832.1	0	23192.5
Plant value (real terms, million INR)	376	3276	6787.64	23546.64	0	335031
Revenue from Sales (real terms, million INR)	393	3471	13470.21	45468.43	0.1	796687.8
Accounting Profits (in real terms, million INR)	393	3517	739.69	5322.77	-88513.98	109993.2
Raw Mat Exp (real terms, million INR)	325	2786	7764.64	33368.59	-63.21	750132.8

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, and those for whom I observe the key outcome variables in 2010-2018 (i.e. balanced panel of firms). All monetary variables are measured in INR million as reported in Prowess database, in real terms using 2015 as the base year.

Table A.3: Court Outcomes - By Sub-Groups of District Courts

	No. of Judges			Disposal Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
	Dropping 1st Tercile Population	Dropping 2nd Tercile Population	Dropping 3rd Tercile Population	Dropping 1st Tercile Population	Dropping 2nd Tercile Population	Dropping 3rd Tercile Population
Pos x <=-4	-0.0260	-0.156	0.0108	0.403	0.656	0.862
	(0.567)	(0.417)	(0.318)	(0.824)	(0.750)	(0.957)
Pos x -3	0.154	-0.138	0.173	-0.0839	0.674	-0.990
	(0.372)	(0.409)	(0.237)	(0.710)	(1.131)	(1.286)
Pos x -2	0.649	0.382	0.341	1.269	1.337	0.456
	(0.449)	(0.339)	(0.201)	(0.776)	(1.140)	(0.819)
Pos x 0	2.482	2.255	1.729	2.203	2.038	1.933
	(0.388)	(0.304)	(0.222)	(0.493)	(0.692)	(0.574)
Pos x 1	1.759	1.878	1.033	2.900	2.358	2.431
	(0.287)	(0.382)	(0.165)	(1.333)	(0.471)	(0.764)
Pos x 2	1.450	1.888	1.018	3.294	2.535	3.221
	(0.332)	(0.369)	(0.156)	(1.528)	(0.847)	(1.013)
Pos x 3	1.563	1.723	0.665	3.010	2.541	3.015
	(0.114)	(0.257)	(0.466)	(1.224)	(1.228)	(1.220)
Pos x >=4	1.140	1.134	0.579	2.897	1.613	2.792
	(0.223)	(0.526)	(0.665)	(0.841)	(1.278)	(0.813)
Observations	6174	6120	6174	6174	6120	6174
No. Districts	124	131	138	124	131	138

Standard errors in parentheses

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

Table A.4: Court Outcomes - Robustness to Dropping Industrial States and Districts

	No. of Judges		Disposal Rate	
	(1)	(2)	(3)	(4)
	Dropping Indus. States	Dropping Metro Districts	Dropping Indus. States	Dropping Metro Districts
Pos x <=-4	-0.00219	-0.0385	0.470	0.763
	(0.393)	(0.230)	(1.089)	(0.573)
Pos x -3	0.0642	0.0856	-1.196	-0.0700
	(0.280)	(0.231)	(0.886)	(0.942)
Pos x -2	0.448	0.474	0.0120	1.115
	(0.386)	(0.272)	(0.483)	(0.617)
Pos x 0	2.173	2.197	1.867	2.157
	(0.319)	(0.266)	(0.624)	(0.634)
Pos x 1	1.444	1.533	1.843	2.574
	(0.269)	(0.218)	(0.703)	(0.727)
Pos x 2	1.248	1.394	2.946	2.921
	(0.301)	(0.151)	(1.150)	(1.214)
Pos x 3	0.952	1.199	2.236	2.832
	(0.685)	(0.488)	(1.317)	(1.345)
Pos x >=4	0.663	0.748	2.145	2.457
	(0.941)	(0.730)	(1.373)	(0.961)
Observations	6588	8964	6588	8964
No. Districts	140	192	140	192

Standard errors in parentheses

Notes: This table presents the event study reduced form estimates of positive staffing changes on court-level variables after dropping large, industrial states (Columns 1, 3) and metropolitan districts (Columns 2, 4) from the sample.

Table A.5: Bank Lending by Banking Sector

	Industry Loans (IHS)		Outstanding (IHS)	
	(1) Public Sector Banks	(2) Private Sector Banks	(3) Public Sector Banks	(4) Private Sector Banks
Pos x <=-4	0.00243	-0.0688	-0.0295	-0.0262
	(0.0132)	(0.0584)	(0.0151)	(0.0284)
Pos x -3	-0.0214	-0.00378	-0.0319	0.0108
	(0.00898)	(0.0635)	(0.0307)	(0.0563)
Pos x -2	-0.0137	0.0747	-0.0118	-0.00118
	(0.00559)	(0.0569)	(0.0243)	(0.0524)
Pos x 0	-0.0109	0.0837	-0.0121	0.00520
	(0.0148)	(0.0798)	(0.00677)	(0.0281)
Pos x 1	-0.00133	0.136	-0.00448	0.0172
	(0.00389)	(0.0926)	(0.00613)	(0.0150)
Pos x 2	-0.00286	0.0819	0.00132	-0.0304
	(0.00420)	(0.0517)	(0.00809)	(0.0350)
Pos x 3	-0.00549	0.166	0.0122	-0.0247
	(0.00604)	(0.0676)	(0.00830)	(0.0234)
Pos x >=4	-0.00491	0.124	0.0212	-0.0504
	(0.00396)	(0.0437)	(0.0132)	(0.0421)
Observations	5670	5670	5670	5670
No. Districts	110	110	110	110

Standard errors in parentheses

Notes: This table breaks down Columns 1-2 of Table 2 by banking sector, i.e. total loans and amount owed to public and private sector banks, respectively.

Table A.6: Firms' Outcomes: Robustness to Dropping Industrial States

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)
Pos x <=-4	0.00430	-0.0844	-0.0119	-0.0550	0.257
	(0.0880)	(0.173)	(0.0671)	(0.123)	(0.303)
Pos x -3	0.00534	0.0106	0.000741	-0.00352	0.744
	(0.0452)	(0.0761)	(0.0839)	(0.0451)	(0.183)
Pos x -2	0.0303	-0.0343	0.0222	0.00161	0.0796
	(0.0284)	(0.0290)	(0.0196)	(0.0652)	(0.375)
Pos x 0	0.0253	0.0237	0.0302	0.0317	0.191
	(0.0171)	(0.0168)	(0.00621)	(0.0237)	(0.103)
Pos x 1	0.0315	-0.00188	0.0692	0.0365	0.364
	(0.0172)	(0.0192)	(0.0212)	(0.0184)	(0.130)
Pos x 2	0.0443	0.000138	0.0698	0.0486	0.207
	(0.0202)	(0.0403)	(0.0272)	(0.0108)	(0.242)
Pos x 3	0.0555	0.0126	0.0623	0.0526	0.483
	(0.0190)	(0.0510)	(0.0273)	(0.00939)	(0.156)
Pos x >=4	0.0564	0.0187	0.0433	0.0231	0.216
	(0.0320)	(0.0585)	(0.0588)	(0.0171)	(0.0767)
Observations	8360	7816	6759	8460	8577
No. Firms	149	143	123	149	149
No. Districts	44	44	43	44	44

Standard errors in parentheses

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

Table A.7: Firms' Outcomes: Robustness to Dropping Largest Districts

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)
Pos x <=-4	-0.0257	-0.0571	-0.0945	-0.0279	-0.245
	(0.0782)	(0.130)	(0.128)	(0.0933)	(0.262)
Pos x -3	-0.00484	-0.00197	-0.0838	0.00350	0.175
	(0.0482)	(0.0539)	(0.143)	(0.0476)	(0.157)
Pos x -2	0.000508	-0.00734	-0.00933	0.0138	0.115
	(0.0332)	(0.0471)	(0.0660)	(0.0650)	(0.419)
Pos x 0	0.00435	0.0126	0.0363	0.0269	0.0886
	(0.0188)	(0.0148)	(0.0308)	(0.0107)	(0.118)
Pos x 1	0.0249	-0.00939	0.0348	0.0189	0.433
	(0.0197)	(0.0188)	(0.0634)	(0.0117)	(0.157)
Pos x 2	0.0322	-0.00583	0.0791	0.0305	0.271
	(0.0195)	(0.0388)	(0.0405)	(0.0121)	(0.144)
Pos x 3	0.0425	0.0197	0.0438	0.0379	0.486
	(0.0130)	(0.0637)	(0.0220)	(0.00634)	(0.116)
Pos x >=4	0.0387	0.0201	0.00526	0.00911	0.233
	(0.0225)	(0.0715)	(0.0317)	(0.00663)	(0.0635)
Observations	11578	10894	9762	11686	11862
No. Firms	217	208	188	217	217
No. Districts	61	61	60	61	61

Standard errors in parentheses

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

Table A.8: Firms' Outcomes: Robustness to Clustering by State and Event

	(1) Wage Bill (IHS)	(2) Plant Value (IHS)	(3) Raw Mat (IHS)	(4) Sales (IHS)	(5) Profit (IHS)
Pos x <=-4	-0.0137	-0.0448	-0.0835	-0.00398	-0.221
	(0.0480)	(0.0780)	(0.0783)	(0.0788)	(0.216)
Pos x -3	-0.00676	0.00767	-0.0729	0.00783	0.145
	(0.0341)	(0.0233)	(0.0955)	(0.0400)	(0.354)
Pos x -2	0.00589	0.00140	-0.00978	0.0136	0.206
	(0.0363)	(0.0400)	(0.0438)	(0.0558)	(0.353)
Pos x 0	0.00255	0.0128	0.0125	0.0173	0.115
	(0.0151)	(0.0177)	(0.0455)	(0.00925)	(0.119)
Pos x 1	0.0268	-0.00178	0.0177	0.00667	0.434
	(0.0155)	(0.00813)	(0.0748)	(0.0224)	(0.107)
Pos x 2	0.0310	-0.00328	0.0612	0.00900	0.327
	(0.0217)	(0.0267)	(0.0654)	(0.0292)	(0.0952)
Pos x 3	0.0419	0.0195	0.0306	0.0239	0.495
	(0.0192)	(0.0413)	(0.0478)	(0.0193)	(0.0665)
Pos x >=4	0.0534	0.0260	0.0110	0.0132	0.356
	(0.0239)	(0.0478)	(0.0413)	(0.0100)	(0.114)
Observations	22004	20982	17592	22206	22522
No. Firms	389	374	323	391	391
No. Districts	64	64	63	64	64

Standard errors in parentheses

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

Table A.9: Reduced Form Effects on Local Crime

	(1) All Crime (IHS)	(2) Crime Against Women (IHS)	(3) Econ. Crime (IHS)	(4) Lesser Crime (IHS)
Pos x <=-4	-0.0144	0.0146	-0.0170	-0.0140
	(0.00543)	(0.00808)	(0.0225)	(0.0248)
Pos x -3	-0.0163	-0.00411	-0.0307	-0.0136
	(0.00941)	(0.0121)	(0.0396)	(0.0266)
Pos x -2	-0.00648	0.00114	-0.0171	-0.0149
	(0.00459)	(0.0104)	(0.0188)	(0.00708)
Pos x 0	-0.0130	-0.0242	0.00416	0.0204
	(0.00747)	(0.00556)	(0.0208)	(0.0156)
Pos x 1	-0.00911	-0.00272	0.00716	-0.0234
	(0.00921)	(0.0156)	(0.0245)	(0.0176)
Pos x 2	-0.0144	-0.0106	0.0160	0.00373
	(0.00822)	(0.0223)	(0.0164)	(0.0146)
Pos x 3	-0.0205	-0.0338	0.0123	-0.0509
	(0.00883)	(0.0288)	(0.0101)	(0.0193)
Pos x >=4	-0.0169	-0.00990	0.0176	-0.0118
	(0.00530)	(0.00916)	(0.0213)	(0.0194)
Observations	7111	7111	7111	7111
No. Districts	195	195	195	195

Standard errors in parentheses

Notes: I use annual district-level reported crime data between 2010 and 2016 available through the National Crime Records Bureau (NCRB). All the crime variables are based on reported crimes under the Indian Penal Code (IPC). Crime against women include rape, domestic violence, harassment for dowry, kidnapping, and sex trafficking. Economic crimes include counterfeiting, breach of trust, and cheating. Lesser Crime include those other than murder, attempt to murder, homicide, robbery or burglary, riots, crime against women, and economic crimes.

Table A.10: Cost-benefit Calculation

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

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

Table A.11: Cost-benefit Sensitivity Analysis

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

Notes: In this table, I use different values of discount rate - both lower and higher than the preferred discount rate used in Table A.10. I report the average benefit-cost ratio for each of these different discounting scenarios along with their bootstrapped standard errors in parentheses.