COURTS REDUX: MICRO-EVIDENCE FROM INDIA

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How does local judicial capacity affect firm behavior? I provide an answer to this question using the universe of litigation data between 2010 and 2018, amounting to 6 million trial records from over a quarter of all district courts in India. I exploit the plausibly random timing of judge additions and removals that affect the total number of judges available in a given court-year to causally examine the effect of judicial capacity constraints on local firms using multiple event studies research design. I find that adding a judge increases local firms' factor-use and value of production, driven by an improvement in the rate of trial resolution in district courts and credit access to industrial borrowers. The results imply that reducing vacancy by hiring more judges will generate orders of magnitude larger benefit relative to its cost. (*JEL* O16, O43, K41, G21)

I. INTRODUCTION

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 prevent effective contracting and weaken *de facto* rights (Johnson et al. 2002). While this is well supported in theory (North 1986; Glaeser et al. 2001), there is little empirical evidence using disaggregated data on the day-to-day functioning of courts.

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In this paper, I exploit the universe of trial-level data from a quarter of local (district) courts over a decade in India to examine the effect of relaxing judicial capacity constraints on economic outcomes.

District courts in India had over 11 million trials pending for more than 3 years as of 2019, implying a 10 times more backlog per capita relative to similar courts in the United States. In addition to affecting overall trust in market transactions (Nunn 2007), long-standing congestion in 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 similar developing economies but also common among the judiciary in many OECD countries (Dimitrova-Grajzl et al. 2012; Coviello et al. 2014).

I measure judicial capacity as the annual number of active judges in a court, which varies year-to-year due to vacancies. Staffing of courts is a critical bottleneck in India, as in other developing countries, which affects the functioning of courts and its ability to enforce rule of law through timely resolution of litigations. State policies on judge assignments and tenure generate plausibly random timing of additions and removals of judges from courts that enable causal identification of the effect of judicial capacity on local incumbent firms' factor use and value of production. I find a strong causal relationship between judge vacancies and local firms' production, highlighting formal credit access through bank loans as one of the important mechanisms underpinning this relationship.[1]

There are fewer than 20 judge posts per million population across these district courts. This ratio further decreases due to chronic vacancies that the state has hitherto failed to address. However, this fact combined with existing state policies on judge assignments and short court-specific judge tenure enable causal identification by exogenously varying the extent of active judges available in a given time period to address court workload. I exploit multiple instances of additions and removal of judges within a court using a sample of 195 district courts over a study period between 2010 and 2018 using multiple events study framework. First, I show that these events exogenously change the number of active judges available within a court. Second, I estimate the reduced form effects of these changes in judicial capacity on key court performance measure - the rate of trial resolution, and on local firms' production outcomes.

Since these events vary the extent of vacancy rate, or conversely, occupancy rate - per-

[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.

centage of total judge posts filled in a court-year, I also employ a generalized event study framework implemented using leads and lags of judge occupancy rate in a distributed lags model. In addition to validating the results by providing another empirical approach to study the relationship, this design also helps examine the effect of marginal changes in vacancy rates.

I execute these designs using a novel dataset on district courts that I construct using the meta data of six million trials that form the universe of sample courts' workload over the study period. I generate court-level aggregate variables from this universe, which I merge with a balanced panel data on firms using their registered office location, and other district-level outcome measures. A majority of firms in India are single plant firms (Hsieh and Olken 2014), therefore the location of registered office is also very likely to be the location of production within the corresponding territorial jurisdiction of the sample courts. While firms can enter into contracting relations with agents outside of their own location, important contracts such as debt and labor are typically entered with agents within their location.[2] Relatedly, I also measure the extent of credit circulated within the district using aggregate banking statistics data.

Causal identification using the generalized event study designs requires the following three assumptions with respect to the outcomes: (a) exogenous timing of judge addition and removal, (b) parallel trends across district courts, and (c) homogeneous treatment effects across cohorts and groups. State policies on judge rotation and tenure provide support to the exogeneity in the timing assumption. I find no significant pre-trends as a support for the parallel trends assumption. And finally, I examine treatment effects by various subgroups to test the homogeneity assumption.

There are three key results. First, I find a significant first stage on court-level variables. Starting with staffing, the addition/removal events change the number of judges by 3 immediately following the event. While addition events eventually converge to 0 additional judges in the long run as newly added judges complete their tenure and rotated away, removals generate persistent decline in staffing resulting in long term vacancies. As a result of staffing changes, the rate of trial resolution improves by 4-5 percentage points over the baseline rate of 14% of annual workload with addition and declines by 2-3 percentage points with removal. This is largely driven by changes in the number of trials resolved, where each additional judge resolves about 200 litigations a year.[3]

[2]Even migrant labor reside in the same location as the firm for their contract duration, which requires local residential address for record keeping. Banks lend capital to firms through their local branch network to minimize adverse selection and moral hazard.

[3]Court workload includes both pending as well as new trials. The average annual workload is 20000 trials. Resolved trials also include those that are dismissed without a final judgement order. The rate of

Second, I find large effects on local firms' production outcomes. Particularly, these firms expand their wage bill and experience higher profits from production and other income sources following judicial capacity improvements (and negative effects with decline in capacity). Specifically, wage bill expands by close to 10%, sales by 5%, and profit by over 80% in the years following judge addition. On the other hand, there is no immediate effect on capital goods although there is some suggestive long run effects.

Third, I highlight credit access, particularly among smaller firms, as an important mechanism underpinning the changes in production outcomes. To see this, I first develop a conceptual framework that builds on standard lending models by introducing variation in the quality of contract enforcement by local courts. This suggests that wealthier borrowers are more likely to litigate in general and that lenders respond to an improvement in enforcement capacity by providing cheaper credit to smaller firms. Empirically, I find that the asset distributions of litigating and non-litigating firms are substantially different, with the distribution of litigating firms to the right of non-litigating firms. Next, I find that total district-level lending by banks to all industrial borrowers increases by over 10% in the years following judge additions (and corresponding decline following removal). These imply substantial differential effects on production outcomes by firms' ex-ante size. In particular, smaller firms differentially borrow more, expand wage bill and experience higher sales revenue relative to large firms.

These findings suggest a substantial policy implication of the persistent judge vacancies in the Indian judiciary. A back of the envelope calculation of the benefit-cost ratio of reducing vacancy shows sizable returns. Using the event study estimates and the corresponding standard errors from specifications involving number of judges, firms' wage bill, and profit as dependent variables, I compute the benefit-cost ratio both from the perspective of public finance as well as social returns. I measure social returns 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. I bootstrap these computations using 1 million simulations, which yields an average benefit to cost ratio of 3.5 from the perspective of public finance (with 95% confidence interval including 1.5 and 9.14). That is, even the most conservative ratio implies a return of 50% to public investment in judicial capacity. The social return on investment is orders of magnitude higher.

trial resolution is a relevant metric of judicial capacity, especially from the point of view of tied-up factors of production. This is also correlated with the average trial duration. 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 or reduction in congestion is more appropriate as a measure of institutional capacity.

This paper contributes to three strands of the academic literature. First, this presents a well-identified causal evidence of the effect of judicial capacity improvements on local firm production. These estimates are likely a lower bound since I examine district courts that are just one, albeit an important component of the formal judicial institutions. Complementary investments in fast-track and specialized courts for debt recovery and bankruptcy resolution will likely have a compounded effect by enabling firm creation and exit, and by increasing access to formal contract enforcement institutions to the informal sector. In this regard, this paper builds on the works by Djankov et al. 2003; Chemin 2009a,b; Visaria 2009; Chemin 2012; Ponticelli and Alencar 2016; Amirapu 2017; Kondylis and Stein 2018; Boehm and Oberfield 2018. The literature hitherto has taken an aggregate view of this relationship using one-time cross-sectional differences in judicial capacity, challenged by a lack of micro-data. Further, to my knowledge, these do not shed light on factors affecting judicial capacity other than the role of legal origins and procedural laws. The richness of my dataset and the plausibly exogenous variation in annual judge vacancies enable me to overcome these limitations to credibly show that the daily functioning of trial courts matter for the economy.

Second, this paper emphasizes that judge vacancy is an important state capacity constraint that exacerbates the rates of trial resolution in district courts. This is consistent with the discussion in Kapur (2020) that India has low levels of investment in local state personnel. This builds on a growing literature on state capacity (Muralidharan et al. 2016; Dhaliwal and Hanna 2017; Finan et al. 2017) by examining the much under-studied sub-national judiciary among state institutions (Dal Bo and Finan 2016). I show that reducing vacancies generates a large benefit-cost ratio. This complements Yang 2016, who shows that judge vacancy increases trial dismissals by prosecutors in the US criminal justice system, reducing the extent of incarceration with mixed social welfare implications (Dobbie et al. 2018; Bhuller et al. 2019; Norris et al. 2020).

Finally, this paper contributes to understanding the role of courts in facilitating credit markets, given a large literature documenting the importance of external, institutional finance for economic growth (La Porta et al. 1998; Acemoglu and Johnson 2005; von Lilienfeld-Toal et al. 2012; Vig 2013; Ponticelli and Alencar 2016). This is particularly salient in the context of developing economies where firms and individuals are typically credit constrained (Rajan and Zingales 1998; Burgess and Pande 2005; Banerjee and Duflo 2014). This paper also highlights the role of tied-up capital in a context where credit supply is limited relative to its demand and where markets are local (Nguyen 2019). Capital released from litigations potentially enables local bank branches to recirculate credit.

The rest of the paper is organized as follows. In section II, I provide the context and discuss the judge assignment policy. In section III, I discuss the data sources and construction of variables. Section IV details the empirical strategy, focusing on causal identification. Section V presents the reduced form results. In section VI, I present a conceptual framework to understand the economic processes behind the observed result. I empirically test the hypotheses generated from this framework in section VII. I present a few alternate explanation in section VII and discuss the findings along with its policy relevance in section IX. Section X concludes.

II. CONTEXT

The judiciary in India is a three tier unitary system in contrast to the executive and the legislature. At the apex is the Supreme Court for the entire country followed by High Courts for one or group of states, and finally the district or trial courts at the level of an administrative district that are the first interface of the judicial system. In this paper, I examine the functioning of courts at the district-level (and therefore, examining the local judicial capacity), focusing on the District and Sessions Court (hereinafter called district court), which is typically the court of first instance for disputes involving firms. There is one district court per district, which is also the court of appeal over other minor courts, including magistrate's courts, small cause courts, etc., within its jurisdiction.[4]

World Justice Project Rule of Law Index[5] ranks India in the bottom half of 128 countries in civil and criminal justice (ranks 98 and 78, respectively). In fact, it isn't surprising that countries in the bottom half of the ranking are mainly low and middle income countries. There are likely multiple reasons behind the lack of an effective judicial system including antiquated laws, difficult legal procedures, as well as severely constrained judicial capacity. India inherited a large part of this system based on English common law from her colonial past, which makes this examination relevant for many other countries in the developing world with similar colonial history.

Due to separation of powers, the judiciary is responsible for setting policies for its own functioning including recruitment of judges and management of courts whereas the budgetary power rests with the executive. So, any reform that the judiciary wants to adopt, can only be implemented with budgetary support from the executive. Such coordination failures underpin many of the constraints in expanding judicial capacity in India and other developing countries. One such key constraint that I examine in this paper, which also pertains to my

[4] The High Courts and the Supreme Court of India serve mostly appellate functions whereas their original jurisdiction pertains to constitutional matters or conflicts involving the organs of state. The district courts system is the main institution responsible for administering justice, has original jurisdiction over a large number of matters arising from both national and state-level legislations, and enforcing rule of law for day-to-day economic and social matters and therefore, forms the population of interest for this paper.

[5] https://www.worldjusticeproject.org/rule-of-law-index/factors/2020/India/

empirical strategy, is judge vacancy that I describe in detail in this section.

II.A. 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 population. In contrast, there are close to 100 judges per million in the United States (IAALS, Univ. Denver)[6] and close to 200 per million in the European Union (Eurostat average over 2017-2019). This ratio is further reduced when we account for the extent of vacancy in these posts.

The total number of judge posts in a district is determined jointly by the respective state high court and the state executive, whereas many other personnel policies such as judge tenure in a specific location and assignment system is under the purview of state high courts. While there is no clear rule on how the number of judge posts is arrived at and revised over time, periodic reports (particularly, report No.245) by the Law Commission of India, an executive body under the central government Ministry of Law and Justice, point out that there is no specific algorithm or approach towards this and is relatively ad hoc. Typically, the numbers are determined at the time of setting up the court establishment and physical infrastructure, which happens once every few decades 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 among judges. 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 bar council through competitive exams. Thus, they typically have 10-15 years before retirement, unless promoted to state high court, if at all. Many district judges retire at the same level. These judges serve a short tenure - 2-3 years (see Top Panel, Figure A.2) - in any given court, and are frequently rotated. The state high courts determine judge assignment and rotations between district courts. Each year, the high court administrative committee examines the list of judges completing their tenure in their current location. The committee then assigns these judges to different locations,

[6] https://iaals.du.edu/sites/default/files/documents/publications/judge_faq.pdf

ensuring no repetition of locations over their tenure. Further, judges are never assigned to their home districts or districts where they have had any legal experience (for example, as a lawyer).

The process of district judge rotation is based on a serial dictatorship mechanism, subject to specific constraints listed above - short tenure, non-repeat, and no home district. A judge coming up for a transfer is asked to list 3-4 rank-ordered locations (i.e. other district courts in their state) for their next posting. These lists are collated during each transfer cycle by the high court administrative committee. First, the senior-most judge is assigned their top ranked location. The next senior judge is assigned their top-ranked location as long as it does not conflict with the senior judge, and so on. In case of conflict, the assignment moves down the ranking order of the junior judge.[7]

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 vacancies in district courts and recommends an algorithm to determine the required number of judges in a court to reduce backlogs based on historical number of cases filed annually and past annual trial resolution rate per judge. However, applying this rule to the observed number of judges per court-year shows that this rule is rarely followed (Bottom Panel, Figure A.2).[8]

Further, I verify whether judge tenure is correlated with past measures of court performance as well as vacancy rates. Any strategic manipulation of tenure suggests deviation from the established policies on judge assignment. I web scrape tenure information on the head judge (Principal District Judge or PDJ) from each of the district court websites using their joining and leaving dates. The average tenure is about 1.5 years, consistent with the short tenure policy, and that the system of rotation leads to gap days before their successor takes charge. The effect of rotation on PDJ vacancy is likely an underestimate as PDJ positions do not remain vacant for long, since these judges play an administrative role in the functioning of their corresponding court. Importantly, I find that their tenure is uncorrelated with past vacancies and post period disposal rate, which suggests that the high courts rarely manipulate either vacancies or tenure lengths to address court performance.

Given the structural vacancies and delays in recruitment, the system of judge assignment generates 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 over time. This is central to

[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.

[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.

my identification strategy, which I discuss in detail in Section IV. below.

III. DATA

III.A. Court-level Variables: Explanatory Variables

I assembled the universe of 6 million publicly available trial records active between 2010 and 2018 from a sample of 195 district courts from the judiciary's E-Courts database by web-scraping the district specific websites (see Figure A.3). These districts were selected to ensure an overlap with 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 active judges: The trial data also records the courtroom number and the judge post where the 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, the 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 active judges in a district court for each year in my study period.

Judge additions and removals: The events that I use for my empirical strategy arise from judge additions and removals that I observe in the data based on the number of active judges I compute for each year. I mark an event as judge addition if the number of active judges is greater than that of the preceding year and as judge removal if the number of active judges is less than that of the preceding year. Years with no addition or removals are those with the number of active judges same as the preceding year.

Calculating vacancy rates: Additionally, I calculate the inverse vacancy rate - judge

[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.

[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.

occupancy - by dividing the number of active judges in a given court-year by the maximum number of judges observed over the study period, expressed in percentage terms. This method of generating vacancy rates would be an underestimate of the true vacancy rate if the maximum number of judges is less than the sanctioned judge strength for a given court. Despite the absence of a centralized source of judicial personnel records, the number of active judges and vacancies generated using this approach is consistent with media reports and compare with the numbers reported in Law Commission Reports.[11]

Constructing annual court performance variables: From individual trial records, I construct court-level annual workflow panel data. I define and construct the key performance variable - disposal rate, by dividing the number of trials resolved in a year by the total number of cases that form the workload for that year, expressed in percentage terms. The denominator is the sum of cases that are newly filed and those that are pending for decision as of a given calendar year. This 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.

III.B. 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 location of production since a large share of firms in India are single-plant firms. Registered office location is also relevant court jurisdiction where potential litigations, when the firm is on the offense, are filed, as determined by the Code of Civil Procedure, 1908. 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 large bank managers and their legal counsels

[11] Once a judge is assigned to a court, she is assigned a courtroom and given a docket of cases for hearing by the administrative judge of the court known as the Principal District Judge. An ideal measurement of vacancy would be constructed through judge attendance rosters from the courts. Unfortunately, such a database does not exist and it wasn't possible for me to contact each of the 195 courts to obtain their attendance rosters. Even if some judges sit on dockets with more slow-moving cases relative to others in the same court, they need to show non-zero workflow for their annual performance appraisal. Since I construct judge occupancy at an annual-level rather than at much finer periodicity, this is likely a reliable measure.

suggest that banks lend to firm borrowers only through their local branches, i.e. branches located in the same district as the firms' corporate headquarters.[12] Therefore, judicial capacity in the corresponding district courts are likely to matter for enforcing debt contracts. This supports the rationale behind the choice of the sampling frame of non-financial firms.

Firm-level data: I use CMIE-Prowess dataset covering 49202 firms to measure annual firm-level outcomes. The data are collated from annual reports, stock exchange reports, and regulator reports covering the universe of all listed companies ($\approx$ 5000 listed on Bombay and National Stock Exchanges) as well as through sample-surveys of unlisted public and private companies representing formal, registered firms. The data represents "*over 60 percent of the economic activity in the organized sector in India, which although a small subset of all industrial activity, accounts for about 75 percent of corporate taxes and 95 percent of excise duty collected by the Government of India*" (Goldberg et al. 2010). Since the organized sector accounts for $\approx$ 40% of sales, 60% of VAT, and 87% of exports (Economic Survey, 2018), this dataset captures a large share of value addition in the economy. Firm specific outcomes include annual financials and borrowing variables. Additionally, detailed identifying information including firm name and registered office location enables me to match them with court-level and trial datasets, respectively.

Banking data: For banks, I examine their district-level lending outcomes aggregated across all banks rather than employing variables from individual banks' annual financial statements, which does not disaggregate data by location of lending operations. The aggregated district-level lending statistics across all commercial banks are provided by the Reserve Bank of India (RBI) that 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 firms were incorporated before 2010, only 393 non-financial firms across 64 districts remain in the balanced panel I generate and form the main sample for analysis. Additionally, 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 the entire sample of firms in Prowess with the trial dataset using firm names and manually verify the resulting matches. Overall, 6417 of 49202 firms (13 percent) have ongoing litigation in the sample courts, of which 4047 firms have litigation

[12] In fact, lending to any borrower 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.

that were filed within the study period (i.e. 2010-2018). Among the main firm sample, about 190 non-financial firms overlap with this pool of litigating firms. Of this, 142 firms are on the defending side, providing support to the assumption that firms within the territorial jurisdiction of district courts form the population of interest to examine the effects of local judicial capacity. Appendix Figure A.4 describes the firm sample construction process in detail.

III.C. Summary Statistics

Panel A of Table I presents summary statistics for the court variables. On average, there are 18 judge posts per district court, with an occupancy of 77 percent. There are 1.62 instances of judge additions and 3.6 instances of removals per district court over the sample period. Average disposal rate is 14 percent with a standard deviation of 12, that is, 14% of the pending cases are resolved in a given year. In other words, it would take nearly seven years to clear all backlog if there were no new litigation. Using the timestamps on individual trials that were resolved within the study period, resolution takes 420 days on average, with a standard deviation of 570 days. The key difference between the disposal rate measure and the average duration of trial 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 measure avoids concerns pertaining to the selection of trials in its construction process.

Panels B and C describe credit market and local firm-level outcomes. Banks make 9138 loans to firms every year and have about USD 42 million worth outstanding loans per district. The summary on annual firm-level financials indicate that these are large firms, with USD 183 million in sales revenue and 10 million in profits. They also routinely borrow from banks and have substantial working capital worth USD 11.5 million. All financial variables are adjusted for inflation using Consumer Price Index (base year = 2015).

IV. IDENTIFYING THE EFFECTS OF JUDICIAL CAPACITY

As detailed in Section II.A., the number of active judges in a court frequently experiences a "shock" due to the addition and removal of judges arising from their periodic rotations as well as natural vacancies from retirements. The timing of these events are plausibly random as they are determined by the policies of higher-levels of the judiciary. Further, it is also likely that the level of vacancy (or conversely, occupancy) in a court-year is plausibly random due to this. Since the number of judges is less than the total number of judge positions across district courts in any state, the year-on-year variation in the number of vacant positions within a district court is likely exogenous to local firms' production outcomes.

The main identification relies on the timing of the multiple judge additional and removal events in a multiple events study design as it requires weaker set of assumptions. I discuss this approach first. Next, I examine the effects of local judicial capacity by using a generalized event-study design using the annual judge occupancy variable as a continuous "treatment" variable using a distributed lags model. This latter approach requires stronger set of assumptions relative to the main specification but serves to confirm the results qualitatively.

IV.A. Multiple Event Study Design: Addition and Removal of Judges from Courts

On average, a district court experiences 1.62 instances of judge additions and 3.6 instances of removals (see Panel A of Table I). This context presents multiple events within the district courts over the study period. The research design, therefore, has to account for the multiplicity as well as reversal of the direction of "treatment" that depend on whether judges are added or removed from a specific court in a particular calendar year.[13] I begin my empirical analyses without assuming exogeneity of judge vacancy rates by using multiple events study research design (following Schmidheiny and Siegloch 2020) around the timing of addition into and removal of judges from a district court, d, using the following specification where $e_{d,k}$ is the k^{th} event of either addition or removal of one or more judges, each case examined separately.

$$court_{dt} = \beta^c_{-3}\sum_{j=-8}^{-3} D_{d,t+j} + \sum_{j=-2,j\neq-1}^{2} \beta^c_j D_{d,t+j} + \beta^c_3\sum_{j=3}^{8} D_{d,t+j} + \delta^c_d + \delta^c_{st} + \epsilon^c_{dt}$$

$$y_{fdt} = \beta_{-3}\sum_{j=-8}^{-3} D_{d,t+j} + \sum_{j=-2,j\neq-1}^{2} \beta_j D_{d,t+j} + \beta_3\sum_{j=3}^{8} D_{d,t+j} + \delta_f + \delta_d + \delta_{st} + \epsilon_{fdt} \tag{1}$$

with D_{dt} defined as

[13] Using a single event study design by coding the largest addition or removal as the event introduces bias given that additions and removals occur so frequently in this data.

$$D_{dt} = \begin{cases} \sum_{k=1}^{K} \mathbb{1}[t \leq e_{d,k} + j] \text{ if } j = -3, \\ \sum_{k=1}^{K} \mathbb{1}[t = e_{d,k} + j] \text{ if } -3 < j < 3, \\ \sum_{k=1}^{K} \mathbb{1}[t \geq e_{d,k} + j] \text{ if } j = 3 \end{cases}$$

where each district court can experience upto K events within the study period, with calendar year denoted by t. δ_d and δ_f are the district and firm fixed effects, respectively, depending on whether the outcome is at the district court-level ($court_{dt}$) or firm-level (y_{fdt}). I flexibly account for state-time trends through state-year fixed effect δ_{st}. I consider an effect window of two periods prior and subsequent to an event and bin periods outside this window as in McCrary 2007. The reference period is the year prior to the event(s). The choice of an effect window of 2 years is based on the average tenure of a district judge, beyond which the judge is rotated out with a very high probability. I also examine a large effect window of size 4 as a robustness check.

To illustrate the implementation of multiple events study, consider the following example. Suppose district court 1 experiences judge additions in 2012 and 2015 and judge removal in 2014. First, I bin events based on additions and create a separate dataset. In this case, additions are only experienced in 2012 and 2015 and therefore, both these years are included in the bin for $t = 0$. The remaining years are added in different event bins based on their time distances from either of the events. For example, year 2011 is included in the bin for $t = -1$ as well as $t = -4$. Similarly, year 2016 is included in bins $t = 1$ and $t = 4$. Next, I create a dataset for removals in a similar way. Since I use an effect window of 2 years prior and subsequent to an event, I aggregate all event bins outside of the effect window by summing up the counts in the corresponding individual bins.

Causal identification using this design requires the following assumptions: (a) exogeneity of timing, (b) parallel trends, and (c) homogenous treatment effects across cohorts and groups. Existing vacancies and the policy of periodic judge reassignment generates plausible exogeneity in the timing of additions and removals. I examine the presence or absence of pre-trends as a test for the common trends assumptions. Finally, I re-estimate the coefficients on various subsets of the data to test for the homogeneity assumption. 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. On the other hand, this does require that the treatment effects be constant outside the effect window. I test for this by varying the effect window to examine whether there is a convergence in the regression estimates in the later periods. These tests give confidence to help interpret the coefficients during the post periods as the causal effect of changes in local judicial capacity.

The equivalent difference-in-difference specification is as follows, where the variable $\textit{Judge Add/Remove}_{dt}$ is a count variable that sums up all post periods across the multiple events from the dynamic specification.

$$y_{fdt} = \gamma_f + \gamma_d + \gamma_{st} + \psi \text{Judge Add/Remove}_{dt} + \nu_{fdt} \tag{2}$$

For inference, I compute cluster robust standard errors at the district-level in all my main specifications since the randomness in the timing of events is only plausible within a district court. I also run these specifications by clustering at the state-level to address concerns regarding any correlation between district courts in a state due to the judge reassignment policy.

IV.B. Generalized Event Study Design Using Variations in Judge Occupancy Rate

The above discussed multiple event study design is agnostic about the "intensive margin treatment" and only examines the "extensive margin" through the event-time bins. On the other hand, each of additional/removal instances introduce varying number of judges who are added or removed. Panel A Table I shows that on average, over 2 judges are added and over 3 judges are removed in one instance. Therefore, I use distributed lags model implementation of a generalized event study design, using leads and lags of annual judge occupancy rate as the explanatory variable. This also serves as a qualitative test of the direction of effects through a different modeling choice. Further, this specification provides an important policy parameter of interest, which is the effect of marginal change in judge vacancy. The specification is as follows where $\Delta Occup$ is the judge occupancy rate in district court d relative to the reference period of $t = -1$.

$$\begin{aligned} court_{dt} &= \gamma^c_d + \gamma^c_{st} + \sum_{s=-8}^{s=-3} \psi_s \overline{\Delta Occup}_{d,t+s} + \sum_{s=-2,\neq -1}^{s=2} \psi_s \Delta Occup_{d,t+s} \\ &+ \sum_{s=3}^{s=8} \psi_s \overline{\Delta Occup}_{d,t+s} + \epsilon^c_{dt} \end{aligned}$$

$$
\begin{aligned}
y_{fdt} &= \gamma_f + \gamma_d + \gamma_{st} + \sum_{s=-8}^{s=-3} \Omega_s \overline{\Delta Occup}_{d,t+s} + \sum_{s=-2,\neq -1}^{s=2} \Omega_s \Delta Occup_{d,t+s} \\
&+ \sum_{s=3}^{s=8} \Omega_s \overline{\Delta Occup}_{d,t+s} + \epsilon_{fdt} \qquad (3)
\end{aligned}
$$

As in the main event study specification, I bin the endpoints outside the effect window of ± 2 years by averaging the relative occupancy rates across the remaining study periods on either side outside the effect window.

As before, causal identification requires the following assumption: (a) exogeneity of judge occupancy rate at time t, (b) parallel trends, and (c) homogenous treatment effects across cohorts and groups. While the multiple event study design provides some assurance on these, exogeneity of occupancy rate is a stronger assumption than exogeneity of timing of judge additions and/or removal. Specifically, this assumes that: (a) the denominator - the total number of judge positions - in the occupancy rate is constant over the study period, and (b) judge choice of locations/rank-ordered list is time invariant or at least orthogonal to time-variations in local firms' outcomes.

Though these assumptions are strong, they are plausible. First, expansion of judge posts is not common and happens only with revised district population estimates after every census, if at all. Since the study period is completely within the two censuses, the total posts are likely constant. Empirically, I examine whether the results are robust to changing the denominator, i.e. the total number of judge posts imputed as the number of judges at the beginning of the study period. Further, I run the same specification with number of judges as the explanatory variable that does not suffer the same potential bias.

Second, it is likely that the judges' rank-ordered choice of district courts is orthogonal to local firms' outcomes. For there to be concerns regarding endogeneity, one needs to believe that judges are able to forecast the distribution of firms' short-term future production across different districts. On the other hand, the choices are more likely to be based on long-run projections if one believes judges to be perfectly rational agents. While unfortunately I do not have the choice data for judges, one empirical validation of this assumption would be to examine whether the results hold after dropping top industrial states or large districts from the sample.

V. REDUCED FORM RESULTS

In this section, I discuss the reduced form results from the multiple events study and generalized event study designs on local firms' production outcomes and corresponding court's performance levels.

V.A. *Exogenous Timing of Judge Additions/Removals*

Figure I shows that addition and removal of judges from courts due to the state policy of judge reassignments (Equation 1) generates a sharp increase or decrease in the number of judges immediately following the respective events. On average, additions and removals leads to ≈ 3 judges being added or removed from a court, respectively, in the same year. Due to their short tenures, the effect on the number of judges wanes over time. While additions and removals generate mostly symmetric effects, the key difference lies in persistence of their effects. The effect of addition converges to 0 over the long run, the effect of removal appears to persist. A likely explanation for this could be that vacancies tend to last longer as recruitment fails to catch up, generating structural vacancies in the Indian judiciary.

The results hold when I cluster the standard errors at the state-level or employ a longer effect window. Comparing the coefficients using the two effect windows of 2 and 4 years, I find that the effects converge within 4 years following the events.

Columns 1 and 5 of Table II presents the difference in difference estimates from Equation 2 specification with number of judges as the dependent variable. On average, judge addition events introduces 1.63 judges over the medium run whereas judge removal events reduce the number of judges by 3 judges. Of 195 district courts, one court experiences neither additions or removal and is automatically dropped from the analysis.

The addition and removal events generate a significant effect on the number of judges of similar magnitude across subsamples of courts, generated by dropping different groups based on their court size and district population densities, respectively (Table A.2). The coefficients are also of similar magnitude when dropping top industrial states and dropping districts abutting large metropolitan areas.[14]

V.B. *Reduced Form Effects on Court Performance*

The sharp changes in the staffing of courts following judge additions and removals have substantive effects on the corresponding court's performance, measured as disposal rate as defined in Section III.. Figure II depicts the multiple events study specifications with court-level disposal rate as the outcome variable. Judge additions results in an increase in disposal rate that lasts over the medium run and correspondingly, removals result in a decrease in disposal rate. The inference is robust to clustering at the state-level to account for serial

[14]The difference in difference estimates for judge addition after dropping top industrial states and districts are 1.26 and 1.45, respectively, significant at 1% (t statistics 3.9 and 5.1, respectively).

correlation between districts. Further, using a larger effect window also depicts similar short and medium run effects.

The improvement in disposal rate following additions is mainly driven by trial resolutions even though new case filings also respond to changes in staffing (see Figure A.5 and Figure A.6). Comparing the coefficients on the event dummies with the number of trial resolutions and new filings as the dependent variables shows that additions enable judges to resolve ≈ 200 more trials than filings in the short run but new filings catch up with resolutions in the long run. The temporary nature of judge addition could potentially explain this catching up of new filings.

Columns 2 and 6 Table II present the difference in difference estimates of judge additions and removals respectively, with court-level disposal rate as the dependent variable. The addition events generate a 3.2 percentage points increase in disposal rate in the post period whereas removals lower disposal rate by 1 percentage point. Using the performance index as the dependent variable in this specification for judge addition events yields an estimate of 0.266, which can be interpreted in terms of standardized units, i.e., implying an effect size of 0.266 standard deviation units.

These events generate similar magnitude of effects on court performance measures across various subsamples of the data, shown in Table A.3. Further, dropping top industrial states or districts lead to similar estimates 3.3 and 3.26, respectively, following judge additions.

One concern is that the removal events do not generate an equal and opposite effect on the court performance measures as additions. A plausible explanation for this stems from the persistence of vacancies, that may lower filing of new cases in addition to trial resolutions. Further, the existing judicial staff may be burdened with excess cases belong to the dockets of departing judge(s) that may arrest the drop in trial resolutions following judge removals.

The generalized event study approach accounts for these differences by exploiting continuous judge occupancy or number of judges variable, that enable examining both the addition and removal events within the same specification. Estimating Equation 3 with court-level outcome variables, confirms the relationship between higher judge occupancy (lower vacancy) and disposal rate observed in multiple events studies specification, depicted in Figure A.7. This is robust to using either the occupancy rate ($\frac{judges_t}{totaljudgeposts}$) or using just the number of judges in a distributed lags model with leads and lags of the explanatory variable normalized to one period lead value.

V.C. Local Firms' Production Outcomes

Given the relatively short term nature of judicial capacity shocks, I focus on incumbent firms based in the same district as the court and examine their key production outcomes - wage bill, capital goods (value of plant and machinery), sales revenue, and profits. Since many of these variables have 0s and negative values (particularly, profit and working capital), I use inverse hyperbolic sine transformation. This transformation also creates log-normal distributions of the outcome variables, which are generally right-skewed due to very few large and highly profitable firms.

I find positive effects of judge additions and corresponding negative effects of removals on wage bill and profits, that appears within a year following the event and persists over the long run (see Figure III). Wage bill displays an increasing (decreasing) trend over the long run whereas the effects on profits quickly converge, without long run dynamics. Sales revenue and capital goods exhibit suggestive long run effects although the estimates are not statistically significant.

Among factor use, the immediate response of wage bill but not capital goods seems consistent with the short term nature of the shocks whereas the persistence of these shocks has a likely implication for investment in capital goods only in the long term (since the negative effects on capital goods is stronger given the persistence of judge removals compared to additions). The effect on wage bill could partly reflect effects on labor productivity, especially if capital goods were functioning at slack capacity in the short run.[15]

On the output side, profit responds immediately most likely due to increases in non-production income such as income from rents, inter-firm lending, and other more "liquid" avenues rather than production since the effects on sales take a while to emerge. An improvement in labor productivity along with long run response of capital goods could effect sales in the long run (although not statistically significant but the magnitude of the estimates implies around 10% increase/decrease post addition/removal).

These results are robust to clustering standard errors by state, to account for any serial correlation between district courts arising out of judge rotation. The effect on wage bill and profits are still significant at 5% in the year(s) following the events (see Figure A.8). Using a longer effect window (Figure A.9) also confirms similar patterns, suggesting immediate and dynamic effects seen in wage bill but constant effects seen in profits.

Further, these effects are driven mainly by non-litigating firms in the sample. Figure A.13 presents the event study graphs using only the subset of firms not involved in any litigation in the sample courts. One concern is that some or many of these firms could be litigating in

[15]For example, it is a well known problem that Indian manufacturing operates 30-40 percent below their capacity.

other courts not in the sample. In such a case, the functioning of these other courts would matter more for such firms rather than their home district courts. This should lead to an attenuation bias, and the estimates presented in Figure A.13 are likely a lower bound.

Panel A Table III presents the difference in difference estimates from Equation 2. These confirm the findings from the multiple events studies specification. Wage bill increases by over 9% and profit by 87% on average in the post-period, subsequent to judge additions. The point estimates in specifications with other production outcome variables are also large and positive, but noisily estimated. The large effect on profit is plausible since profit includes not just profit from production but also income from other sources such as rent and investments. These latter components of profits are more likely to respond to short-term improvements in judicial capacity even though production responds by expanding sales but also input expenditure through higher wage bill (which may lead to a smaller impact of production on profit).

The point estimates remain of similar magnitude through many different robustness checks: (a) further restricting the sample of firms to those that report all five variables, (b) dropping top industrial states, and (c) dropping large districts. If anything, I gain more precision with other production outcome variables, particularly sales revenue, that was noisily estimated in the main specification (see Table A.4).

Finally, the results from the generalized event study specification Equation 3 provides an estimate of the "intensive" margin effects using variation in judge occupancy rates (Figure A.10) or number of judges (Figure A.11). This is qualitatively consistent with the results from multiple events study specification. Higher judge occupancy or lower vacancies generate long run benefits for firm production.

VI. CONCEPTUAL FRAMEWORK: UNDERSTANDING MECHANISMS

Role of Courts: Most economic models of contracts implicitly or explicitly assume perfect enforcement by courts. This masks the fact that courts are state institutions and their functioning can vary spatially as well as temporally. Imperfect staffing of courts and overall judicial/legal environment question this perfect enforceability assumption. I take this into account in a standard debt contract model and arrive at testable hypothesis that depend on the underlying judicial capacity.

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, which follows a given ex-ante distribution. 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 provides a minimum borrower wealth threshold below which the lender does not lend. Since the ensuing equilibrium is determined by stochastic shocks faced by the borrower in their production process as well as the extent of debt contract enforcement by the courts, this wealth threshold is a decreasing functioning of the court's effectiveness. Further, total debt payoff (principal + interest) charged by lenders also decreases for every level of borrowing with an increase in disposal rate. The framework is discussed in detail in Section A.II.

Production behavior: As banks begin to lend to smaller firms and lower overall interest rates, 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. I assume these transaction costs to also vary by the firm's ex-ante asset size, where larger firms might incur additional monitoring and enforcement costs on their own. While the effect on borrowing is hypothesized to vary by firm size, the average effect on input use, production and profit is expected to increase.

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 increased repayment from better debt contract enforcement, wealth threshold for lending decreases and interest rates weakly decrease for all levels of borrowing.
- H3: Firm sales and input use increase with judicial capacity through their ability to borrow.
- H4: Firm profits increase with judicial capacity, particularly for larger firms. Among small firms, the effect on profit depends on the trade-off between increased input costs and benefits from reduction in other transaction and monitoring costs.

VII. ECONOMIC MECHANISMS

VII.A. Litigation Behavior

Matching firms to the trial records in the sample courts generates the set of litigating 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 III., a large majority of the litigating local non financial firms appear as defendants. On the other hand, banks and financial sector firms appear as plaintiff across many districts, outside of their own registered office location. Figure A.15 shows the distribution of trials involving firms as litigants, which highlights the following key facts: (a) financial firms have more cases per firm, with an average of over 200 cases per firm whereas non-financial firms, on average, have less than half of the caseload per firm, (b) the value of litigation is orders or magnitude higher for banks relative to other contract enforcement litigation ("NI Act", which is essentially a bounced check case), or claims under road accidents and other types of contract disputes, and (c) there is some suggestive evidence that banks rely on better judicial capacity which makes them more likely to file more cases a few periods after judges are added and correspondingly, less likely to file cases subsequent to judge removal.

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. 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. Moreover, the industry structure of banks is based on credit contracts, which automatically make them contract intensive compared to non-financial firms.

Among local non-financial firms, the above framework suggests that wealthier firms are more likely to litigate, particularly as defendants. Figure IV shows the kernel density distributions of total asset value by the litigating status of local firms. Litigating (defendant) firms have larger asset value than other non-litigating firms in their corresponding district.

VII.B. Credit Channel

One way to understand the reduced form effects of judicial capacity on local firms' production outcomes is how these firms gain from an improvement in the contract enforcement environment. The framework above suggests that credit is one of the key channels through which firms expand production, particularly smaller firms who were perhaps credit constrained under weaker enforcement environment.

VII.B..1 Bank lending

I begin by examining the effects on bank lending to industry, aggregated across all banks at the district-level, in response to exogenous variations in judicial capacity. 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.e. the number of trials involving banks stuck in courts, I weight the regressions by the number of cases filed by banks in a given court each year. Specifically, I run the following specification, weighted by number of cases filed by banks in a court-year:

$$\text{Industry loans}_{dt} = \beta^b_{-3} \sum_{j=-8}^{-3} D_{d,t+j} + \sum_{j=-2, j\neq -1}^{2} \beta^b_j D_{d,t+j} + \beta^b_3 \sum_{j=3}^{8} D_{d,t+j} + \delta^b_d + \delta^b_{st} + \epsilon^b_{dt} \qquad (4)$$

The first row in Figure V depicts the weighted multiple event-study results with aggregate bank lending to all industry borrowers at the district-level. Total lending to industry borrowers in the district increases by 10-20% in years subsequent to judge addition. There is a corresponding drop in lending subsequent to removals.

This increase in lending by banks resulting from relatively short-term increase or decrease in judicial capacity raises two natural questions: (a) why don't the banks lend to firms in districts experiencing better enforcement environment than their own?, and (b) even if banks are constrained to lend within their district, why do they increase lending when improvement in judicial capacity is potentially reversible?

To understand why lending by banks are not fungible across borrowers in different districts, it is important to note that banks lend mainly through their local branch-network. Practically, what this means is that the branch managers and lending officials verify the loan paperwork by visiting the firm's headquarter, which is typically also their registered office location. This is done to reduce moral hazard and adverse selection. Equivalently, this means that a firm cannot borrow from a bank branch in a different district relative to the location of their operations.

Banks' lending responds to temporary changes in judicial capacity. There are two plausible reasons for this. First, there is some extent of persistence in judicial capacity. This is a relevant time horizon for loans for short maturity periods, such as those due in 1-2 years, as well as many short-term loan products (repayment $<$ 1 year). Second, timely resolution of debt trials enable banks to recover stuck capital, which increases their liquidity (by lowering provisions they need to make in their accounts for any debt write-offs). This additional liquidity is likely recirculated as fresh credit.

Table IV shows that both private and public sector banks increase lending to industry borrowers subsequent to changes in judicial capacity. The point estimates suggest some heterogeneity by the ownership structure of banks, with private sector banks increasing their lending by 22% post increase in the number of judges relative to public sector banks that increase their industry loans by 6%. This seems consistent within the economic framework involving rational actors, i.e. private banks and borrowers since public sector banks likely are motivated by different objective function than maximizing the rate of return.

VII.B..2 Credit access to smaller firms

As per the framework, smaller firms are expected to gain better access to credit from improved judicial capacity as banks reduce the wealth threshold for collateral. Firms do not consistently report borrowing data for each year, therefore, I use working capital as a key outcome measure to examine the extent of borrowing. Working capital is defined as current assets net of current liabilities. Current assets include cash reserves held by the firm in addition to value of inventory and raw material. On the other hand, current liabilities include all forms of debt including any outstanding borrowing from bank (principal + interest accrued thus far) as well as any form of trade credit (for example, money owed to input suppliers and other such accounts payable). Thus, to examine whether borrowing including the interest amount increases, I test whether working capital decreases without any decrease in current assets, and vice versa to examine if borrowing reduces under worse enforcement environment.

$$\begin{aligned} y_{fdt} &= \alpha_{-3} \sum_{j=-8}^{-3} Small_f \text{ x } d_{i,t-j} + \sum_{j=-2}^{2} \alpha_j Small_f \text{ x } d_{i,t-j} + \alpha_3 \sum_{j=3}^{8} Small_f \text{ x } d_{i,t-j} \\ &+ \beta_{-3} \sum_{j=-8}^{-3} d_{i,t-j} + \sum_{j=-2}^{2} \beta_j d_{i,t-j} + \beta_3 \sum_{j=3}^{8} d_{i,t-j} + \delta_f + \delta_d + \delta_{st} + \epsilon_{fdt} \end{aligned} \tag{5}$$

Figure V, second row, plots α_j from the above event study estimates with working capital as the dependent variable, and the third row plots the same coefficients with just the current assets as the dependent variable. The observed patterns of negative effects on working capital without any effects on current assets imply that judge addition leads to higher debt for small firms relative to large ones. Small firms also expand production relative to large firms, as seen in the form of increase in wage bill and sales revenue (Figure VI). These results taken together suggest that an improvement in judicial capacity enables better credit access among small firms, enabling better production outcomes.

Panel B Table III shows the coefficients on the interaction term from the following difference-in-difference specification equivalent to the above multiple event studies as follows:

$$\begin{aligned} y_{fdt} &= \gamma_f + \gamma_d + \gamma_{st} + \psi_1 Small_f \text{ x Judge Add/Remove}_{dt} \\ &+ \psi_2 \text{Judge Add/Remove}_{dt} + \nu_{fdt} \end{aligned} \tag{6}$$

These results suggest that judicial capacity improvements enable small firm production relative to large firms through better credit access that spur production through higher use of labor and generating more sales. Though ψ_1, the coefficient on the interaction term from the difference in difference specification, is positive and significant with capital goods as the dependent variable, this is likely driven by pre-trends. This can be rationalized since judicial capacity shocks are short term in nature whereas investment in capital goods would require a longer term and more sustained change in the enforcement environment. The short term shock is sufficient to circulate capital within local markets that help firms obtain credit for operational expenses. Finally, though ψ_1 is not significant and slightly negative, the overall effect on profit is positive. That is, while small firms probably earn less profit relative to large firms, their overall profit improves subsequent to judge additions.

On the other hand, there is no consistent differential effect on small firms subsequent to judge removals even though the market-level credit outcomes - total loans to all industry borrowers - drop. One plausible reason for this could be that banks may have contracted lending to informal firms first. Though the firms sample contains smaller firms, all of these firms belong to the formal sector and therefore, may not experience credit contraction. Correspondingly, the differential response by production outcomes is also muted even though these outcomes drop on average across all firms following judge removal.

VIII. ALTERNATE EXPLANATIONS

Judicial capacity could also effect firms' production outcomes through channels other than credit access. For example, better enforcement environment could improve labor-industry relation and increase salaried employment in manufacturing and tertiary sectors. Additionally, it can improve supply-chain networks through better enforcement of trade contracts.

First, I examine the dispute-type of trials involving firms, including banks, in the trial data (Panel E Figure A.15). Disputes including labor-industry relations are fewer in number across the courts relative to debt-related cases. Therefore, any improvements in judicial capacity reduces hold-up problems in debt cases that have been stuck in courts for long relative to labor cases. Further, labor disputes first go through administrative channels for resolution through the district labor commissioner - an arm of the executive - before being filed as a trial in a court. Judicial trial only follows if administrative resolution leaves any of the disputing parties unsatisfied with the verdict.

Second, trade contracts typically have arbitration clauses for those involved in the supply-chain system. Arbitration clauses under corresponding laws imply that the parties can themselves draw-up a system of resolving disputes and identify a neutral third party to help with resolution. Courts come into picture only if either of the parties want a court decree on the arbitration award or if any of the parties challenge the verdict. Again, examining the distribution of case types, arbitration cases in district courts are smaller in number relative to debt recovery disputes (Panel E Figure A.15).

Third, better courts could also improve the general law and order situation in the district. Lower crime could boost productive activities including industrial production. However, I find no evidence in support of reduction in crime, including petty crime, as a result of the judicial capacity variation I use (see Table A.5).

Finally, given the relatively frequent changes within district court capacities, its effect on firm entry, exit, and large business expansions are likely minimal. Higher-level judiciary and legislative changes are more likely to move these outcomes compared to temporary changes in local court capacities that I examine. While all these present other plausible channels through which courts can influence firm behavior, the context and the data shows the importance of credit markets as an important if not dominant channel.

IX. DISCUSSION

IX.A. On Debt Recovery Litigation

The results indicate that the shocks to local court capacities result in credit market adjustments and an increase in local firm production with a lag of 1-2 years. Courts play an important role in facilitating recovery of tied-up capital, in addition to creating an environment of trust where economic agents can expect market-based transactions to work. Given the temporary nature of the shock(s) to judicial capacity, rational expectations based mechanisms are less likely to underpin the observed effects. In contrast, a greater number of resolved debt recovery trials is likely to infuse local bank branches with recovered capital that could be immediately deployed for subsequent lending. As long as the expected returns from lending operations is higher than market returns, banks would recirculate the recovered capital.

To assess the distribution of consequent welfare effects, the average effects across the sample of firms could mask those of litigating firms. Figure A.16 presents the differential response of litigating firms relative to non-litigating firms based in the sample districts. Litigants' value of capital goods and sales revenue diminish relative to non-litigants following judge additions. This could arise if the increased trial resolutions are associated with decisions against the litigants. Since a majority of the litigating firms appear as defendants in contract dispute cases (including debt recovery), resolutions against the "offending" firm enable enforcement of contracts. The judgements provide redressal to the plaintiff, which in the case of debt recovery imply liquidation of pledged capital.

The findings here 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, the debt recovery tribunals are specialized courts with the jurisdiction to adjudicate litigation involving higher valued debts, which would otherwise had to be filed in state high courts. In contrast, this paper examines effectiveness of local (district) courts that adjudicate a variety of debt recovery litigations including those involving smaller debt sizes. Second, this paper examines the capacities of regular civil and criminal courts belonging to the judiciary rather than tribunals that are governed by the executive. Third, the natural experiment employed for causal identification addresses an important concern in the state capacity literature - that of persistent vacancies in the public sector, in contrast to the introduction of additional agencies addressing public services.

Finally, this paper presents a different aspect of the relationship between trial courts and local firms in relation to the key results presented in Ponticelli and Alencar (2016) in the context of Brazilian trial court capacity and changes in bankruptcy laws. First, I study the relationship in the absence of any changes in national or state laws, which are netted out as state-year fixed effects. Second, I exploit quasi-random temporal variation in judge vacancy within a district court in contrast to the cross-sectional variation in trial court jurisdiction examined in the Brazilian context. Third, this paper emphasizes the role played by trial courts in recovering tied-up capital in ordinary debt recovery litigation that does not necessarily evoke bankruptcy proceedings. Bankruptcy itself is a costly procedure and is typically the measure of last resort after trying other methods of recovering defaults. Easy and relatively fast debt recovery facilitates credit circulation within an economy.

IX.B. Benefit-cost analysis

In this section, I use a simple back-of-the-envelope computation of the benefit-cost ratio using the causal estimates of the effect of judge addition on increased returns to firms and its labor-force as well as the costs incurred by the state on additional judges. The implicit assumption I make is that the expenditure on additional judges at the district courts are the only major costs, both to the government and the society. This is a plausible assumption if the addition of judges mainly addresses existing vacancies and does not lead to other expenses such as infrastructure costs. Since judge vacancy is a first order problem in the Indian judiciary, this is likely to hold.

Additional costs could be incurred by those losing out from better functioning courts, including existing and potential litigants. Heterogeneity analyses based on whether a firm in the sample appears as a litigant in the court sample (Figure A.16) reveals that litigant firms experience no differential impact on their wage bill and plausibly a modest positive effect on profits (perhaps due to liquidation of assets that enter their profit and loss statement). However, there may be political benefits from keeping the courts inefficient, and therefore, the loss in rents to such a group of actors is not accounted for in the calculation of social benefits as it is inherently unobservable. While this could lead to an underestimation of the social costs, the cost to the state in the form of public expenditure on courts is likely well accounted for.

In Table V, I present the assumptions and the calculated benefit-cost ratio using the estimates from the analysis in this paper and a few assumptions. On the benefits side, I use the median values of profit and wage bill among the sample firms to compute the increase in firm-level surplus and salaried income in a district, with an average of 6 firms per district in my sample. Since both formal sector firms and salaried individuals pay corporate and income tax on their net income, I also compute the benefit-cost ratio from the perspective of state revenue and expenditure from improving judicial capacity at the district-level. I use the corporate tax rate for registered domestic firms in India as specified in the Taxation Laws Amendment Ordinance (2019). I calculate the effective income tax rate on salaried individuals as 7.3 percent based on applying the exemptions and tax-slabs specified in the Union Budget, 2018-19.[16]

On the expenditure side, I apply the estimates on the increase in the number of judges following an exogenous addition of judges to a court as the additional manpower at the district-level that the state has to incur expenses on. I compute the increase in expenses by multiplying this number by the median proposed salary of a district judge in the Second National Judicial Pay Commission. I further inflate this figure to account for other costs incurred by the state to cover judges' benefits and allowances, including transport, housing, etc. The actual salaries and benefits of judges would be lower than this figure depending on the extent of compliance of the report at the individual state-level.

In order to calculate the benefit-cost ratio, I need to take into account that benefits

[16]These assumptions are motivated by articles in the news media, with sources mentioned in Table V. 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 pays an effective tax of 7.3 percent.

occur with a lag whereas the expenditure is incurred in the current period as well as upto 3 years later. This can be seen in Figure I, where the event of judge addition results in an addition of about 3 judges immediately on average, this declines to 0 over the next 4 years. Averaging this over the post-period yields 1.63 additional judges per year, whose expenditure I account for as public cost. The increase in firm-level profit and wagebill occur with a one-year lag (Figure III), but one that potentially lasts over the medium run of at least 5 years (Figure A.9).[17] To be conservative, I calculate the present discounted value of firm profits, wage bill (which accrue to labor), and tax revenue (which accrue to the state) using the average value in the post-period but incurred only 5 years later. I assume the discount rate to be 5% in the base calculation and perform sensitivity analyses using lower and higher discount rates (Table A.6).

Figure VII 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 95% confidence intervals. To generate these distributions and confidence intervals around the computed benefit-cost ratio, 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 from the difference in difference specification (as per the Central Limit Theorem). This is akin to "running" the natural experiment 1 million times and computing the benefit-cost ratio every time the experiment is "run". This basic computation shows that the benefits are orders of magnitude larger than the costs. For the state, the ratio implies revenues that are 3.5 times higher than the expenditure on additional judges, whereas the social returns are even higher at 19. The 5% levels are 1.5 and 9.14, respectively, so even the most conservative estimates suggest that the returns to investing in district judicial capacity is high and more than pays for itself.

X. CONCLUSION

To conclude, I present well-identified causal estimates of ordinary trial court capacity on formal sector firm growth using trial level microdata from 195 district courts and quasi-random variation in judge vacancy. I show that the current state of trial resolution is abysmally low and around 23 percent of judge posts are vacant on average. Therefore, reducing vacancy substantially increases the rate of trial resolution. This is an important factor determining courts' capacity in enforcing credit contracts, freeing tied-up capital, and enabling credit circulation that has significant ramifications for local firms' production.

[17] This window is limited by data. Data from additional years of ecourts functioning could help examine longer run effects of judge additions and vacancies.

This role of courts is concordant with the observation that banks form the largest litigant group relative to any other type of firm. Initiating litigation against defaulting borrowers is a necessary first step before taking collateral into possession or initiating bankruptcy proceedings. Consequently, firms that borrow substantially from banks experience the need to repay in a timely fashion, as seen in the data. However, other firms benefit from an increase in credit access, expanding production. I show that access to finance is important for capital expansion.

This paper highlights judge vacancy as an important state capacity constraint, consistent with the current demand by legal and policy experts to strengthen the district judiciary in India. Given the benefits in the form of an expansion of industrial production, the state will be able to more than recover the costs of hiring additional judges from increased tax revenue and an expansion in employment.

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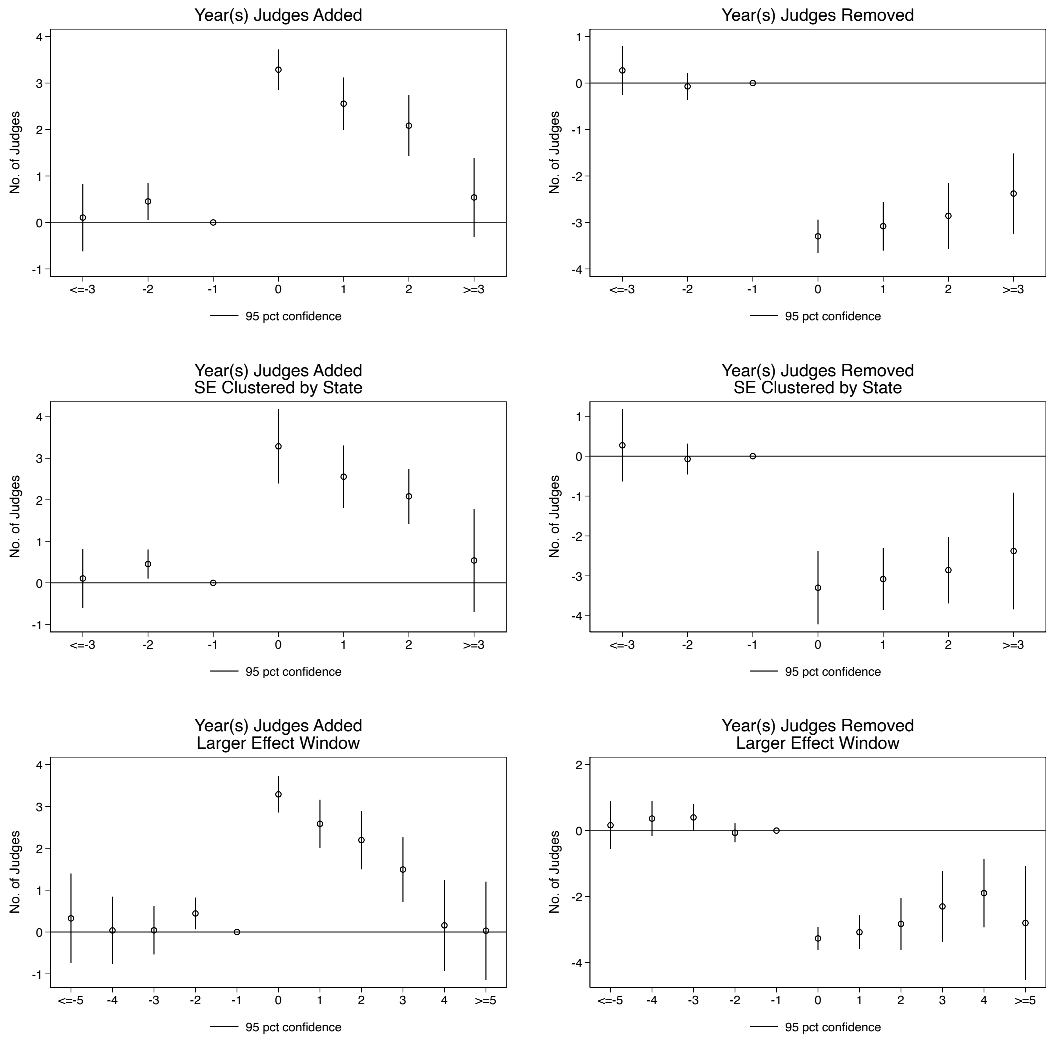
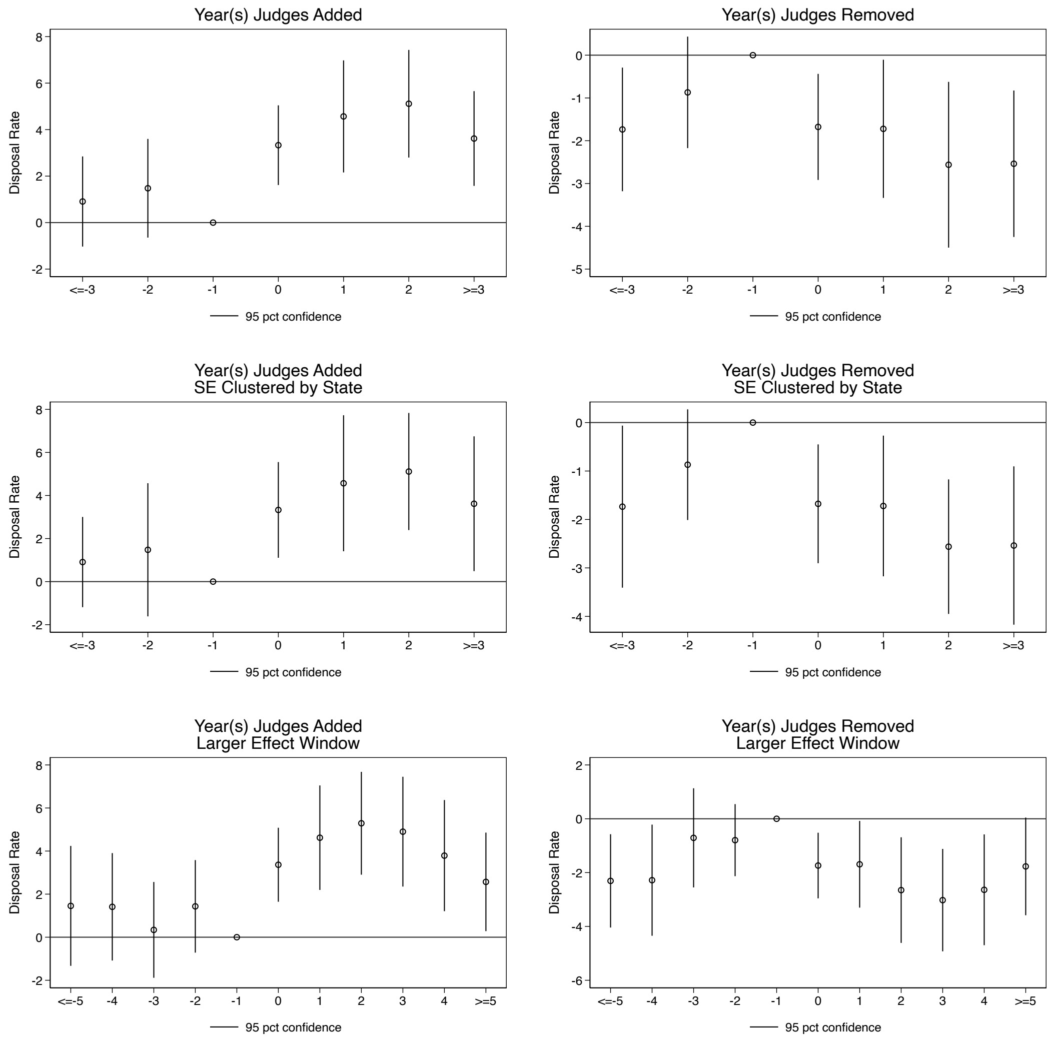
XI. Figures

Figure I: No. of Judges in District Courts



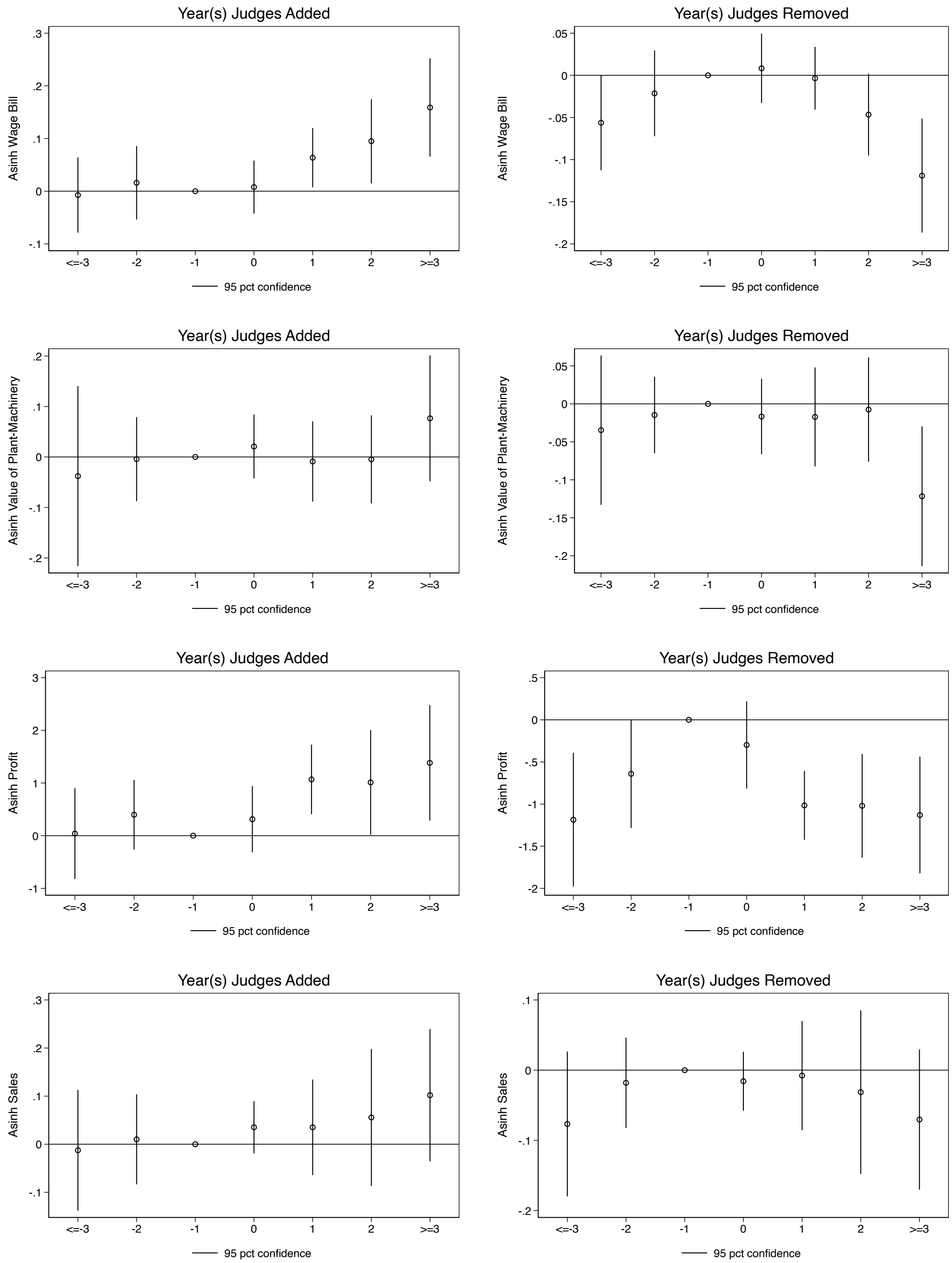
Notes: The figures above plot the event studies coefficients from estimating Equation 1 for number of judges in a given court-year, separately for judge additions and removals from district courts. The first row presents the coefficients with standard errors clustered by district. The second row presents the coefficients with standard errors clustered by state. The last row presents coefficients with a larger effect window. 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.

Figure II: Judge Staffing and Court Performance



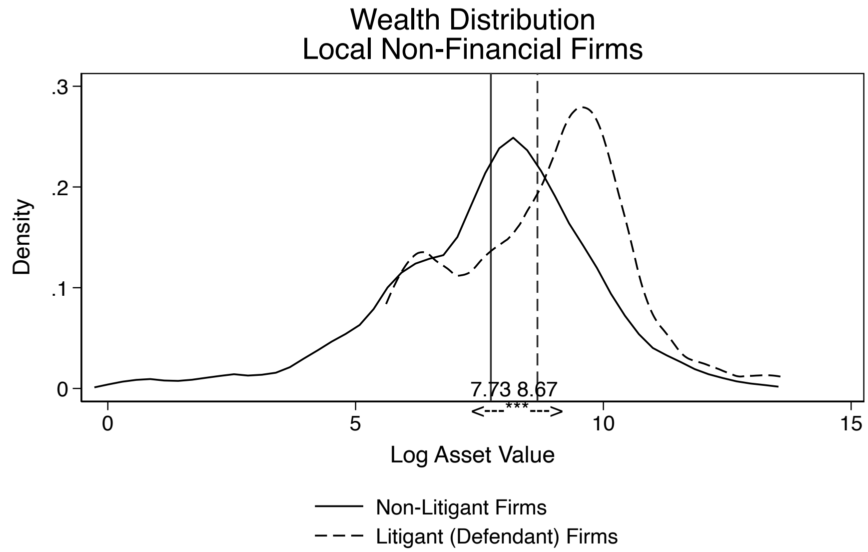
Notes: The figures above plot the event studies coefficients from estimating Equation 1 for disposal rate in a given court-year, separately for judge additions and removals from district courts. I define disposal rate as the percentage of all cases in a given year - newly filed as well as those pending from past years - that are resolved in that year. This is a frequently used measure of (inverse) court congestion in the literature as well as in policy. The first row presents the coefficients with standard errors clustered by district. The second row presents the coefficients with standard errors clustered by state. The last row presents coefficients with a larger effect window. 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.

Figure III: Reduced Form Results on Local Firms' Production



Notes: The figures above plot the event studies coefficients from estimating Equation 1 for firm-level variables, separately for judge additions and removals from district courts. 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 on these outcomes are % changes following the respective event(s). The first row presents the coefficients with wage bill as the dependent variable, the second row value of plant and machinery, third row profit including profit from production/services as well as income from other sources, and the fourth sales revenue. 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 an event and standard errors are clustered by district. Clustering by state and larger effect window figures are reported in the appendix Figure A.8 and Figure A.9.

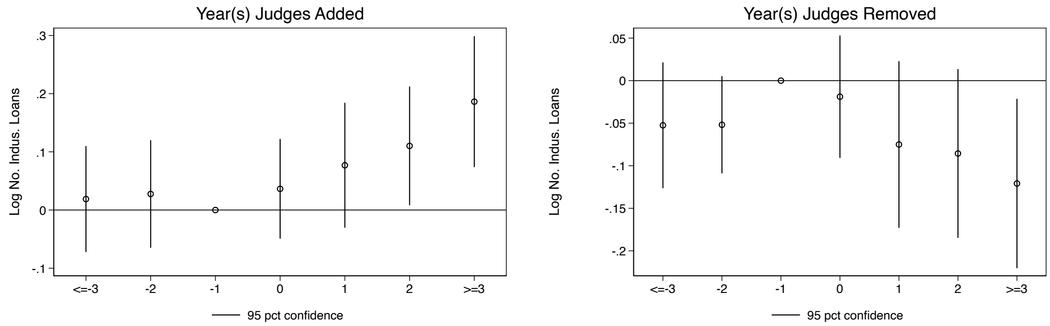
Figure IV: Wealth Distribution of Local Firms By Litigation Status



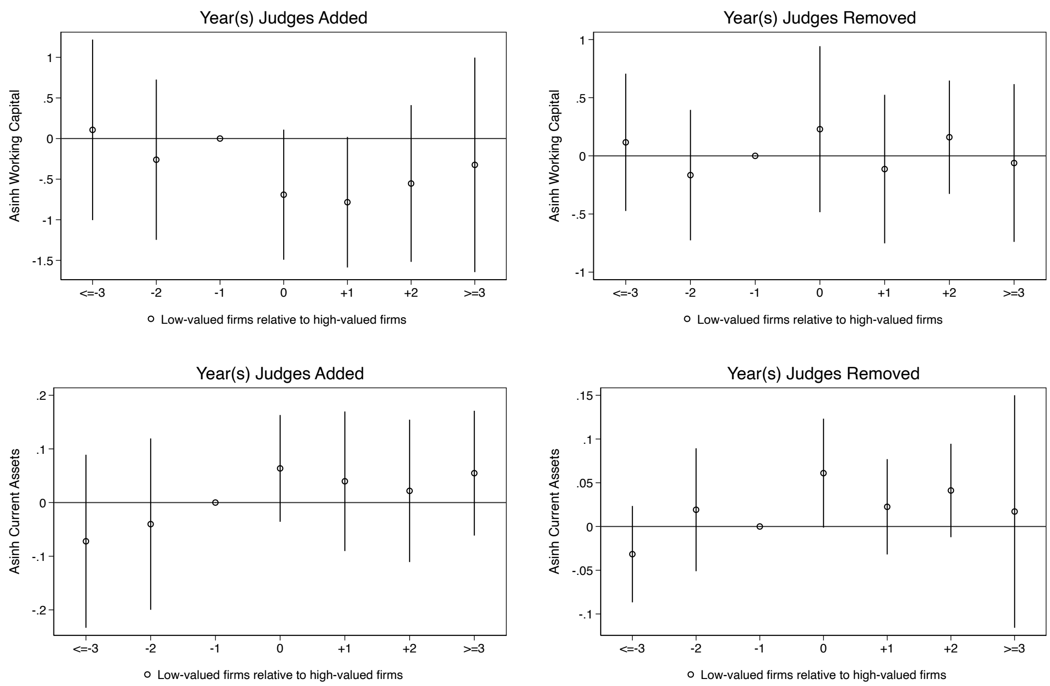
Notes: The above graph presents the kernel densities of firms' total assets by whether or not I observe the firm as a litigant - specifically as a defendant - in my sample courts. The lines represent the average asset value of non-litigant and defendant firms, respectivity, showing that the difference in their means is statistically significant with $p < 0.01$.

Figure V: Credit Mechanism

Panel A: Number of Bank Loans to All Firms in the District

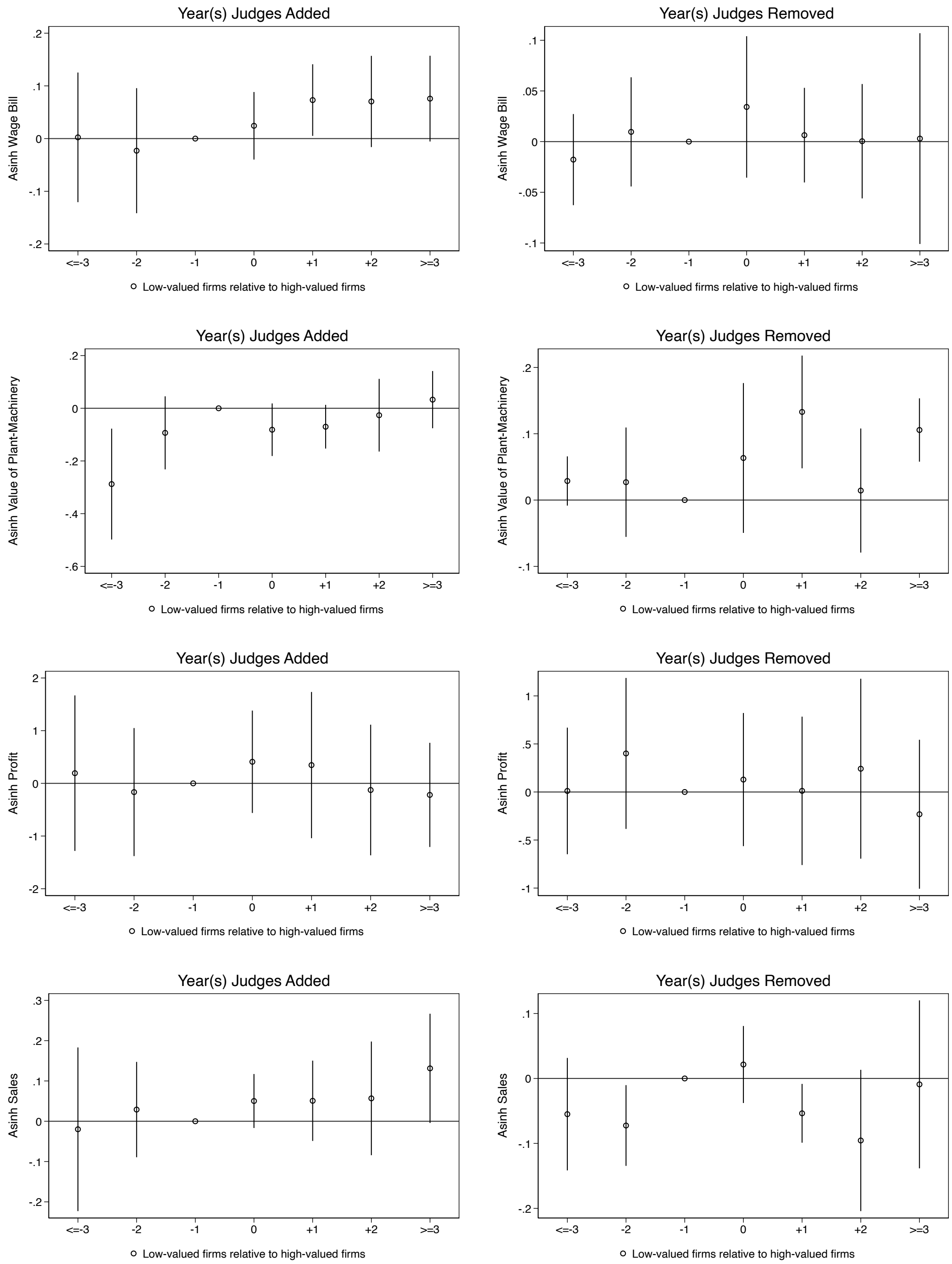


Panel B: Working Capital - Sample Firms



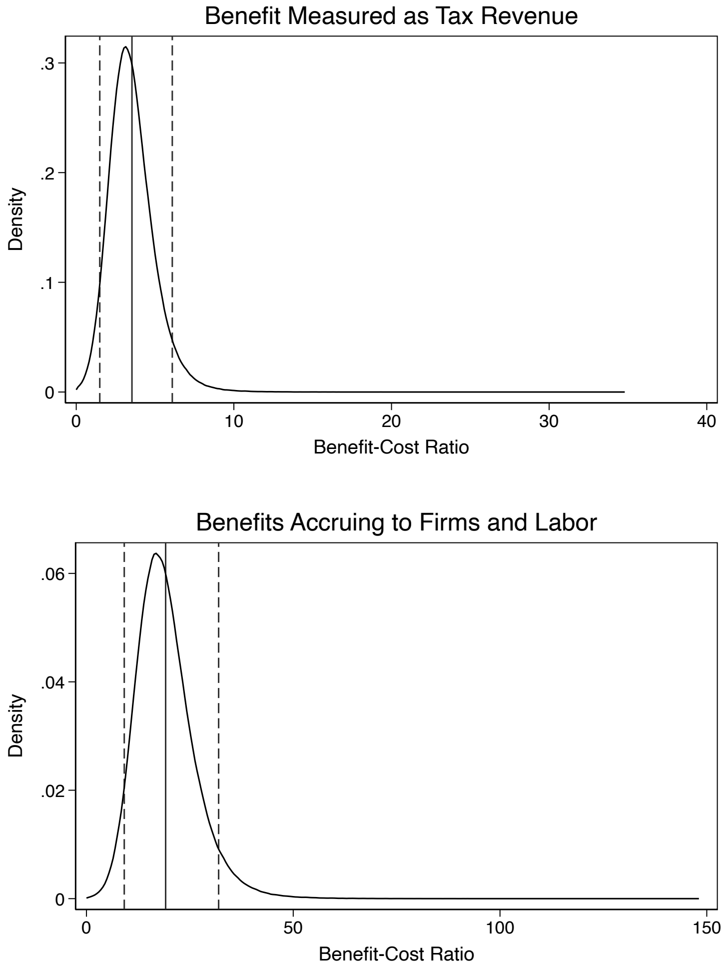
Notes: I examine the credit-channel by estimating the event-study coefficients using log total number of industrial loans lent by all banks within a district, after weighting the specification in Equation 1 by the number of cases filed by banks in a court-year. On the firms side, I examine the effects of their working capital as borrowing data is not reported consistently for all years in the study period by estimating Equation 5. Working capital is defined as the difference between current assets that includes cash and value of inventory and raw material, and current liabilities that include outstanding debt and accounts payable. Therefore, higher working capital means higher cash and/or lower debt, whereas lower working capital implies lower cash and/or higher debt. Standard errors are clustered by district.

Figure VI: Heterogeneity by Firms' Ex-Ante Asset Size



Notes: The figures above plot the event studies coefficients from estimating Equation 5 for firm-level heterogeneous treatment effects by asset size. The coefficients presented are those for low asset-valued firms relative to high asset-valued. As before, 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 an event and standard errors are clustered by district.

Figure VII: Benefit-Cost Ratios



Notes: Average benefit-cost ratio from tax-revenue perspective is 3.53, with 95% confidence interval [1.5, 6.1]. The average ratio computed using benefit accruing to firms and labor is 19.15, with 95% confidence interval [9.14, 31.96]. These ratios were calculated using the parameter estimates and their standard errors on number of judges, profits, and wage bill from the event of judge addition. I generate the distribution of these estimates using 1000000 random draws from normal distribution as per Central Limit Theorem and calculate the benefit-cost ration for each draw. Standard errors of the benefit-cost ratios are calculated as bootstrapped standard errors.

XII. Tables

Table I: Summary statistics

	(1)					
	No. of Units	Observations	Mean	Std Dev	Min	Max
Panel A: Court Variables						
Total Judge Posts	195	1755	18	19	1	108
Percent Judge Occupancy	195	1723	77	21	10	100
No. Judge Addition Events	195	195	1.621	1.153	0	6
No. Judges Added (per event)	158	158	2.31	2.54	1	24
No. Judge Removal Events	195	195	3.6	1.66	1	8
No. Judges Removed (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	194	1737	9138	15531	30	188456
Outstanding Amount (real terms, million USD)	194	1737	41.73	151.95	0.0032	2103.9
Panel C: Firm Variables						
Wage Bill (in real terms, million USD)	389	3425	11.45	24.8	0.001	313.41
Plant value (real terms, million USD)	374	3259	92.08	318.98	0	4527.45
Revenue from Sales (real terms, million USD)	391	3458	182.67	615.5	0.001	10766.05
Accounting Profits (in real terms, million USD)	391	3503	10.06	72.07	-1196.14	1486.39
Working Capital (real terms, million USD)	393	3536	7.21	145.85	-3008.02	2177.47

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 USD million in real terms, using 2015 as the base year.

Table II: Court Outcomes: Difference in Difference

	(1) No. of Judges	(2) Disposal Rate	(3) Disposal Rate	(4) Performance Index	(5) No. of Judges	(6) Disposal Rate	(7) Disposal Rate	(8) Performance Index
Post Judge Addition	1.631***	3.235***	3.235***	0.266**				
	(0.328)	(0.586)	(0.731)	(0.0942)				
Post Judge Removal					-3.02***	-1.050*	-1.050	-0.0769
					(0.255)	(0.543)	(0.815)	(0.0576)
Observations	1746	1746	1746	1478	1746	1746	1746	1478
No Districts	194	194	194	182	194	194	194	182
Pre-period Mean	12.26	10.13	10.13	-0.46	12.68	10.72	10.72	-0.73
Pre-period SD	16.1	10.88	10.88	1.24	15.37	14.78	14.78	1.08
District FE	X	X	X	X	X	X	X	X
State-Year FE	X	X	X	X	X	X	X	X
SE Cluster	District	District	State	District	District	District	State	District

Standard errors in parentheses

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

Notes: This table presents the estimates from Equation 3 on the all district courts in the sample. This presents the difference in difference implementation of multiple event studies specification in Equation 1 for court-level variables - number of judges and disposal rate, respectively. Clusters for standard error computation is specified in each column.

Table III: Firms' production outcomes

	(1) Working Cap	(2) Wage Bill	(3) Plant Machinery	(4) Sales Revenue	(5) Profits
	Panel A:	Difference in Difference			
Post Addition	0.383	0.0913***	0.0515	0.0686	0.873***
	(0.402)	(0.0337)	(0.0614)	(0.0618)	(0.314)
Observations	3536	3425	3258	3458	3503
No Districts	64	64	64	64	64
No Firms	393	389	374	391	391
Wald F-Stat (First Stage)	4.49	4.99	4.61	4.77	4.53
Firm FE	X	X	X	X	X
State-Year FE	X	X	X	X	X
	Panel B:	Heterogeneous Effects			
Low Asset x Post Addition	-0.396	0.0806**	0.150***	0.114	-0.147
	(0.524)	(0.0366)	(0.0462)	(0.0776)	(0.292)
Post Judge Addition	0.585	0.0538*	-0.0194	0.0131	0.947**
	(0.496)	(0.0309)	(0.0586)	(0.0582)	(0.357)
Observations	3536	3425	3258	3458	3503
No Districts	64	64	64	64	64
No Firms	393	389	374	391	391
Firm FE	X	X	X	X	X
State-Year FE	X	X	X	X	X

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

Notes: This table presents the estimates from Equation 2 (Panel A) and Equation 6 (Panel B), which are the difference in difference implementation of multiple event studies specification. Due to restricting the sample of firms to a balanced sample, only 64 district courts are retained from the original sample of 195 courts. All firm-level variables are inverse hyperbolic sine transformations of their corresponding raw numbers. Panel B presents heterogeneous effects by firms' asset size. Low Asset firms are those in the bottom three quartiles of pre-2010 asset value across all firms, including those not in the balanced panel. Standard errors are clustered at the district level in all specifications.

Table IV: District-level Total Bank Loans to Industry

	(1) All Banks No. Loans	(2) Pvt Banks No. Loans	(3) Pub Banks No. Loans
Post Judge Addition	0.0966**	0.222**	0.0605*
	(0.0466)	(0.112)	(0.0364)
Observations	1217	1207	1217
No Districts	169	168	169
District FE	X	X	X
State-Year FE	X	X	X
Post Judge Removal	-0.0331	-0.112	-0.0295
	(0.0334)	(0.0743)	(0.0307)
Observations	1217	1207	1217
No Districts	169	168	169
District FE	X	X	X
State-Year FE	X	X	X

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

Notes: This table presents the difference in difference estimates from Equation 2 but using district-level number of bank loans to industrial borrowers as the dependent variable. The regressions are weighted by number of cases filed by banks in the corresponding district court in a given year. The dependent variable Column 1 is log number of loans to industrial borrowers by all banks in a district, Column 2 is log number of industrial loans by private sector banks, and Column 3 is log number of industrial loans by public sector banks. Public sector banks account for $\approx 85\%$ of all banks in the study period. Standard errors are clustered by district.

Table V: 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
No. Judges Added ($\widehat{\beta}$, $\sqrt{\widehat{V}(\beta)}$)	(1.631, 0.328)	Increase Post Addition	Estimation
Profit ($\widehat{\beta}$, $\sqrt{\widehat{V}(\beta)}$)	(87.3, 31.4)	% Increase Post Addition	Estimation
Wage ($\widehat{\beta}$, $\sqrt{\widehat{V}(\beta)}$)	(9.13, 3.37)	% Increase Post Addition	Estimation
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)	3.53 (1.63)	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social)	19.15 (8.15)	Ratio	Calculation Bootstrapped SE

Notes: I focus on the event of judge addition to compute benefit-cost ratios. Since the results are relatively symmetric for the event of judge removal or vacancies, the ratio for the event of judge removal should be interpreted as forgone benefits to the cost "saved" from lower judge payroll. 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. Standard errors are bootstrapped from 1000,000 random draws.

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

A.I Data Appendix

A.I.A. *Representativeness of district courts sample*

Figure A.3 illustrates the sample districts covered in the dataset. While firms in the sample districts are three years older than the average firm in the excluded districts, publicly listed as well as privately held limited liability firms are similarly represented in the sample districts. Additionally, firms in banking and manufacturing sector are also similarly represented. Since the focus is non-metropolitan districts, firms common in metro areas such as those owned by government and business groups are less represented. **??** in the appendix provides the details on the distribution of firm types across sample and excluded districts.

Since the e-courts system came into full operation from 2010, I consider 2010-2018 - which is the entire period over which the trial data is available - as the period of study. This gives me the population (universe) of all trials that were active anytime between these years - either pending from before 2010, or filed between 2010 and 2018.[1]

A.I.B. *Other complementary datasets*

I use population census data, district-wise annual crime data for balance checks, and consumer price indices to convert the financial variables in real terms. [2]

A.I.C. *Outcome variables*

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

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

[2]All data used here, with the exception of Prowess, are publicly available. District wise credit data are available through the Reserve Bank of India data warehouse. National Crime Records Bureau annual crime statistics available on their website.

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

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

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/wear and tear.

A.I.D. Matching firms with trial data

I follow the steps below to match firms with registered cases in the e-courts database:[3]

1. Identify the set of cases 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. Common patterns include firm names starting with variants of "M/S", ending with variants if "Ltd", and so on. This produces about 1.2 million cases, or 20% of the universe of cases.

2. Create a set of unique firms appearing in above subset of case data. I note that same firm appears as a litigant in more than one district. This is because the procedural

[3]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 heuristics as listed in the appendix. I only retain one-to-one match between a firm and a trial.

laws pertaining to civil and criminal procedures determine where a specific litigation can be filed based on the issue under litigation.

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

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

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

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

A.II A model of credit market with enforcement costs

A.II.A. Credit Market

I follow and extend the credit contract model in Banerjee and Duflo (2010) to include the possibility of litigation given the rate of trial resolution in the corresponding local 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 borrowing.

At the start, borrower needs to invest, K, in a project which returns $f(K)$. Her exogenous wealth endowment is W. She needs an additional $K_B = K - K_M$ from the lender to start the project, where K_M is the amount she raises from the market. The lender earns a return $R > 1$ if the borrower repays on time. The project suceeds 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. The game is depicted in Figure A.14. 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 mostly win as seen in the data. The intuition behind this relationship behind litigation costs and judicial capacity can be explained by the fact that the litigants need to spend more on travel, logistics, and lawyer fees if the trial takes a long time to be resolved.[4]

When her project fails, the borrower litigates only if the value of her assets net litigation costs is positive. At the same time, the lender seeks to liquidate part of 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 her litigation costs $C_B(\gamma)$ 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 the distribution of firms by their ex-ante 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 she can successfully evade. However, default gives rise to the possibility of litigation. In this situation, borrower will litigate if

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

This gives a distribution of firms willing to litigate under default. Since K_B only depends on the project, with an ex-ante distribution given by CDF, $G(.)$, and R is fixed by the lender,

[4] Introducing a probability of winning, $p >> 1-p$ does not add much to the exposition and for tractability, I skip this stochastic component. Sadka et al. (2018) notes overconfidence among individual litigants that supports the idea why borrowers continue to litigate when decisions typically favor the lender.

a fraction $1 - G(\tilde{W})$ of borrowers will litigate. Therefore, by backward induction, litigation will be lender's weakly dominant strategy if

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

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

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

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

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

The timing of the game where the lender and borrower decide on their strategies are depicted as an extensive form game in Figure A.14.

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 threshold wealth, W^* required to borrow, as depicted in **??**.

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.II.B. Firm Production

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

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

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

where w_1 and w_2 are the unit costs of inputs X_1 and X_2, $m_i(\gamma)$ is the monitoring costs arising in the production process, which weakly decreases with improvements in judicial capacity, i.e. $\frac{\partial m_i}{\partial \gamma} \leq 0$. i represents firm size based on their initial wealth endowment, denoted by S for small firms and by L for large ones. Further, I assume that fixed costs form a large share of monitoring costs for small firms such that $\frac{\partial m_S}{\partial \gamma} \approx 0$ whereas for large firms, $\frac{\partial m_L}{\partial \gamma} < 0$ reflecting a lowering of the variable cost. $K_i = K_M + K_B$, is the total capital available to finance production, including borrowing from bank K_B as in Banerjee and Duflo (2014). From the credit market model below, 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 and profits increase on an average.
3. Heterogeneity in effects are as follows:
   (a) For large firms, L, optimal inputs and profits increase if decrease in monitoring costs and cheaper credit more than offsets the increase in input expenditure.
   (b) For marginal small firms, S, optimal inputs and profits increase if increase in borrowing is sufficiently large to offset the increase in input expenditure.
   (c) For inframarginal small firms, S, optimal inputs and profits remain unchanged because borrowing and monitoring costs for these firms remain unchanged.

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

Constrained Optimization:

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

FOC:

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

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

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

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

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

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

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

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

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

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

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

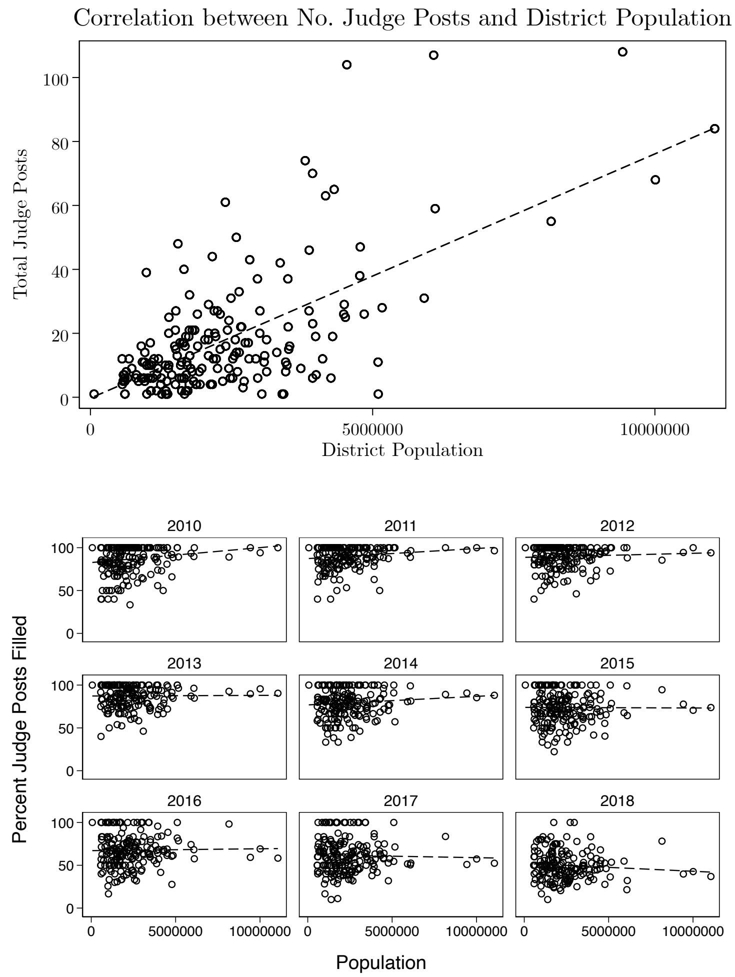
in monitoring costs is greater than the marginal increase in input costs, then profits for such firms will increase.

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

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

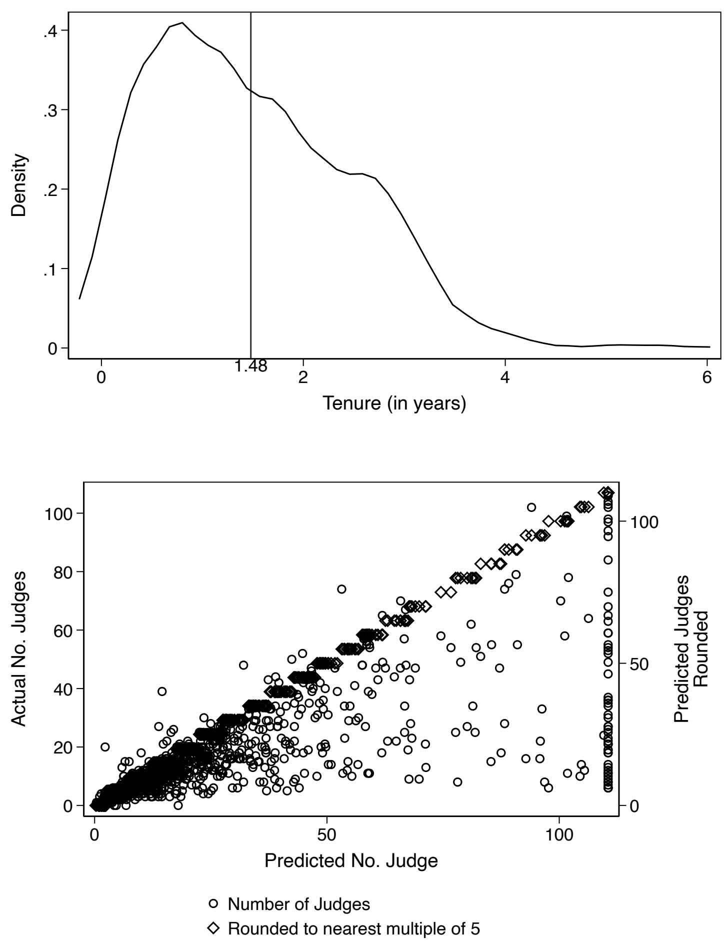
A.III Appendix: Figures

Figure A.1: Total Number of Judge Posts and District Population



Notes: 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: Sample district courts

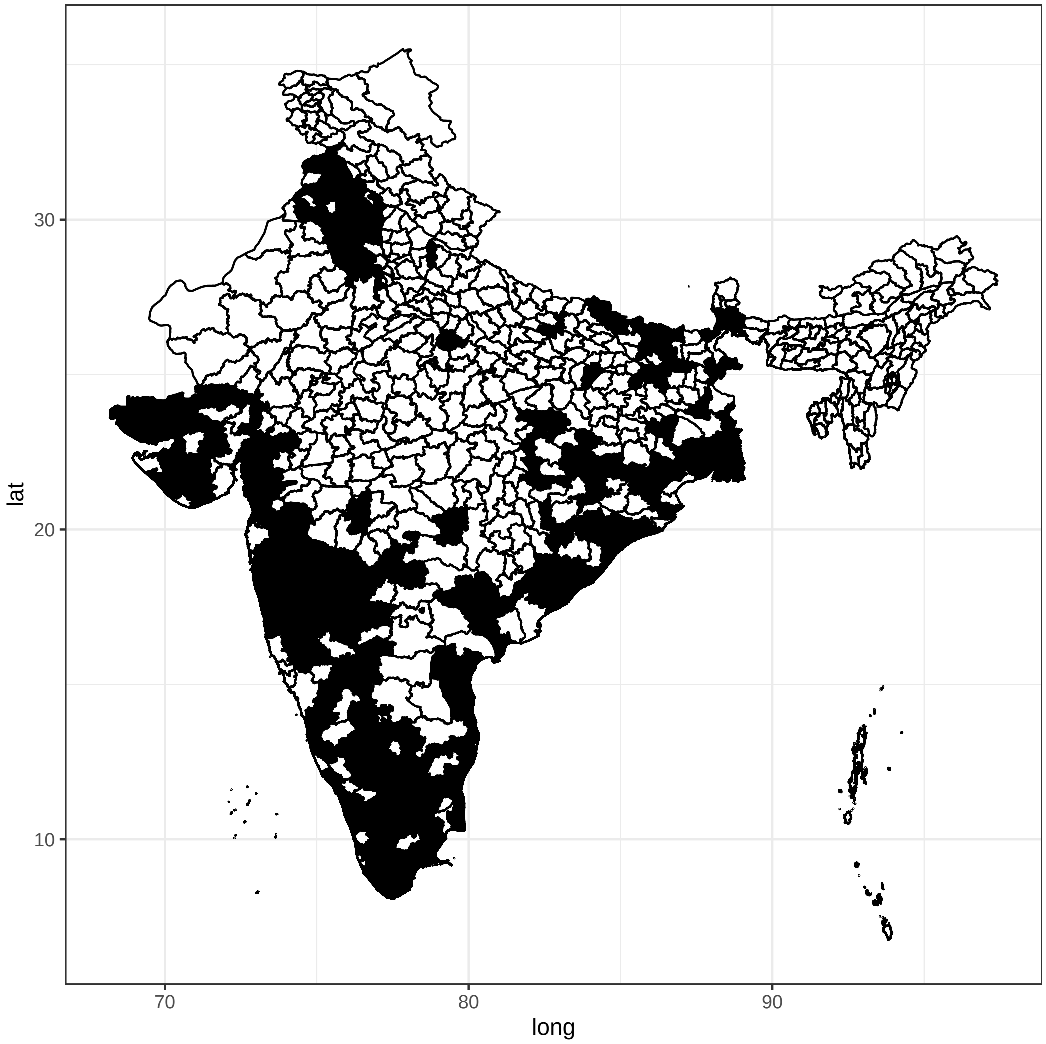


Figure A.4: Construction of firm sample

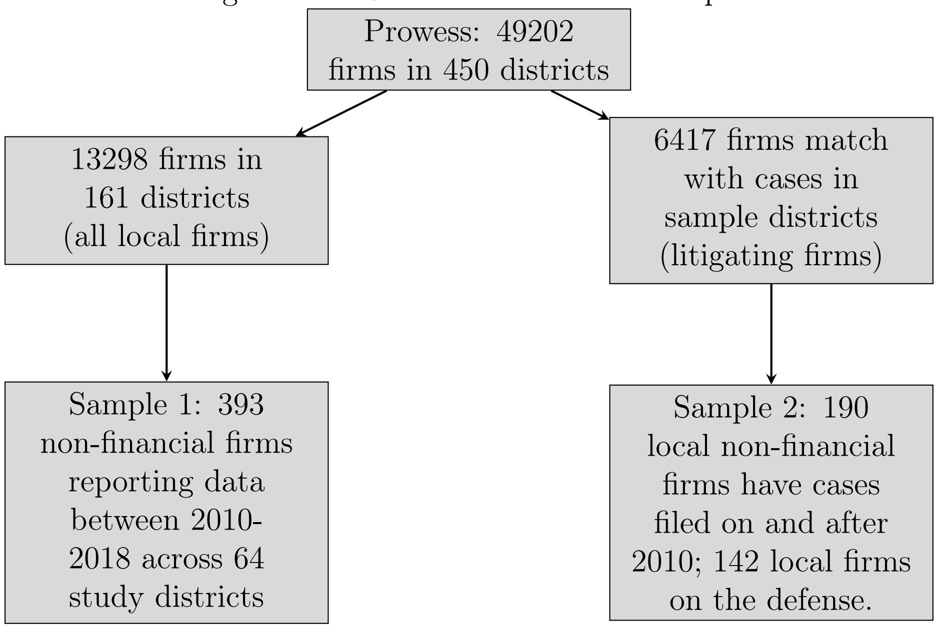
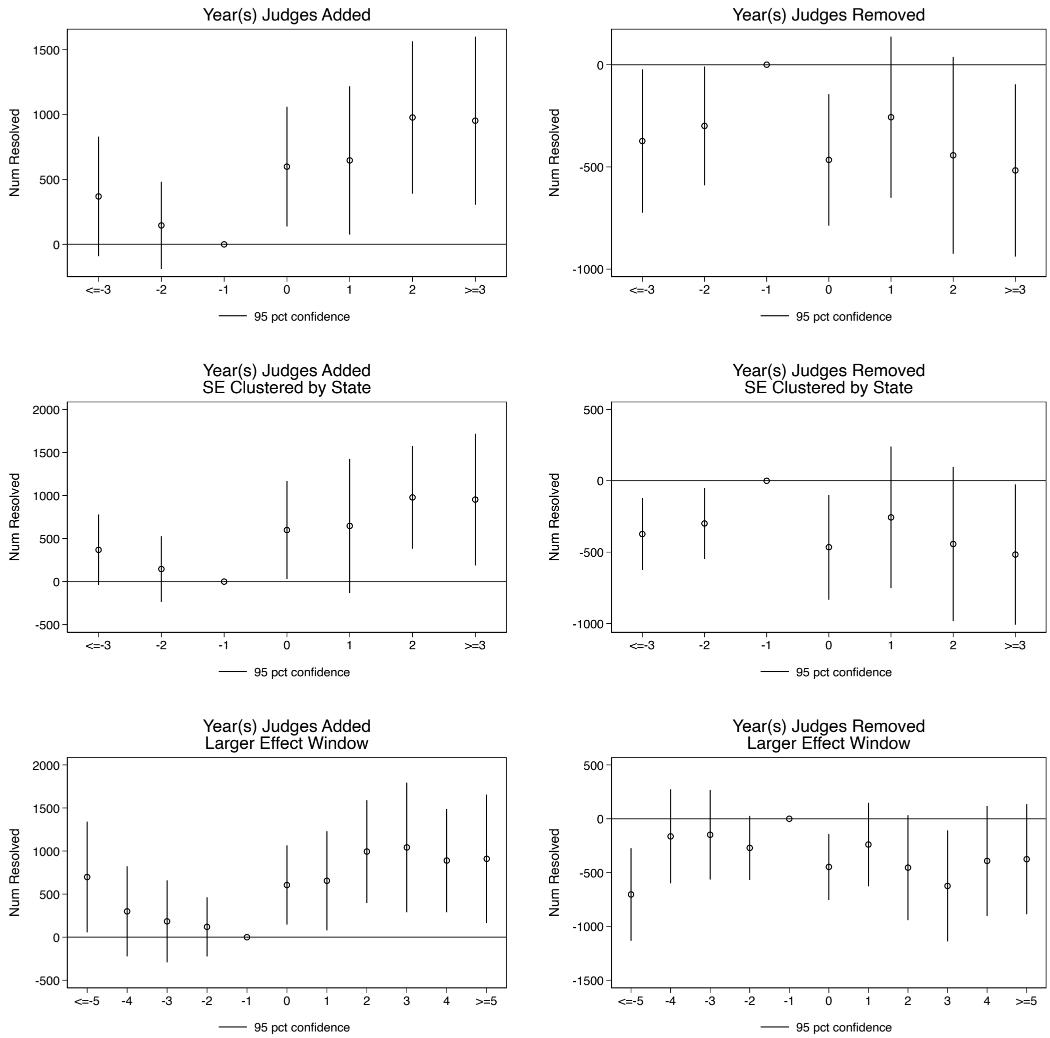
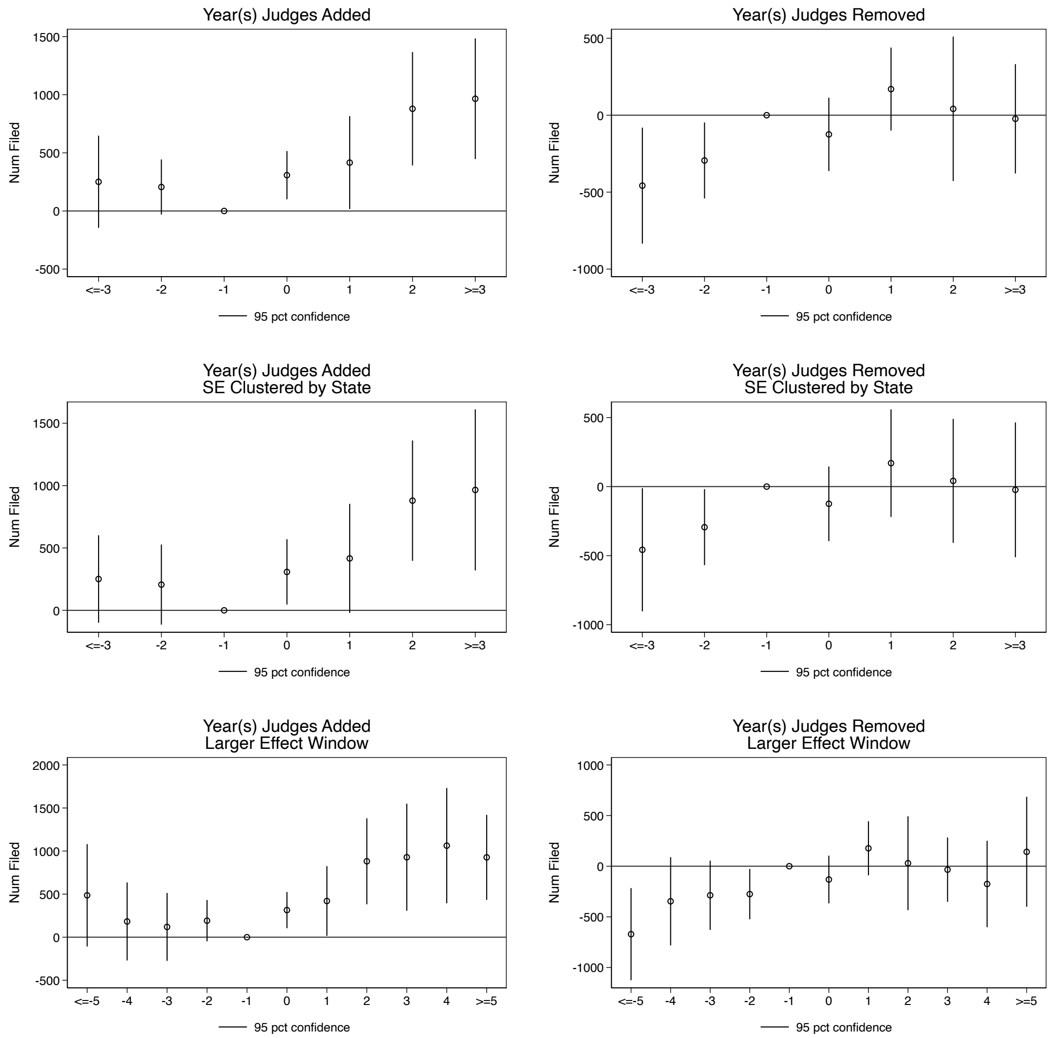


Figure A.5: Judge Staffing and Trial Resolutions



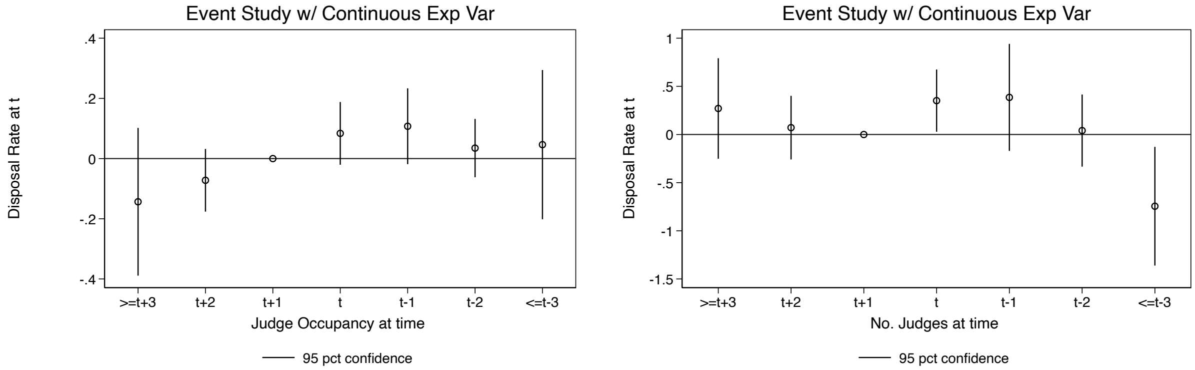
Notes: The figures above plot the event studies coefficients from estimating Equation 1 for number of resolved cases in a given court-year, separately for judge additions and removals from district courts. The first row presents the coefficients with standard errors clustered by district. The second row presents the coefficients with standard errors clustered by state. The last row presents coefficients with a larger effect window. 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.

Figure A.6: Judge Staffing and New Filings



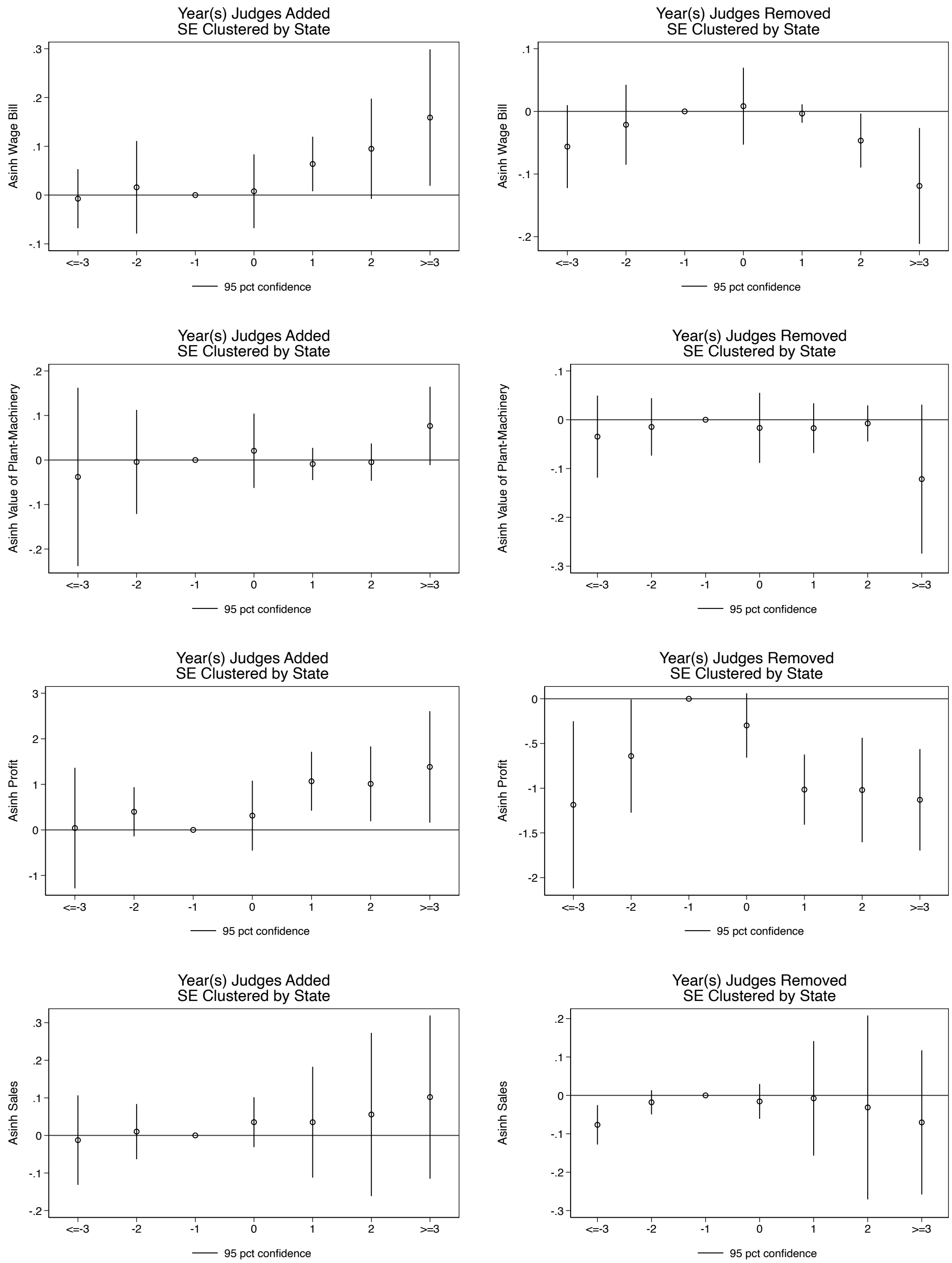
Notes: The figures above plot the event studies coefficients from estimating Equation 1 for newly filed cases in a given court-year, separately for judge additions and removals from district courts. The first row presents the coefficients with standard errors clustered by district. The second row presents the coefficients with standard errors clustered by state. The last row presents coefficients with a larger effect window. 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.

Figure A.7: Distributed Lags Model For Continuous Event Study: Disposal Rate



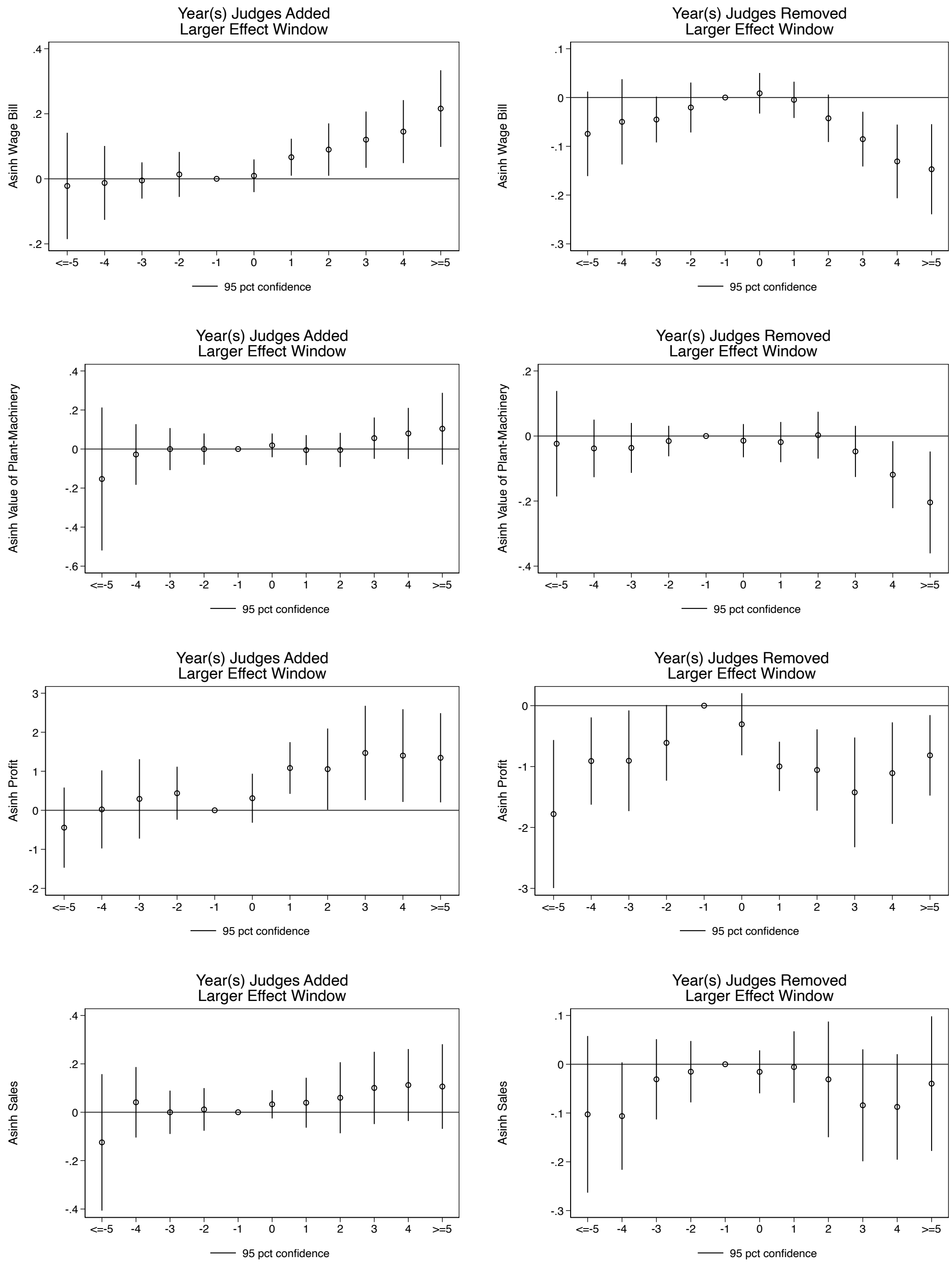
Notes: The figures present the generalized event study estimates relative to judge occupancy or number of judges from $t+1$ when the court-specific outcome is measured at t. The explanatory variable at period $t+1$ is differenced out from its leads and lags. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district. Clustering standard errors by state produces similar patterns.

Figure A.8: Robustness to Clustering SE by State



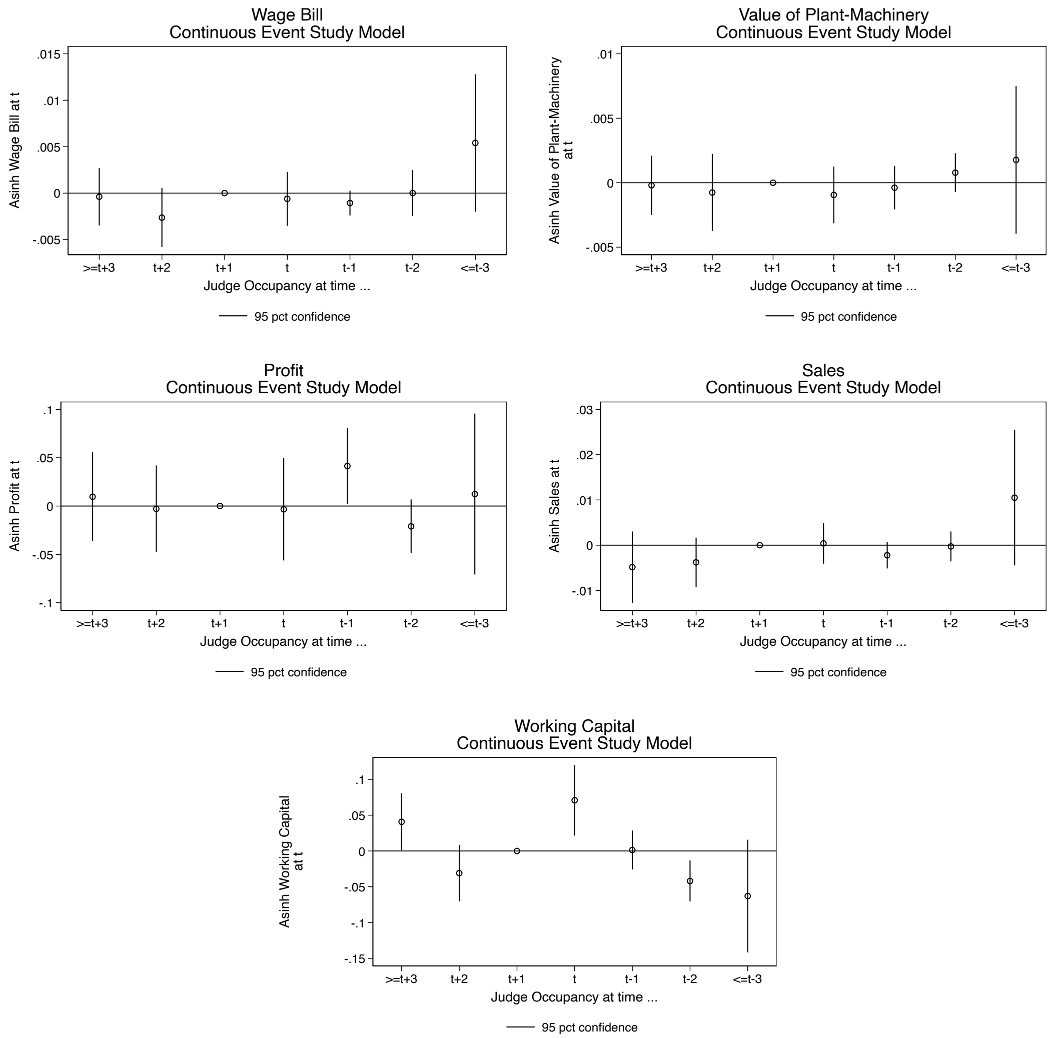
Notes: These graphs reproduce the reduced form graphs from Figure III but with standard errors clustered by state.

Figure A.9: Longer Effect Window



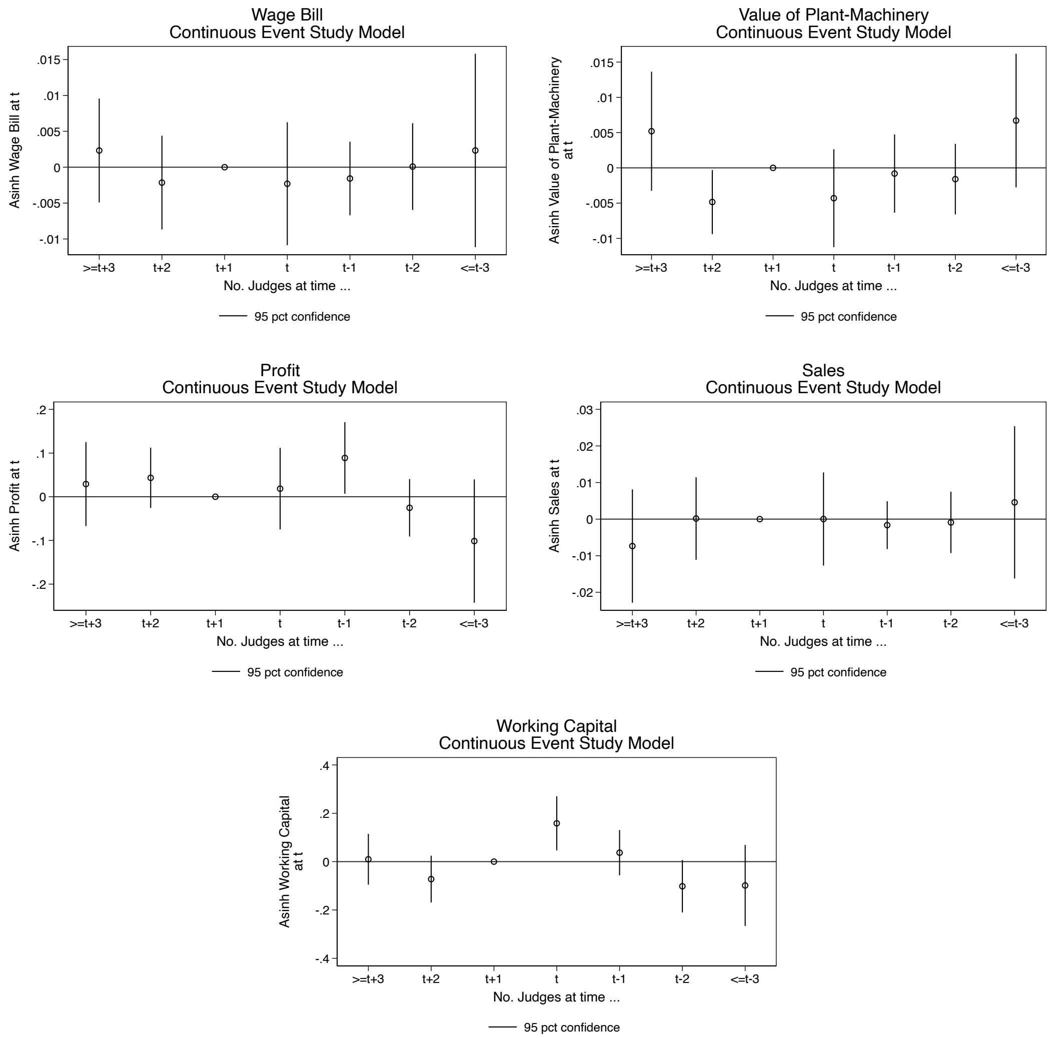
Notes: These graphs reproduce the reduced form graphs from Figure III with a larger effect window.

Figure A.10: Distributed Lags Model For Continuous Event Study



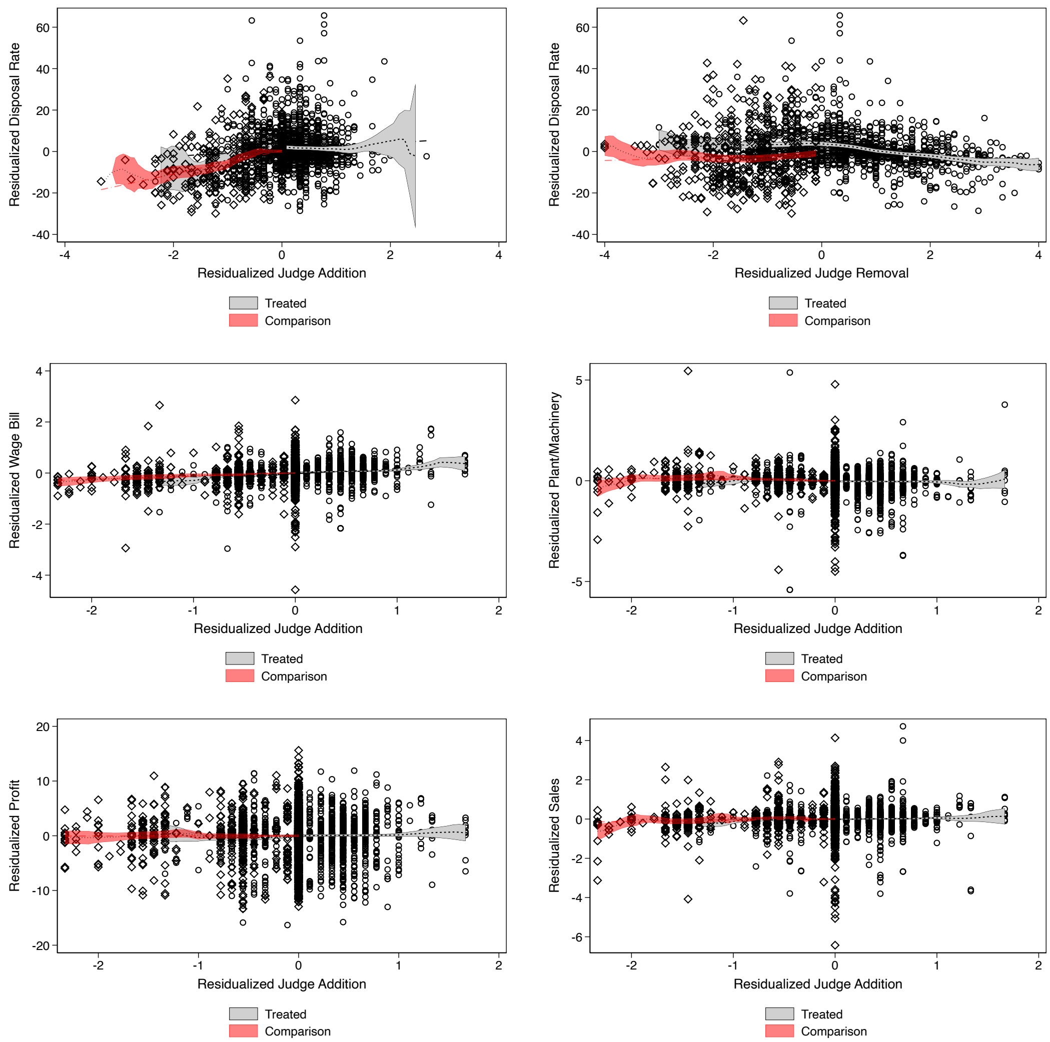
Notes: The figures present the generalized event study estimates relative to judge occupancy from $t+1$ when the outcome is measured at t. Judge occupancy at period $t+1$ is differenced out from the judge occupancy in each period. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district. Clustering standard errors by state produces similar patterns.

Figure A.11: Distributed Lags Model For Continuous Event Study: No. Judges



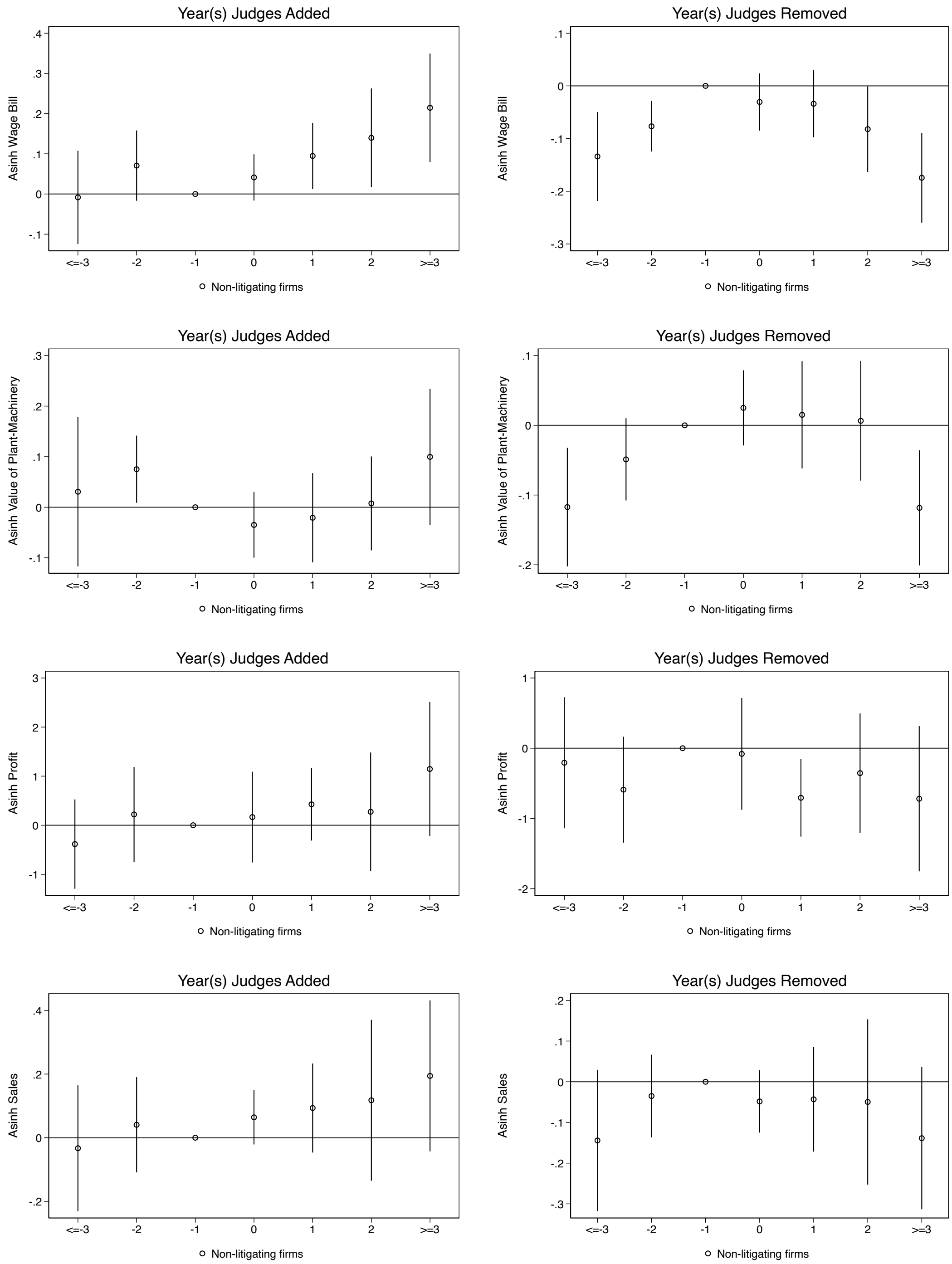
Notes: The figures present the generalized event study estimates relative to number of judges from $t+1$ when the outcome is measured at t. Number of judges at period $t+1$ is differenced out from the number of judges in each period. Each estimate is presented along with 95% confidence interval. Standard errors are clustered by district. Clustering standard errors by state produces similar patterns.

Figure A.12: Homogeneity Assumption



Notes: The above figures plot the relationship between residualized outcome variable and residualized treatment, i.e. judge addition as a test for homogeneity assumption suggested in Jakiela (2021)

Figure A.13: Subset of Non-Litigating Firms Only



Notes: These graphs reproduce the reduced form graphs from Figure III but only on the subsample of non-litigating firms.

Figure A.14: Model: Credit and Litigation

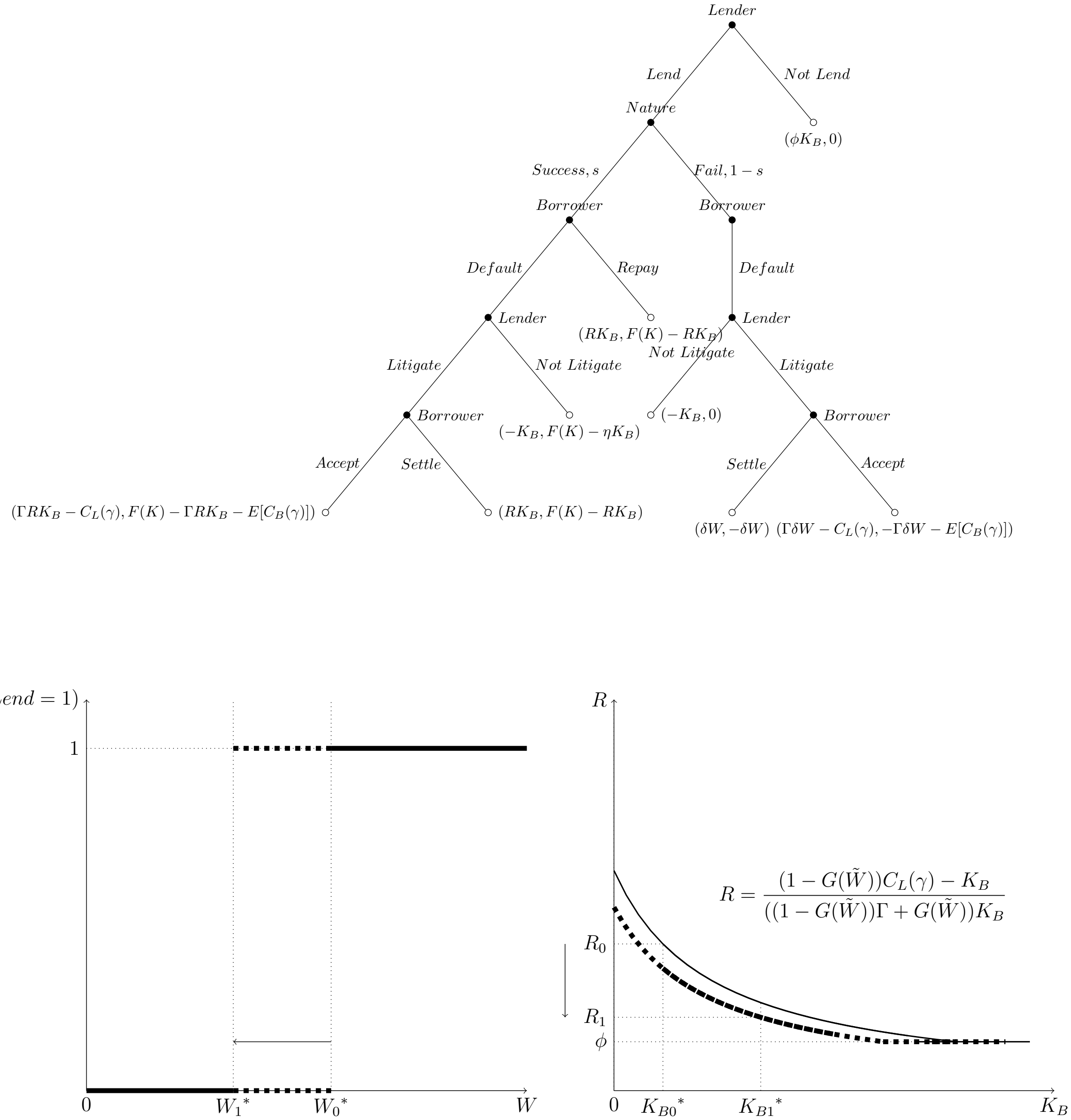
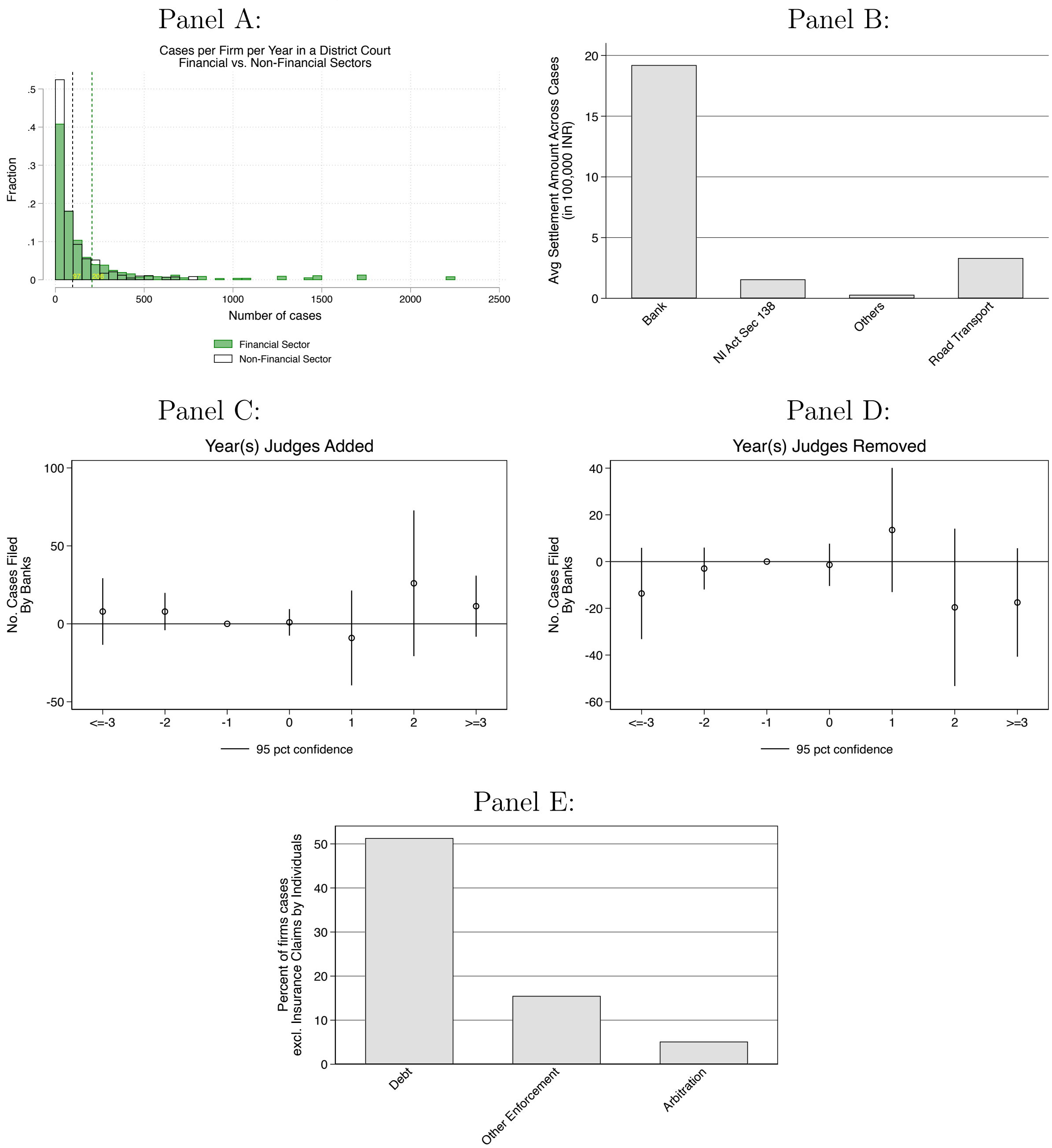
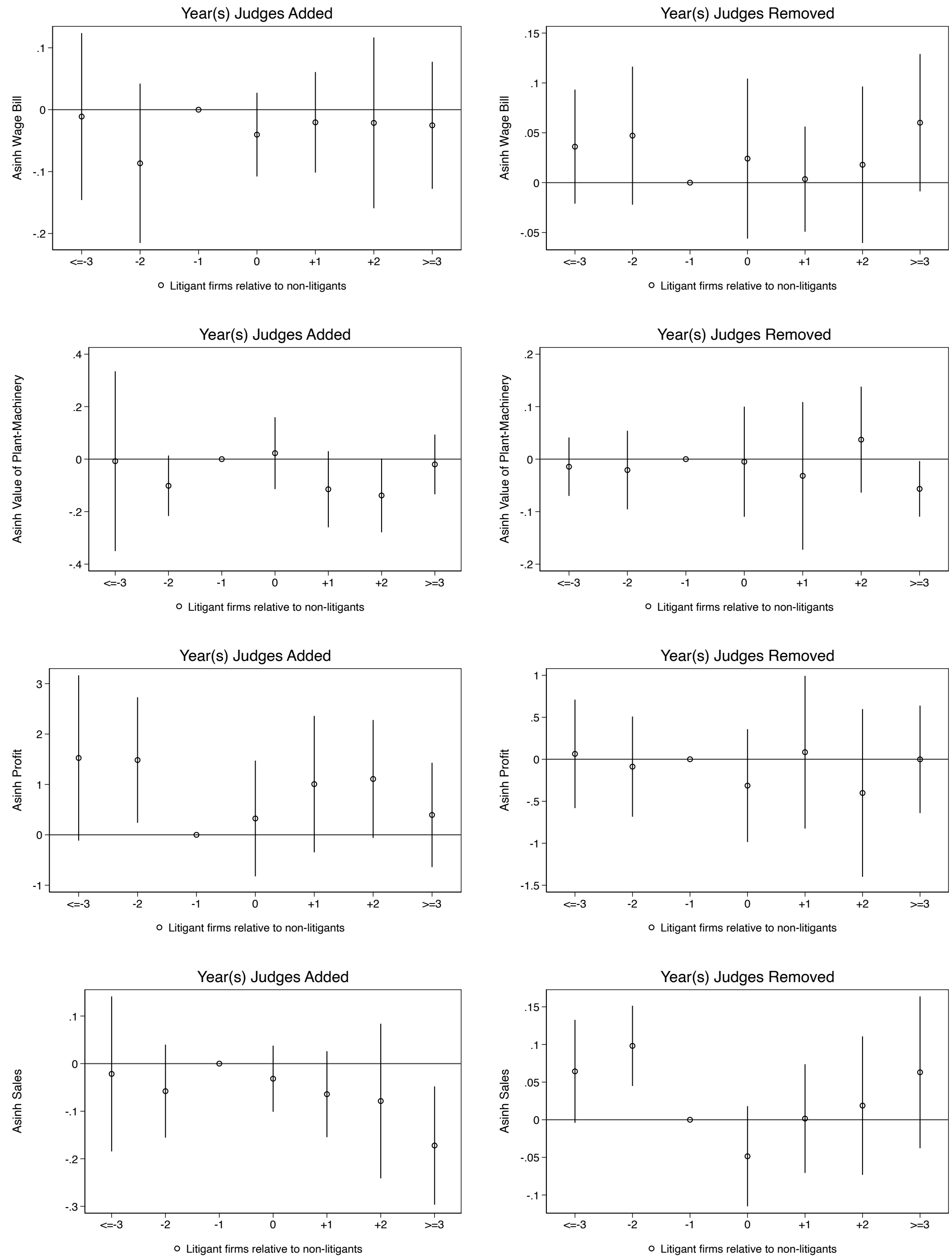


Figure A.15: Firms' Cases in Courts



Notes: Standard errors clustered by district for figures in panel C and D.

Figure A.16: Reduced Form Results on Local Firms' Production by Litigant Status



Notes: Graphs present the relative effects on litigating firms with reference to non-litigating firms. Standard errors clustered by district.

A.IV 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						

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

Notes: All measures of court performance are constructed using the trial level data, aggregated at the level of 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: Number of Judges - By Sub-Groups of District Courts

	(1) Drop Court Size tercile 1	(2) Drop Court Size tercile 2	(3) Drop Court Size tercile 3	(4) Drop Pop. Density tercile 1	(5) Drop Pop. Density tercile 2	(6) Drop Pop. Density tercile 3
Post Judge Addition	2.763***	1.117**	1.137***	1.711***	1.572***	1.438***
	(0.490)	(0.439)	(0.139)	(0.376)	(0.435)	(0.372)
Observations	1170	1125	1197	1170	1161	1170
No. Districts	130	125	133	130	129	130
District Fixed Effects	X	X	X	X	X	X
State x Year Fixed Effects	X	X	X	X	X	X
Adj R-Squared	0.930	0.940	0.900	0.940	0.940	0.940
Post Judge Removal	-3.592***	-3.379***	-1.657***	-2.904***	-3.100***	-2.952***
	(0.392)	(0.359)	(0.0945)	(0.334)	(0.340)	(0.275)
Observations	1170	1125	1197	1170	1161	1170
No. Districts	130	125	133	130	129	130
District Fixed Effects	X	X	X	X	X	X
State x Year Fixed Effects	X	X	X	X	X	X
Adj R-Squared	0.940	0.950	0.930	0.950	0.950	0.950

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

Notes: In this table, I compare the overall first stage estimates on judge occupancy with those estimated using different sub-samples of the district courts. All specifications include district and state-year fixed effects. Standard errors are clustered at the district level.

Table A.3: Disposal Rate - By Sub-Groups of District Courts

	(1) Drop Court Size tercile 1	(2) Drop Court Size tercile 2	(3) Drop Court Size tercile 3	(4) Drop Pop. Density tercile 1	(5) Drop Pop. Density tercile 2	(6) Drop Pop. Density tercile 3
Post Judge Addition	2.468***	3.350***	3.307***	4.324***	2.687***	2.891***
	(0.769)	(0.614)	(0.802)	(0.722)	(0.569)	(0.831)
Observations	1170	1125	1197	1170	1161	1170
No. Districts	130	125	133	130	129	130
District Fixed Effects	X	X	X	X	X	X
State x Year Fixed Effects	X	X	X	X	X	X
Adj R-Squared	0.470	0.460	0.450	0.460	0.500	0.410
Post Judge Removal	-2.153***	-0.974	-0.625	-1.300*	-0.660	-1.611**
	(0.618)	(0.696)	(0.730)	(0.705)	(0.661)	(0.670)
Observations	1170	1125	1197	1170	1161	1170
No. Districts	130	125	133	130	129	130
District Fixed Effects	X	X	X	X	X	X
State x Year Fixed Effects	X	X	X	X	X	X
Adj R-Squared	0.470	0.450	0.430	0.440	0.490	0.410

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

Notes: In this table, I compare the effect on court performance using different sub-samples of the district courts. All specifications include district and state-year fixed effects. Standard errors are clustered at the district level.

Table A.4: Reduced Form Effects on Local Firms: Robustness

	(1) Working Cap	(2) Wage Bill	(3) Plant Machinery	(4) Sales Revenue	(5) Profits
Main Estimates	0.383	0.0913***	0.0515	0.0686	0.873***
	(0.402)	(0.0337)	(0.0614)	(0.0618)	(0.314)
Firms w/	0.402	0.0741**	0.0477	0.0842	1.006***
all 5 non-missing	(0.454)	(0.0355)	(0.0543)	(0.0554)	(0.333)
Dropping	0.936*	0.119**	0.0948	0.237***	1.089**
WB, MH, TN	(0.547)	(0.0533)	(0.108)	(0.0658)	(0.538)
Dropping	0.298	0.0968***	0.0499	0.122*	0.867**
large districts	(0.453)	(0.0338)	(0.0704)	(0.0631)	(0.358)
District FE	X	X	X	X	X
State-Year FE	X	X	X	X	X
SE Cluster	District	District	District	District	District

Standard errors in parentheses

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

Notes: The specifications here focus on the reduced form effects from judge addition event.

Table A.5: Reduced Form Effects on Local Crime

	(1) Log All Crime	(2) Log Bailable Crime
Post Judge Addition	0.00466	0.0462
	(0.0127)	(0.0308)
Observations	1341	1341
No. Districts	192	192
District FE	X	X
State-Year FE	X	X
Post Judge Removal	0.0154	0.0223
	(0.0113)	(0.0307)
Observations	1341	1341
No. Districts	192	192
District FE	X	X
State-Year FE	X	X

Standard errors in parentheses

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

Notes: I use annual district-level reported crime data provided by the National Crime Records Bureau.

Table A.6: Cost-benefit Sensitivity Analysis

Parameter	**Mean/SD**	**Units**	**Source**
Benefit-Cost (Tax Revenue) ($\delta = 0.03$)	4.01 (1.85)	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social) ($\delta = 0.03$)	21.72 (9.24)	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Tax Revenue) ($\delta = 0.1$)	2.6 (1.202)	Ratio	Calculation Bootstrapped SE
Benefit-Cost (Social) ($\delta = 0.1$)	14.1 (5.998)	Ratio	Calculation Bootstrapped SE

Notes: Bootstrapped standard errors in parentheses.