Public Eyes on the Bench: The Effects of Live Streaming on Judicial Bias and Firm Outcomes

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Abstract

We examine whether increasing judicial transparency through live streaming of courtroom proceedings affects judicial behavior and economic outcomes. Exploiting the staggered adoption of live streaming across Indian High Courts following a 2018 Supreme Court directive, we find that transparency significantly alters judicial conduct. Government win rates in disputes between businesses and the state rise by about 9 percentage points after live streaming begins. Text analysis of judgments shows a clear increase in pro-regulation language, indicating that higher government success rates are driven by shifts in judicial orientation rather than changes in case composition. These effects are stronger in states where state governments enjoy high public support. Live-streamed cases also receive substantially greater amplification on social media, magnifying public sentiment and reputational pressures on judges. This transparency-induced shift in judicial behavior translates into real economic consequences: firms with high legal risk, located in jurisdictions that adopt live streaming, experience declines in investment and revenue, reductions in borrowing, and higher borrowing costs. Our findings imply that increasing judicial visibility can amplify pro-government bias and influence firm behavior and economic performance.

Keywords: Judicial Transparency; Judicial Behavior; Legal Institutions; Government–Business Disputes; Regulatory Enforcement; Text Analysis
JEL Codes: K22, K42, K40, G30, O43, D73

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1 Introduction

Judicial bias is a well-documented phenomenon in both the economics and legal literature. A large body of work exploiting quasi-random assignment of cases to judges shows that judicial identity, and the biases associated with it, can systematically influence case outcomes (Abrams et al. (2012); Dobbie et al. (2018); Frandsen et al. (2023); Bhuller and Sigstad (2025)). Biases, whether racial, gender, ideological, or institutional, shape who gains access to justice and how economic disputes are resolved, including in corporate and financial contexts (Gormley et al. (2025); Chen et al. (2025)). Because judicial decisions affect contracts, property rights, and the enforcement of regulation, understanding the forces that either mitigate or exacerbate such bias is a first-order question for institutional credibility and economic performance.

A long-standing view is that increasing transparency within the courtroom and thus making judicial behavior more observable can serve as a check on judicial bias by increasing accountability (European Network of Councils for the Judiciary (2024), Youm (2012), Lasser (2004), France (2019)). Live streaming of court proceedings has emerged as a popular mechanism for enhancing such transparency: it exposes judicial reasoning, demeanor, and interactions to public and professional scrutiny in real time, potentially disciplining implicit or explicit biases. In recent years, several countries have introduced or are considering live streaming of judicial proceedings.[1] Whether such interventions can meaningfully improve judicial accountability and reduce bias in the judiciary remains an active debate among scholars and policymakers (Brown (2018); Rehavi and Starr (2014); Chen et al. (2025)). In this paper, we examine disputes between government and businesses, a context where judicial bias has particularly significant economic and policy implications, and investigate how transparency through live streaming shapes both the prevalence and impact of such biases on case outcomes.

Ex ante, the existence and direction of judicial bias in government-business disputes under transparency remain ambiguous, because the incentives and public perceptions surrounding such disputes can push judges in either direction. Public scrutiny could discipline judges, promoting accountability and reducing arbitrary or government-leaning decisions, while also limiting the scope for corruption or preferential treatment of business interests. At the same time, heightened visibility can create performative pressures, pushing judges to respond to

[1]The United Kingdom, Canada, and Brazil have adopted live streaming in their apex courts, while Australia and Singapore have expanded audiovisual access and remote observation, and South Africa allows broadcasting in defined circumstances (UK Supreme Court (2023); Supreme Court of Canada (2023); Supremo Tribunal Federal (Brazil); High Court of Australia (2023); Singapore Judiciary (2023); South Africa Department of Justice (2023))

public sentiment or media narratives. If the public interprets pro-business outcomes as signs of favoritism towards wealthy, live streaming may prompt judges to rule more cautiously against corporate litigants. Indeed, recent evidence suggests that judges exhibit greater caution when handling cases involving large firms or corporate misconduct, particularly under public or political scrutiny (Gormley et al. (2025); Huang et al. (2025); Cohen and Yang (2019)). Whether transparency ultimately enhances impartiality or instead reinforces pro-government or anti-business tendencies remains an open empirical question.

India provides a compelling setting to examine the impact of judicial transparency on business for three reasons. First, as a democracy, public opinion shapes the behavior of all branches of government, implying that greater visibility can plausibly influence judicial conduct through reputational and accountability channels. Second, India's judiciary is highly independent. The executive plays virtually no role in judicial appointments, which are made by a collegium of senior judges (Supreme Court of India (2015)), so individual judicial discretion and bias matter. Third, contract enforcement in India is slow, costly, and often viewed as biased against business, a key reason for the country's poor ranking on the World Bank's "Enforcing Contracts" index (World Bank (2020); Amirapu (2021); India Justice Report (2025)). As a result, any reduction or amplification of pro-regulation bias in judicial decisions is likely to have first-order consequences for firms and economic activity.

Against this backdrop, we study the Supreme Court of India's 2018 directive requiring all state-level High Courts, the apex courts within each state's judicial hierarchy, to begin live streaming proceedings to promote openness and accountability. The directive did not prescribe a uniform timeline, resulting in staggered adoption across states. By the end of our sample period, 13 of 25 High Courts had introduced live streaming, and the remaining courts eventually have been adopting it thereafter. Thus, for identification, what we require is that the timing of adoption is plausibly exogenous, rather than the decision to adopt itself.

Our core result is that live streaming substantially biases judicial outcomes toward the government in government–business cases: government win rates rise by 8.7 percentage points in High Courts that adopt live streaming. Mechanism tests, based on machine-learning analysis of judgments, reveal a marked increase in pro-regulation language and a greater reliance on the government's arguments in judicial reasoning. Live-streamed cases also receive significantly higher social-media amplification, and the results are stronger in states where the incumbent government is more popular—consistent with public visibility and political sentiment, reinforcing a pro-government tilt. Finally, firms exposed to judicial and regulatory risk in live-streaming jurisdictions experience a 12.28% decline in investment, an 8.16% drop in borrowing, and a 31-basis-points higher interest costs relative to less-exposed firms. As expected, these changes translate into lower operating performance: firm

revenue declines by 6.48% after live-streaming adoption.

Our primary data source is India Kanoon, a comprehensive digital repository of Indian legal documents. We compile all High Court judgments related to commercial cases settled between 2016 and 2024, yielding a total of 48,647 decisions. Among these, 8,005 cases involve disputes between the government and private businesses, which form the core of our analysis. Each judgment follows a structured format comprising seven distinct sections: a brief overview of the case, the legal issue under consideration, the plaintiff's arguments, the defendant's arguments, the judge's analysis of relevant precedents, the judge's interpretation, and the final conclusion. We identify case outcomes based on the concluding section, classifying decisions as government or business victories, and use the first six sections to quantify sentiment and regulatory orientation using text-based machine learning algorithms.

In terms of empirical analysis, we exploit the staggered implementation of live streaming across High Courts in a difference-in-differences framework. Organizing the data at the case level and controlling for court, judge, and year fixed effects, we find that live streaming leads to a 8.7 percentage-point increase in the likelihood of government victory in government–business disputes. Given an average government win rate of 22.54 percent in the pre–live streaming period, this represents an economically meaningful increase of approximately 38.59 percent.

To address concerns about identification, we conduct several robustness exercises. First, we find no evidence of pre-existing trends in government victories prior to the adoption of live streaming. Second, to rule out the possibility that region-specific factors drive our results, we examine government–business disputes in lower courts and tax tribunals where live streaming was not adopted. These courts show no significant change in government win rates, even in states where High Courts adopted live streaming. Third, we find no statistically significant differences in the economic, institutional, or political covariates related to the timing of adoption of live streaming. Finally, since all High Courts eventually adopted live streaming, it is unlikely that inherent institutional or regional differences between early and late adopters drive our findings. The differences in the speed of adoption plausibly reflected administrative and logistical factors, such as local court capacity, technology readiness, or resource allocation, that are exogenous to the time-varying pro-regulation bias we examine in this paper.

We next examine the mechanisms underlying this shift. Specifically, we ask whether the higher likelihood of government victory reflects an increase in pro-government bias among judges. We conduct two complementary tests.

In the first, following Larochelle et al. (2008) and Lampert et al. (2009), we employ Zero-Shot Learning (ZSL), a machine-learning method that helps classify the economic orientation

of judgment texts. Unlike traditional supervised learning models, which require extensive manually labeled training data, ZSL leverages the semantic understanding already embedded in large-scale, pre-trained language models. Using the BART-large-MNLI model, a state-of-the-art natural language inference system, we generate pro-regulation (pro-government), neutral, and pro-market orientation measures for each judgment. Applying our difference-in-differences specification to these measures, we find a 7.6% increase in the pro-government orientation score in response to live streaming, with no corresponding change in the pro-market or neutral sentiment scores. We also find no evidence of pre-existing trends in these measures.

Second, we study whether live streaming alters the substantive attention judges devote to the factual and legal narratives advanced by litigants. Building on recent advances in text analysis (Kelly et al., 2021; Chen et al., 2025), we construct a measure of judicial incorporation that captures the extent to which the judge's written reasoning aligns more closely with the government's factual submissions than with those of the opposing corporate litigant. Using the structured organization of our corpus, we extract the petitioner's factual narrative, the respondent's narrative, and the judge's recognized facts from each judgment, and compute a relative similarity score based on Term Frequency-Inverse Document Frequency (TF-IDF), representations (validated using transformer-based embeddings). It measures textual similarity by weighting terms according to their frequency within a text relative to their frequency across the entire corpus. We first show that this similarity measure is strongly predictive of actual case outcomes: judgments that more closely mirror government submissions are significantly more likely to result in government victories. We then estimate how live streaming affects this measure of judicial incorporation. Applying our difference-in-differences specification, we find that live streaming leads judges to integrate government narratives more heavily into the recognized-facts section of their judgments. This shift in textual alignment indicates that the pro-government tilt in judgment sentiment stems from a change in how judges weigh the competing narratives.

Third, we find that cases heard under live streaming receive at least 1.47 times greater amplification on social media than comparable cases in non–live-streaming courts, indicating that public exposure substantially increases visibility and reputational stakes for judges. Fourth, we also find that the increase in probability of government winning is stronger in states where incumbent governments hold large legislative majorities, consistent with the idea that public opinion matters. In such states, where the government enjoys broad popular support, live streaming may further shape public perceptions in its favor, especially in disputes between businesses and the state government, thereby reinforcing the incentives for judges to align with dominant public sentiment. Taken together, these results suggest

that public scrutiny likely plays an important role in shifting judicial behavior.

Our thesis is that even a non-elected judiciary gives weight to public opinion, and that this weight increases with greater transparency. While we cannot definitively pin down why an independent judiciary would be sensitive to public opinion especially when public sentiment is pro-government, the evidence we document is consistent with a broader phenomenon: judges appear to care about public sentiment even when institutional design suggests they should not. Chen et al. (2025), for instance, show that Chinese courts which operate in a non-democratic system, nonetheless adjust their decisions in ways that reflect public preferences. If judges respond to public sentiment even in such a context, it is all the more plausible that they do so in a democracy like India, where judicial legitimacy is deeply intertwined with public trust and where courts operate under far greater transparency and media scrutiny.

We next examine whether the shift in judicial leanings toward the government impacts firms. If judges become more favorable to the government in business-state disputes, firms facing higher regulatory and enforcement risk should rationally anticipate less favorable treatment in potential legal conflicts. This heightened legal uncertainty can affect firms ex-ante through several channels: firms may curtail borrowing if they perceive weaker contract enforcement or greater regulatory unpredictability; they may scale back investment in long-term projects that depend on stable legal protections; and lenders, anticipating these risks, may demand higher interest rates to compensate for the increased probability of adverse judicial outcomes. These effects should be driven by sectors where legal exposure is intrinsically high: industries that face greater regulatory scrutiny, rely more heavily on contract enforcement, or incur higher litigation costs as a share of their operations. We identify such sectors using firms' reported legal expenses relative to total expense, classifying industries in the top half of this distribution as high legal exposure sectors. Consistent with this reasoning, our difference-in-differences estimates show that firms in high legal exposure sectors experience an 8.16 percent decline in borrowing and a 12.28 percent decline in investment following the introduction of live streaming. We also find a 2.98 percentage point increase in interest rates for these firms. These changes translate into lower operating performance: firm revenue declines by 6.48 percent after live streaming adoption.

Our paper contributes to several related strands of the literature. First, it speaks to finance, economics, and law studies, examining how judicial bias affects firm-level outcomes. We contribute to the debate on whether such bias reflects judge-specific fixed effects (Canay et al. (2024); Frandsen et al. (2023)) or evolves endogenously through exposure, learning, or institutional incentives. Recent work shows that judges update their behavior in response to external factors such as training (Ash et al. (2025); Cao (2023)), experience (Bernstein et al. (2019)), and reversals of decisions by higher courts (Bhuller and Sigstad (2025)). Our

findings complement this literature by showing that public scrutiny, brought about by live streaming, can itself shift judicial decision-making.

Second, we contribute to the growing literature that studies how judicial bias affects firms, particularly biases that tilt against business and in favor of workers, regulation, or the state (Cahuc et al. (2024); Araujo et al. (2023); Coupé et al. (2021)). Related evidence from bankruptcy and enforcement settings shows that judicial characteristics and ideology have meaningful effects on firm outcomes – employment, investment, recoveries, and valuation (Bernstein et al. (2019); Huang et al. (2025)). We extend this evidence by showing that increased transparency can amplify pro-government bias, thereby having adverse real effects on firm performance.

Finally, our paper relates to the emerging work on the consequences of courtroom transparency and live broadcasting, and the broader debate on the potential effectiveness of such policies (Brown (2007),Houston and Johnson (2024)). Chen et al. (2025) shows that live streaming in Chinese courts reduced gender disparities in case outcomes, while Liu and Tang (2025) and Tang et al. (2022) find that broadcasting affects lawyer and witness behavior but not judicial outcomes. In contrast, we document that live streaming alters judicial conduct itself, aligning decisions more closely with public sentiment in business–state disputes and heightening pro-government bias. Together, these findings suggest that the effects of transparency depend on context: while visibility may reduce certain biases, it can reinforce others, warranting caution in the broad implementation of live-streaming reforms.

2 Institutional Details

2.1 Legal System in India

The judicial system of India is organized through a hierarchical structure of courts. At the apex is the Supreme Court of India (SC hereafter), which serves as the final court of appeal and the ultimate authority on constitutional interpretation. Below the SC, each state and union territory of India has a corresponding high court.[2] At the bottom of the hierarchy are the district and sessions courts, which operate at the district and sub-divisional levels and handle the bulk of trial proceedings and fact-finding.

India's judiciary is independent, with structural features that insulate judges from executive influence. Judicial appointments to the higher judiciary are made through a collegium system, in which a committee of senior judges selects and recommends candidates for appointment. The executive has virtually no role in this process, and judges, once appointed,

[2]India is geographically divided into 28 states and 8 union territories.

enjoy security of tenure until retirement. Proposals to create a National Judicial Appointments Commission that would have given the government a role in judicial appointments were struck down by the Supreme Court in 2015 as unconstitutional, reaffirming the judiciary's commitment to self-governance.[3] Furthermore, the doctrine of basic structure, established in Supreme Court of India (1973), declares judicial independence to be part of the Constitution's basic structure that cannot be altered even by constitutional amendment. This doctrine provides an additional layer of protection against any legislative attempts to undermine judicial autonomy. Judges also have constitutionally guaranteed salaries and allowances that cannot be reduced during their tenure, and removal from office requires impeachment by Parliament with a two-thirds majority, a threshold that has never been successfully crossed. These institutional safeguards make India's judiciary independent, with the executive branch having minimal formal influence over judicial appointments or tenure. Since the judiciary operates independently, the personal beliefs, biases, and ideological leanings of judges can shape the outcomes of cases. Understanding these influences is therefore essential, and that is precisely the aim of our study.

Our analysis focuses on the High Courts. There are 25 high courts in India, each with jurisdiction over one or more of the 36 states and union territories. We provide a mapping between the states and union territories and the corresponding High Courts in Table A1 of the online appendix. The High Courts primarily hear appeals against decisions made by subordinate courts and adjudicate writ petitions, which involve the enforcement of fundamental rights and the review of administrative or legislative actions. Cases are assigned to judges through a random allocation system, ensuring that the composition of benches hearing particular cases is not systematically related to case characteristics (Government of India and Justice (2020)). Each case in a high court is presided over by a bench of one or more judges. Single judge benches typically handle writ petitions, bail applications, and certain civil and criminal appeals. Division benches of two or more judges are constituted to hear matters involving substantial questions of law, appeals from orders of single judges, and cases requiring broader judicial consideration (Orissa High Court (2019)). Decisions are rendered based on a majority verdict.[4]

The judiciary in India primarily follows the common law system. Hence, the decisions of High Court judges are largely guided by precedents established by past rulings on similar cases (Djankov et al. (2003)). However, within this framework, High Court judges retain substantial interpretive discretion in determining which precedents are most relevant or binding

[3]For more details on this, see: https://www.thehindu.com/news/national/Supreme-Court-verdict-on-NJAC-and-Collegium-system/article60384480.ece

[4]In case of a split verdict, the case is referred to a larger bench and decided by the majority opinion of the bench

in a given context. Critically, all 25 High Courts in India operate under the same constitutional framework, follow uniform procedural rules established by the Code of Civil Procedure and the Code of Criminal Procedure, and are bound by the same body of precedent set by the Supreme Court of India. This institutional uniformity ensures that High Courts are highly comparable to one another despite serving different geographic jurisdictions.

2.2 Live Streaming of Courtrooms in India

Calls for greater transparency and public accessibility in the Indian judiciary had been growing for several years, driven by concerns about opacity in court functioning, inconsistent judicial behavior, and the need to strengthen institutional accountability. Responding to these concerns, in September 2018 the Supreme Court of India, in principle, approved the live streaming of judicial proceedings in *Swapnil Tripathi vs. Supreme Court of India (2018)*.[5] The Court argued that real-time access would enhance openness, reduce bias, reduce information asymmetry between courts and citizens, and promote confidence in judicial outcomes. Live streaming was explicitly framed as a tool to improve judicial accountability and reduce bias by making judges' reasoning, demeanor, and interactions publicly observable and as a measure to expand access to justice for litigants, journalists, researchers, and the broader public.

Building on this principle, in February 2020 the Supreme Court issued an administrative directive to operationalize the live-streaming framework and instructed all High Courts to adopt similar practices.[6] This marked a nationwide institutional push toward audiovisual transparency.

To standardize the reform, the Supreme Court released the *Model Rules for Live Streaming and Recording of Court Proceedings*,[7] which provided detailed procedural and technical guidelines. These rules were adopted by the Supreme Court and 13 of the 25 High Courts in a staggered manner between October 2020 and August 2024, corresponding to our sample period. The remaining High Courts are in the process of implementation; for example, the Bombay High Court adopted live streaming on 5 July 2025, three months beyond our sample window. Table A2 in the online appendix lists the adoption dates across High Courts.

To operationalize live streaming, adopting High Courts installed audio–video equipment in designated courtrooms. Cameras are typically positioned to capture the bench of judges

[5] A three-judge bench led by the Chief Justice of India upheld a plea for live streaming and directed the framing of rules.

[6] https://www.livelaw.in/top-stories/cji-on-administrative-side-sc-on-application-for-framing-live-streaming-rules-152328

[7] See: https://ecommitteesci.gov.in/document/model-rules-for-live-streaming-and-recording-of-court-proceedings/.

rather than lawyers or litigants. Proceedings are broadcast in real time through widely accessible digital platforms such as YouTube or the official websites of the respective courts. Figure A1 in the online appendix provides screenshots of selected live-streamed cases. Consistent with the Supreme Court's model rules, certain sensitive matters, including criminal trials, matrimonial disputes, and cases involving sexual offences, are excluded from live streaming.[8]

The staggered introduction of live streaming across High Courts was shaped primarily by differences in administrative capacity, technological readiness, and the prioritization of judicial reforms by individual Chief Justices. The adoption of live streaming was plausibly unrelated to local economic factors, the courts' efficiency, or the pro-government or pro-business sentiments of the judges serving at the time of adoption. We estimate a hazard model of adoption and find that none of these observable characteristics predict the timing of live-streaming entry. We report this result in Table A3. This evidence supports our identification assumption that the staggered rollout generated exogenous variation in exposure to transparency, which we exploit to identify the causal effects of live streaming on judicial decision-making.

3 Data

The dataset we use is varied, ranging from rich textual data on court-case judgments to financial and accounting data on firms. Our primary dataset consists of final judgment copies of all Indian High Court cases decided between January 2016 and December 2024. We obtain these data from India Kanoon, an organization that compiles judgments from the Supreme Court, High Courts, and select tribunals.[9] We focus on this period because the scraped archive was complete through December 2024 at the time of data collection, giving us a sufficiently long pre-period before the introduction of live streaming and full coverage of the staggered rollout. To construct our sample, we first identify commercial disputes using a comprehensive keyword list drawn from relevant statutes.[10] The judgment copies report rich case-level data, including the date of judgment, the name of the High Court, the judges on the bench, and the names of both litigating parties. Based on the names of the parties, we classify litigants as Government or firm and restrict analysis to these government–business cases.

Each judgment is segmented into distinct sections that reflect the conventional structure of judicial reasoning. We label the text into seven components: (1) the facts of the case,

[8]For an exhaustive list of exclusions, see: `https://cdnbbsr.s3waas.gov.in/s388ef51f0bf911e452e8dbb1d807a81ab/uploads/2021/06/2022091599.pdf`.

[9]India Kanoon can be loosely translated as "Indian Law." See: https://indiankanoon.org/

[10]We have listed the keywords in Table A4 of the online appendix.

which summarize the background events and circumstances that gave rise to the dispute; (2) the legal issue, which specifies the precise question of law the court must decide; (3) the petitioner's arguments, outlining the claims and legal grounds advanced by the party challenging the action; (4) the respondent's arguments, detailing the counterarguments offered in defense; (5) the precedents cited, which list prior judicial decisions invoked to support legal interpretation; (6) the judge's reasoning, where the bench applies legal principles to the facts and explains the logic behind its decision; and (7) the conclusion or final judgment, which states the outcome and identifies the winning party.[11] Examples of these labeled segments are provided in Figure A2 of the online appendix. We use the Conclusion section to identify the winner in each case. To understand judicial bias, we focus on sections (1) through (6), which collectively capture the informational content, legal framing, and reasoning process that shape the final decision.

For the robustness analysis, we employ two complementary placebo tests using courts and tribunals that did not adopt live streaming. First, we use judgment data from the District Courts of Bengaluru and Delhi. India Kanoon does not report data from any other District Courts of the country. Both courts operate in major commercial hubs and handle a substantial volume of business-related litigation, making them well suited for examining whether region-specific shocks drive our findings. The Bengaluru District Court falls under the jurisdiction of the Karnataka High Court, while the Delhi District Court operates under the Delhi High Court. Critically, while Karnataka's High Court adopted live streaming during our sample period, Delhi's High Court did not, yet neither state implemented live streaming at the district court level. Second, we compile a dataset of judgments from 23 Income Tax Appellate Tribunals (ITATs) across various Indian states, covering the same sample period as our primary analysis (January 2016 to December 2024). These tribunals did not adopt live streaming during the study period, providing an additional robustness sample. Each judgment in this dataset is structured analogously to the High Court data, containing standardized sections corresponding to facts, arguments, precedents, reasoning, and the final decision.

For the analysis examining the amplification of judicial cases through media exposure, we collect data from the social media platform X (formerly known as Twitter). Specifically, we compile all tweets published between January 2023 and December 2024 by two prominent and verified legal news outlets, LiveLaw India and Bar & Bench.[12] We restrict the sample to

[11] These labels were identified by India Kanoon using a combination of algorithmic text parsing and legal expert validation.

[12] LiveLaw India and Bar & Bench are independent digital legal news organizations that provide real-time reporting on court proceedings, judicial developments, and legal policy in India. Both platforms are widely regarded as authoritative sources for legal news and maintain verified accounts on major social media

this period due to budgetary and API access constraints. For the tests linking government victory with electoral outcomes, we obtain state-level election results from the official website of the Election Commission of India for each state in India.

For our firm-level analysis, we use the firm-level dataset provided by the Centre for Monitoring Indian Economy (CMIE), known as the Prowess dataset. The dataset provides detailed financial information for both listed and unlisted Indian firms, including variables on borrowings, investments, and other balance sheet and income statement indicators. We also extract data on firms' legal expenses from the same source to measure firms' litigation-related costs.

For the analysis of the cost of borrowing, we complement this dataset with loan-level information from the Ministry of Corporate Affairs (MCA). The MCA database contains detailed records of secured loan contracts, including interest rates, loan amounts, the identity of lenders, the date on which the loan is extended, and the date of repayment of the loan. Both the above datasets are restricted to the period between 2016 and 2024 to align with the time frame of our judicial data.

3.1 Sample Construction

Table 1 presents our sample construction. Panel A describes the main High Court sample. We begin with 48,647 commercial cases across 25 Indian High Courts decided between January 2016 and December 2024. Of these, 8,005 cases involve disputes between firms and government bodies. In our context, we define "government" to be both central (federal) government and the state government. Government litigants, therefore, are both central government agencies (such as ministries, departments, and statutory authorities operating at the federal level) and state government agencies (such as state departments, public corporations, and local regulatory bodies). For clarity, throughout the paper we use the term government to denote all such central and state public bodies collectively. These 8,005 government–business cases constitute our primary sample for estimation. The cases are adjudicated by 786 unique judges.

The unit of observation varies depending on the analysis. For our main results examining case outcomes, we organize the data at the judge-judgment level. Since multiple judges may preside over a single case through bench composition, the 8,005 government-business disputes yield 24,015 judge-judgment observations. For our text-based sentiment analysis, we aggregate judgments at the judge-month level to capture temporal variation in judicial language, resulting in 2,131 observations.

platforms.

Panel B presents the samples used in placebo tests. At the district-court level, we use data from the Bengaluru and Delhi district courts, which together contribute 18,643 commercial cases, including 160 disputes between businesses and the government. We also assemble data from 27 Income Tax Tribunals, yielding 71,684 cases in total, of which 52,105 involve government–firm disputes.

Panel C describes the social media sample. We collect 73,666 posts from the X handle of LiveLaw India and Bar & Bench published between January 1, 2023, and December 31, 2024. Out of these, we find 17,052 cases with attachment of video.

Panel D presents the firm-level sample. We begin with 40,672 unique firms from Prowess, spanning 2016 to 2024. For these firms, we have 225,206 firm-year observations for borrowing and 177,619 for additions to fixed assets. For additions to plant and machinery and sales, we have 111,604 and 223,924 firm-year observations, respectively.

Panel E describes the loan-level sample. Matching MCA loan records to firms and lenders in Prowess produces 29,041 loan observations covering 4,486 unique firms and 198 unique lenders for our interest rate analysis.

3.2 Summary Statistics

Table 2 reports the summary statistics for all dependent, explanatory, and control variables used in our analysis. For each variable, we report the mean, standard deviation, median, and the 1st and 99th percentiles to characterize both central tendency and distributional spread.

Panel A presents summary statistics at the case level, including the government's win rate and the sentiment measures capturing the pro-government, pro-market, and neutral orientation of judgments. The mean winning rate of the government across the full sample is 22.8%. The mean sentiment scores for pro-government, pro-market, and neutral judgments are 0.353, 0.314, and 0.332, respectively. The higher pro-government score indicates a tilt in judicial sentiment toward regulatory perspectives on average.

Panel B reports the variables aggregated at the Judge–Year level, which form the basis of our analysis of changes in judicial bias over time. The average pro-government score at this level is 0.355, while the average pro-market score is 0.312.

Panel C summarizes the characteristics of our social media (X) sample. The sample comprises 70,913 posts over the period from January 2023 to December 2024. The average number of bookmarks, views, likes, quotes, comments, and re-posts per post are 1.408, 11,134, 48.825, 2.190, 4.173, and 13.939, respectively. The median values are substantially lower (0, 4,483, 11, 0, 1, and 3, respectively), while the 99th percentile values are considerably higher

(20, 109,221, 684, 38, 62, and 222, respectively), reflecting highly skewed distributions. The standard deviations are large relative to the means across all engagement metrics, with total engagement exhibiting a mean of 11,203 and a standard deviation of 40,140. These patterns are consistent with the power-law distributions characteristic of social media engagement, where a small number of posts receive disproportionately high attention while the majority receive minimal engagement (Jo et al. (2013)).

Panels D summarizes the firm–year–level and loan–level characteristics of our sample. The average outstanding borrowing and investment levels are 531.5 Crores and 401.6 crores, respectively. Loan-level variables derived from the MCA dataset including interest rates, loan amounts, and lender concentration. The average interest rate faced by firms in our sample is 9.66%. Panel E summarizes the state-year level control variables used in the analysis.[13]

Taken together, these statistics offer a comprehensive picture of the legal and financial environment in which firms operated during the sample period. Detailed variable definitions are provided in Table A6 in the Online Appendix.

4 Main Result

We begin with our baseline investigation into the effect of introducing live streaming of court proceedings on the likelihood of a judgment being in favor of the government in government-business cases. As elaborated in Introduction, the live streaming potentially expands the set of audiences that can monitor judges, ranging from litigants and lawyers to media organizations and the general public. This heightened observability can alter judges' incentives through two competing mechanisms, yielding opposing predictions about the impact on judicial outcomes in government–business disputes.

On one hand, transparency can promote accountability by discouraging arbitrary, biased, or ideologically driven decisions. Prior works suggest that visibility and monitoring discipline discretion, thereby improving institutional performance (Stromberg (2004)). Within the judicial context, greater exposure may reduce scope for corruption, favoritism, or regulatory capture by aligning judicial incentives with norms of impartiality and professionalism (Posner (1993); Garoupa and Ginsburg (2015)). Moreover, in contexts where executive or political pressure leads courts to favor state interests over private parties (Ginsburg (2003); Helmke and Rosenbluth (2009)), transparency can strengthen judicial independence. Hence, live streaming may reduce anti-business bias, leading to more favourable outcomes for firms in

[13]In Table A5 of the online appendix, we have summarized the variable representing government wins for district courts (panel A) and tax tribunals (panel B). Additionally, we have also summarized the high court-level control variables used in our analysis in panel C.

government-business disputes.

On the other hand, increased visibility can induce performative pressures, prompting judges to "play to the gallery". Public scrutiny, amplified through media and social platforms, can shift judges' reference group from professional peers to the broader public, making them sensitive to popular sentiment (Lim et al. (2015); Lim (2013); Canes-Wrone et al. (2014)). Judicial decisions have been shown to respond to political cycles, public mood, and media attention (Gordon and Huber (2007); Berdejó and Chen (2020)). In the context of business-government disputes, ruling in favor of a business can be portrayed as siding with private interests against public welfare. Consequently, judges may lean toward the government to align with populist or pro-state sentiment. Which mechanism dominates, disciplining accountability or populist conformity, is theoretically ambiguous and must be determined empirically.

To examine the above theses, we use the staggered rollout of live streaming across Indian High Courts, described in section 2. We use a staggered difference-in-differences design, comparing case outcomes in High Courts that adopted live streaming earlier (treatment group) with those that adopted later (control group). As explained in section 2.2, the timing of the live streaming adoption for different high courts was plausibly exogenous.

To implement the empirical test, we organise the data at a judge-judgment level. As described in section 3.1, we identify the cases in which one of the litigating parties is a government entity and the other is a private firm. We use the Conclusion section of each judgment to determine the outcome of the case and construct a binary indicator denoting whether the government won. We then estimate the following baseline regression specification:

$$Y_{ijkt} = \beta \cdot Post_{it} + \alpha_i + \gamma_t + \delta_k + X_{it-1} + \varepsilon_{ijkt} \tag{1}$$

where Y_{ijkt} is a binary variable that equals 1 if the government wins the case j in court i presided by judge k in year t and 0 otherwise. $Post_{it}$ is the staggered treatment indicator variable. It equals one for all observations in court i after live streaming is introduced and zero before introduction, with the indicator switching from zero to one at different time points across different high courts due to the staggered rollout. For high courts that never adopt live streaming during our sample period, the variable remains zero throughout.

We include court fixed effects (α_i) to absorb all time-invariant differences across High Courts, such as persistent variation in administrative practices, staffing norms, or historical patterns of case management. Year fixed effects (γ_t) account for nationwide shocks or institutional changes that affect all courts in a given year, including macroeconomic conditions,

shifts in litigation demand, or changes in higher-court directives. Finally, we include judge fixed effects (δ_k) to compare changes in case outcomes within the same judge over time. This specification ensures that our estimates are identified from variation in a judge's behavior before and after the introduction of live streaming, holding constant all judge-specific factors that do not vary across cases. We cluster the standard error at the court level to account for serial correlation in judicial behavior within each High Court.

We include a set of lagged time-varying high court-level (X_{it-1}) control variables in our full specifications. The High Court-level controls (X_{it-1}) capture contemporaneous state-level economic and political conditions that may influence judicial functioning. These are: state GDP growth (the annual percentage change in real GSDP), credit growth (the year-on-year percentage change in outstanding credit), the winning margin in the most recent state assembly election (the percentage-point difference between the vote shares of the winner and the runner-up), investment (the real gross capital formation), inflation (the annual percentage change in the state-level consumer price index), pendency per judge (the number of pending cases per sitting High Court judge), and the unemployment rate (the percentage of the labor force without work). These measures allow us to net out broader state-level conditions that could independently influence judicial outcomes.

The key coefficient of interest, β, measures the differential change in the probability of a government victory following the adoption of live streaming. Table 3 reports the estimation results. Column (1) presents the baseline specification without control variables and with fixed effects. Column (2) augments the baseline model with control variables. Across all specifications, the coefficient on the *Post* indicator is positive and statistically significant. The magnitude of the coefficient in column (1) is 0.087, which implies that the probability of a government victory in commercial disputes against private firms increases by approximately 8.7 percentage points in High Courts that have adopted live streaming relative to those that have not adopted. This is economically significant 38.59% of the unconditional likelihood of government victory.

4.1 Test for Pre-existing Trends

To examine whether the estimated effects reflect a continuation of pre-existing trends in judicial decisions favoring the government, we conduct an event-study analysis based on our baseline model around each High Court's year of live-streaming adoption. Specifically, we estimate the probability of a government victory as a function of leads and lags relative to the year of adoption, while controlling for court, judge, and year fixed effects. High Courts that did not adopt live streaming during our sample period serve as the reference group. The

specification includes three leads and three lags, with the year preceding adoption serving as the baseline period.

We estimate the following regression specification:

$$Y_{ijkt} = \alpha_i + \gamma_t + \delta_k + \sum_{k=-5, k\neq -2}^{k=-1} \beta_k \cdot \text{Pre}_{k,it} + \beta_0 \cdot \text{Post}_{0,it} + \sum_{k=1}^{4} \beta_k \cdot \text{Post}_{k,it} + \varepsilon_{ijkt} \qquad (2)$$

where Y_{ijkt}, α_i, γ_t, and δ_k are the same as defined in equation 1. The variables $\text{Pre}_{k,it}$ are dummy indicators that take the value one if the judgment in court i occurred k years prior to the adoption of live streaming ($k = 2, 3, 4, 5$). $\text{Post}_{0,it}$ is a dummy for the year of live-streaming adoption, and $\text{Post}_{k,it}$ indicates k years after adoption ($k = 1, 2, 3, 4$). We cluster standard errors at the court level.[14]

The coefficients β_k trace the evolution of the probability of a government victory in the years leading up to and following the adoption of live streaming. We present the estimates in Figure 1. The horizontal axis denotes years relative to the adoption of live streaming (with zero representing the entry year), while the vertical axis reports the estimated change in the likelihood of a government victory relative to the pre-adoption baseline.

We find that the coefficients on the pre-treatment indicators ($\hat{\beta}_{-5}$ to $\hat{\beta}_{-1}$) are statistically indistinguishable from zero and low in magnitude, suggesting no systematic pre-trend in government win rates across courts that adopted live streaming at different times. This supports the validity of the parallel trends assumption underlying our identification strategy. Starting from the year of adoption ($\hat{\beta}_0$), the coefficient becomes positive and statistically significant. In the post-adoption period, the effect strengthens progressively. This indicates that, following the introduction of live streaming, the probability that the government prevails in commercial disputes against private firms rises significantly relative to the pre-adoption period.

4.2 Robustness: Evidence from District Courts

A natural concern is that our High Court results may be driven by contemporaneous, region-specific factors unrelated to live streaming itself, such as shifts in local political conditions, changes in litigation behavior, or administrative reforms undertaken during the same period. We use the fact that district courts in any state did not adopt livestreaming to design a placebo test to address the concern. Specifically, we examine government-business disputes adjudicated in district courts, which operate below the High Courts in the judicial hierarchy and hear a similar range of civil and commercial cases.

[14]The omitted category or the base year is -2 (two years before adoption).

Our data cover district courts in Delhi and Bengaluru, two of the largest and most active commercial jurisdictions, for which complete case-level records are available. The Bengaluru District Court falls under the jurisdiction of the Karnataka High Court, while the Delhi District Court operates under the Delhi High Court. While the Karnataka High Court adopted live streaming during our sample period and the Delhi High Court did not. This provides a natural placebo test: if the increase in government win rates we observe in High Courts were driven by region-specific factors, we should observe similar patterns in district courts within those same jurisdictions. Conversely, if our results reflect the causal effect of live streaming, district courts should exhibit no systematic change in government win rates, even in states where the corresponding High Courts adopted transparency reforms.

The district court dataset is structured in the same way as the High Court sample. Unlike the High Court data, however, the district court records do not include the names of the adjudicating judges. We identify all government–firm disputes and construct the outcome variable analogously to our main analysis: equal to one if the government prevails and zero otherwise. We then estimate the same specification as in Equation 1, applying the corresponding court and year fixed effects and clustering standard errors at the court level. Due to the non-availability of the judge identity, we cannot include judge fixed effects.

Columns (3) and (4) in Table 3 report the results. The coefficient of *Post* in both columns (3) and (4) remains statistically indistinguishable from zero. Thus, we find no statistically significant change in government win rates in district courts following the live-streaming adoption by their respective High Courts.

4.3 Robustness: Evidence from Tax Tribunals

As a second piece of evidence, we examine outcomes in the Income Tax Appellate Tribunals (ITATs), which did not implement live streaming during the study period. ITATs provide a close comparison group. These tribunals adjudicate disputes between taxpayers and the income tax agency, making the underlying structure of litigation similar to government–business cases in High Courts. Furthermore, High Courts hear statutory appeals arising from ITAT orders, meaning both institutions operate within the same legal and commercial framework and apply related principles of statutory interpretation. This institutional link makes ITAT outcomes a relevant benchmark for assessing whether the pro-government shift we observe is specific to courts exposed to live streaming. As described in section 3, the dataset comprises judgments from 27 tax tribunals across Indian states, covering the same period as our primary High Court sample (January 2016 to December 2024). Each judgment is structured analogously to the High Court data.

We organize the data and construct the outcome variable in exactly the same manner as in our primary analysis, as described in the main result. We then estimate regression specification as in equation 1, applying the same set of fixed effects and clustering procedures. Similar to section 4.2, we do not have the judge details for the Income Tax Tribunals cases. Thus, we cannot include judge fixed effects in the specification.

Columns (5) and (6) in Table 3 present the results. The coefficient of *Post* is statistically indistinguishable from zero across specifications. In contrast to our findings in the High Court setting, we find no evidence of a systematic pro-government shift in the tribunal data where the corresponding High Court implemented live streaming.

Taken together, the null results from the district court and Income Tax Tribunals sample further strengthen our interpretation that the observed shift in High Court outcomes is driven by the live-streaming reform itself rather than by unobserved regional shocks, contemporaneous changes in the local litigation environment, or state-specific policy interventions.

5 Mechanism

Following Chen et al. (2025), we investigate whether shifts in case outcomes are accompanied by corresponding changes in the text of judicial reasoning and judgments, which can reveal underlying judicial bias. If judges become more inclined to favor the government after the introduction of live streaming, the sentiment of the judgment should become more pro-government, and the reasoning should place greater emphasis on the government's representations. To test this mechanism, we analyze judgment text to measure latent bias in judicial reasoning and language, assessing whether the substance and tone of legal argumentation shift systematically pro-government with transparency. Finally, to evaluate the public-scrutiny channel outlined in the Introduction, we examine how live-streamed cases are amplified on social media, a pathway that plausibly shapes public opinion and may exert external pressure on judicial behavior.

5.1 Text-Based Evidence on Ideological Orientation

In our first text-based test of the mechanism, we examine whether judges become more pro-government in their written reasoning under live streaming (Liu and Tang (2025)). Specifically, we test whether the linguistic orientation of judicial reasoning shifts following the adoption of live streaming. To do so, we employ a text-based Zero-Shot Learning (ZSL) framework to quantify the economic orientation of judgment text. Following Larochelle et al. (2008) and Lampert et al. (2009), we use the BART-large-mnli model, a natural language

inference architecture pre-trained on an extensive textual corpus to classify each judgment along three semantic dimensions: (i) pro-regulation (pro-government), (ii) pro-market, and (iii) neutral orientation. The model assigns a continuous score between 0 and 1 to each category, reflecting the degree of semantic alignment between the judgment text and the label. We provide technical details of the algorithm in section B1 of the online appendix.

We then collapse our judgment-level data to judge–court–year level by computing the average pro-government score, the average pro-market score, and the average neutral score for each judge-court-year combination. The sample spans the years 2016 to 2024. We estimate the following specification for the test:

$$\mathrm{Y}_{ijt} = \beta \cdot Post_{it} + \alpha_i + \gamma_t + \delta_j + X_{jt-1} + \varepsilon_{ijt} \tag{3}$$

where Y_{ijt} denotes the orientation score for judge j in court i during year t. The variable $Post_{it}$ equals one for years after High Court i adopts live streaming, and zero otherwise. The terms α_i, γ_t, and δ_j denote court, year, and judge-level fixed effects, respectively. The vector X_{jt-1} includes lagged High Court-year-level control variables, as described in equation 1. Standard errors are clustered at the court level. The coefficient of interest β measures the average change in the linguistic orientation of judicial reasoning following the adoption of live-streaming.

Table 4 presents the results of our sentiment analysis. Even-numbered columns include the full set of control variables. In columns (1) and (2), the dependent variable is the pro-government score. The coefficient on $Post_{it}$ is positive and statistically significant with an estimated magnitude of 0.027, indicating that the pro-government score increases by 2.7 percentage points following the adoption of live streaming. This effect represents approximately 7.6% of the unconditional mean pro-government score, suggesting an economically meaningful shift in judicial language toward positions more aligned with government or regulatory interests.

Columns (3)-(4) and (5)–(6) present the results with pro-market and neutral scores, respectively, as dependent variables. In columns (3) and (4), the coefficients on $Post_{it}$ are statistically indistinguishable from zero, suggesting that there is no change in the pro-market sentiment after the live-streaming. Additionally, the coefficients are statistically indistinguishable from zero for neutral scores as the dependent variable in columns (5) and (6). Overall, the above estimates suggest that the pro-government score is going up.

Figure 2 plots the dynamic event-study coefficients for the pro-government sentiment score. The pre-treatment coefficients for the three years preceding live-streaming adoption are statistically insignificant, confirming the parallel trends assumption. In contrast, the

post-treatment coefficients are positive and statistically significant. Together, these results demonstrate that the language of judicial reasoning becomes systematically more aligned with state and regulatory perspectives following the introduction of live streaming, consistent with the creation of pro-government bias rather than the correction of pre-existing anti-government bias.

5.2 Judicial Attention and Incorporation of Litigant Narratives

Having uncovered the pro-regulation tilt of the language of the judgments in response to livestreaming in Section 5.1, we now turn to understanding how this shift arises within the text of judicial decisions. In particular, we ask whether the observed pro-government tilt reflects a broader change in the substantive attention judges devote to the arguments advanced by different litigants. If live streaming creates a new pro-government bias, this shift should manifest not only in aggregate sentiment scores but also in the substantive content of judicial reasoning itself. In particular, judges may devote greater attention to government arguments and incorporate government narratives more extensively into their legal analysis. Such adjustments would translate into higher textual incorporation of government-side representations in the final judgment, thereby generating the measured linguistic convergence toward pro-government content. To test this mechanism, we analyze whether the relative prominence of government arguments within judgment text increases following live-streaming adoption.

To empirically examine this mechanism, we exploit the structured organization of our corpus as described in section 3. This segmentation allows us to isolate the government's factual narratives and the judge's subsequent synthesis of those facts and arguments. Following Kelly et al. (2021) and Chen et al. (2025), we develop a text similarity–based measure of judicial incorporation. For each judgment j, we extract three textual components: (i) the petitioner's factual narrative, (ii) the respondent's factual narrative, and (iii) the set of facts and reasoning acknowledged by the judge in the Judge's interpretation section. Using these components, we compute cosine similarity scores between the vectorized text representations of the judge's recognized facts and those of each party. Text is represented using term frequency–inverse document frequency (TF–IDF) weighted embedding. TF-IDF method is used to determine the importance of a word within a text piece compared to a collection of such text pieces (corpus). It is calculated by multiplying two values: Term Frequency (TF), which measures how often a word appears in a specific document, and Inverse Document Frequency (IDF), which measures how rare a word is across the entire corpus.

Formally, we construct similarity measures that capture the textual alignment between

the judge's reasoning and the factual narratives advanced by each side. Let V_{Judge} denote the embedding of the judicial reasoning section, and V_{Gov} and V_{Corp} denote the embeddings of the government's and corporate party's factual submissions, respectively. We compute:

$$\text{Similarity}_{Gj} = \text{sim}(V_{\text{Judge}}, V_{\text{Gov}}), \quad \text{Similarity}_{Cj} = \text{sim}(V_{\text{Judge}}, V_{\text{Corp}}),$$

where $\text{sim}(\cdot)$ represents the cosine similarity between the corresponding embedding vectors. We then define:

$$\Delta\text{Similarity}_j = \text{Similarity}_{Gj} - \text{Similarity}_{Cj},$$

which measures the relative degree of judicial incorporation of government versus corporate narratives in judgment j. A higher value of $\Delta\text{Similarity}_j$ indicates that the judge's reasoning more closely reflects the government's submissions relative to those of the corporate litigant.

We first validate this measure by formally examining its relationship with case outcomes. Specifically, we test whether higher relative similarity to the government's narrative predicts a greater likelihood of a government victory in the pre-livestreaming period (before 2020). To do so, we estimate the following regression:

$$Win_{ijkt} = \beta \cdot \Delta\text{Similarity}_{ijkt} + \alpha_i + \gamma_t + \delta_k + \varepsilon_{ijkt},$$

where Win_{ijkt} is a binary variable equal to one if the government wins case j in court i presided over by judge k in year t, and zero otherwise. $\Delta\text{Similarity}_{ijkt}$ is the relative textual similarity between the judge's reasoning and the government's submissions compared to those of the corporate litigant, as defined above. Rest of the variables are as defined in equation 1. Standard errors are clustered at the court level.

We report the results of this validation exercise in columns (1) and (2) of Table 5. All columns include Court, Year, and Judge fixed effects. Column (2) reports the results incorporating control variables listed in equation 1. The coefficient β in both columns is positive and statistically significant. The magnitude in column (1) indicates that a one–standard-deviation increase in $\Delta\text{Similarity}_{ijkt}$ is associated with about 3.4% higher probability of government success in the case. This statistically robust correlation supports the interpretation of ΔSimilarity as a credible measure of judicial attention and textual alignment toward government narratives.

To estimate how live streaming influences this relative incorporation, we employ the following difference-in-differences specification:

$$\Delta\text{Similarity}_{ijkt} = \beta \cdot Post_{it} + \alpha_i + \gamma_t + \delta_k + X_{it} + Z_{it} + \varepsilon_{ijkt},$$

where $\Delta\text{Similarity}_{ijkt}$ measures the relative incorporation of government versus corporate narratives in case j heard by judge k in court i at time t. The rest of the variables carry the same definition as defined in section 1. Standard errors are clustered at the court level.

The key coefficient of interest, β, measures the differential change in judicial incorporation of litigant statements following the adoption of live streaming. We report the results in columns (3) and (4) of Table 5. Column (3) presents the specification with court, judge, and year fixed effects. We find the coefficient to be positive and statistically significant, indicating that the introduction of live streaming increased the similarity between judges' recognized facts and the government's statements relative to those of firms. The magnitude of the effect implies that ΔSimilarity increases by approximately 0.104 units, equivalent to a 53% shift relative to the pre-reform mean, indicating a measurable increase in the textual alignment of judicial reasoning with government narratives in treated courts. The coefficient remains qualitatively unchanged when we add the control variables in Column (4).

Overall, these results provide evidence consistent with the aggregate linguistic shifts documented earlier. The post-reform increase in the incorporation of government statements into judicial reasoning suggests that the observed pro-government tilt in the language of judgments originates from changes in the composition of factual attention and narrative weight.

5.3 Social Media Amplification

Having established that live streaming increases the likelihood of government victories in government–business disputes and that the text of judgments becomes more pro-regulation, a key question remains: why does transparency induce this pro-government bias? Our central thesis is that live streaming makes judicial proceedings more visible and accessible to the public, prompting judges to become more attentive to public perceptions. In an environment where the optics of siding with private interests can be politically or socially unpopular, judges may avoid rulings that appear to favor business over the state. Consider, for instance, a mining dispute where the case concerns the division of revenue between the government and a large private, possibly multinational, firm, or a property-rights dispute between a corporation and the state. In such cases, the public may perceive judgments favoring business as privileging private profit over public welfare. While we do not have direct evidence on public perceptions, we test whether live streaming increases public awareness and engagement with judicial proceedings, a plausible channel through which transparency could shape judicial behavior.

To examine whether live streaming increases public engagement with judicial proceedings,

we test whether live-streamed proceedings we collect data from prominent legal journalism accounts on the social media X (formerly Twitter): *LiveLaw India* and *Bar & Bench*. These accounts routinely share real-time updates, video clips, and summaries of ongoing court proceedings. Our identification idea is straightforward: if posts containing video clips of hearings generate higher engagement than those without videos, this provides direct evidence that live-streamed cases attract greater public attention and visibility.

We compile a dataset of social media posts from these two accounts covering judicial proceedings between January 1, 2023, and December 31, 2024.[15] For each post, we record engagement metrics, including the number of likes, reposts, and comments. This dataset allows us to systematically assess how live streaming affects the public salience of judicial activity. We estimate the following regression specification:

$$\text{Engagement}_{it} = \beta \cdot \text{Media}_i + \alpha_h + \gamma_t + \varepsilon_{it} \tag{4}$$

where Engagement_{it} is the total number of likes, retweets, and comments associated with post i in month t. The variable Media_i is an indicator equal to 1 if post i has a video attached to it and 0 otherwise. γ_t and α_h are the month and hour fixed effects in our specification. We employ month rather than year fixed effects to capture finer temporal variation in social media dynamics, as engagement patterns and news cycles evolve more frequently. Month fixed effects control for temporal variation in social media activity and news cycles, while hour-of-day fixed effects account for within-day variation in posting times that may affect visibility and engagement. Standard errors are clustered at the month level.

We present the results in Table 6. In Column (1), we do not include any fixed effects. The estimated coefficient on Media_i is positive and statistically significant, indicating that posts with a video have substantially higher online engagement than non-video posts. The magnitude of the coefficient 16,668.30 implies that live-streamed cases attract at least 1.47 times greater amplification on social media platforms.[16] Similarly, in column (3) when we include both Month and hour-of-day fixed effects, the coefficient is positive and statistically significant, and qualitatively unchanged. This result provide consistent evidence that live streaming increases public engagement with judicial proceedings. The findings support the hypothesis that enhanced visibility serves as a key mechanism through which transparency reforms influence judicial behavior.

While we document systematic changes in sentiment and judicial reasoning, we cannot definitively identify why judges respond to public scrutiny in this manner, particularly given

[15] We obtained these data from the Centre for Analytical Finance, Indian School of Business. The data are available beginning in 2023.

[16] The unconditional mean of total engagement in our sample is 11,202.

their formal institutional independence. Notably, Chen et al. (2025) find similar shifts in judicial behavior in response to transparency even in China which is not a democracy. This cross-national pattern suggests that the responsiveness of judges to public observation may transcend specific institutional contexts and operate through channels beyond formal accountability structures. As discussed in Introduction, the desire to conform to perceived public expectations or to avoid public criticism may constitute a powerful behavioral force even among judges with strong de jure independence. The precise mechanisms linking transparency to pro-government bias remain an open question: whether judges are motivated by career concerns, reputational incentives, anticipated public reaction, or other considerations cannot be conclusively determined from our analysis.

5.4 Government Strength and Case Outcomes

If public opinion matters in shaping judicial biases in cases between government and firms, we hypothesize that the pro-government bias induced by transparency may be more pronounced when governments hold stronger electoral mandates. When a government enjoys a decisive electoral victory, judges exposed to public scrutiny through live streaming may perceive greater political pressure or public support for government positions, leading them to rule more favorably toward the state. Conversely, when governments are weaker, reflected in narrow electoral margins, the public signal about popular preferences may be more ambiguous, potentially attenuating the transparency-induced pro-government bias. We expect this moderating effect of electoral strength to be present only for state government cases, where local electoral mandates provide clear signals of political strength. In contrast, cases involving the central government (union cases) should not exhibit this pattern.

We expect this moderating effect of electoral strength to be present only for state government cases, where local electoral mandates provide clear signals of political strength that are salient to both judges and the public within the High Court's jurisdiction. State governments are geographically proximate to the courts adjudicating disputes, and their political strength is directly observable through state-level election outcomes. In contrast, cases involving the central government should not exhibit this pattern. The central government is geographically and politically distant from individual High Courts and operates at the national level across all states. Therefore, state-level public sentiment regarding government strength is unlikely to moderate judicial behavior in cases involving the central government.

To test this hypothesis, we construct a measure of government strength based on electoral outcomes. Specifically, we define a variable *Strong Gov* as the percentage difference between the number of electoral seats won by the ruling party in the state and the number of seats

won by the runner-up. The higher the difference, the stronger the political mandate for the ruling party.

We then estimate the following regression specification for the test:

$$\begin{aligned}\text{Gov Win}_{ijkt} = \beta_0 + \beta_1 \cdot Post_{jt} \times \text{Strong Gov}_{jt} \times \text{Non-Union Case}_i + \beta_2 \cdot Post_{jt} \\ \times \text{Strong Gov}_{jt} + \beta_3 \cdot Post_{jt} \times \text{Non-Union Case}_i + \beta_4 cdot Post_{jt} \\ + \beta_5 \text{Strong Gov}_{jt} \alpha_j + \beta_6 \cdot \text{Non-Union Case}_i + \alpha_j + \gamma_t + \delta_k + \varepsilon_{ijt}\end{aligned} \tag{5}$$

Where the variable Non-Union Case$_i$ takes a value of one when case i involves a non-central government entity and zero otherwise. We identify such cases where either of the party names does not contain "Union of India" or "Government of India." The rest of the variables are as defined in equation 1. The coefficient of interest is β_1, which represents the increase in differential likelihood of the government winning after the introduction of livestreaming in cases involving local government as the strength of ruling party increases.

Table 7 presents the results. We include court, judge, and year fixed effects in all columns. We also include the control variables listed in equation 1 in column 2. The first noteworthy result is that the coefficient on *post* continues to be positive and statistically significant. Hence, there is a generally higher likelihood of government win after the introduction of livestreaming. Importantly, the coefficient β_1 on our variable of interest is positive and statistically significant at 5% level. Hence, the differential likelihood of the government winning increases as the local government gains strength, specifically in cases where one of the parties is a non-central government entity.

Taken together, these findings provide evidence that the effect of judicial transparency on government win rates is conditional on political context. The amplification of pro-government bias under strong electoral mandates in state-level cases suggests that judges may be responsive to signals of political strength and public support when their decisions are publicly visible. This heterogeneity supports the interpretation that transparency-induced changes in judicial behavior operate through channels related to public perceptions.

6 Real Effects

In this section, we examine the real effects of live streaming of court proceedings that operate through the judicial bias channel. Specifically, we test whether the pro-regulation bias induced by live streaming is large enough to generate measurable adverse effects on firms operating under the jurisdiction of affected courts. Our focus is on ex ante effects rather than the obvious ex post consequences for firms that lose individual cases. Firms that per-

ceive the judiciary to be increasingly favorable to government authorities may become more cautious in their investment and borrowing decisions, anticipating weaker legal protection against arbitrary regulatory or state action. This perceived increase in policy and enforcement risk can dampen investment and credit demand. Additionally, the greater probability of unfavorable rulings may raise the perceived risk of these firms in the eyes of lenders and investors, leading to higher borrowing costs.

Critically, not all firms face equal exposure to judicial outcomes in government-business disputes. Many firms have limited interaction with the legal system and thus are less likely to be affected by shifts in judicial behavior. However, firms operating in sectors with higher legal exposure, those that incur greater litigation costs, engage more frequently with legal proceedings, or face disputes that involve government entities, are more directly affected by changes in judicial orientation. In the High Court setting, particularly through writ petitions, the government often becomes a party to disputes even when the underlying conflict may originate from commercial or administrative matters, as firms challenge regulatory actions or seek judicial review of government decisions. For these firms with higher legal exposure, an increase in pro-government judicial bias represents a shift in the expected legal environment. If our hypothesis holds, the effects of live streaming should be driven by firms with high legal exposure, while firms with minimal legal involvement should show little response.

To test these hypotheses, we assemble a firm–year–level dataset. We classify firms as being under the jurisdiction of a High Court that adopted live streaming if the state in which firm is registered falls within that court's territorial jurisdiction. This classification allows us to exploit the staggered rollout of live streaming across High Courts to identify the impact of transparency-induced judicial bias on firm behavior. To construct the measure of legal exposure, we use data from the Prowess database on legal expenses and total expenses. For each two-digit National Industrial Classification (NIC) industry, we compute the average ratio of legal expenses to total expenses in the year 2020, the year immediately preceding the first adoption of video telecast in our sample.[17] We then classify those industries with an above median value of this ratio as the ones with high legal exposure. The indicator variable $High_legal_Expenses_i$ equals one for firms belonging to high legal-exposure industries and zero for other firms. This measure captures the degree to which industries face legal disputes, compliance burdens, and regulatory interactions.

We then estimate a specification that interacts the live-streaming indicator with legal exposure.

$$Y_{ijt} = \beta_0 + \beta_1 \cdot Post_{jt} \times High_Legal_Expenses_i + \alpha_i + \lambda_{jt} + X_{it} + \epsilon_{ijt} \tag{6}$$

[17]Industry defined at the two-digit NIC level.

The dependent variable Y_{ijt} represents various firm outcomes for firm i in state j in year t. Specifically, we examine: (i) the natural logarithm of total borrowings, (ii) the natural logarithm of gross fixed asset additions, (iii) the natural logarithm of additions to plant, machinery, land, and buildings and (iv) the natural logarithm of sales revenue. The variable $Post$ is an indicator that equals one if the High Court j under whose jurisdiction firm i operates had adopted live streaming by year t, and zero otherwise. The live streaming adoption year is defined based on the financial year.[18] The regression includes firm fixed effects (α_i) to control for time-invariant firm characteristics and state $\times$ year fixed effects (λ_{jt}) to absorb aggregate shocks that vary across regions over time. Standard errors are clustered at the state level. The interaction term $Post \times High_Legal_Expenses_i$ captures the differential effect of live streaming adoption on firms with greater exposure to judicial proceedings. The coefficient β_1 identifies whether the real effects of judicial bias are concentrated among firms more likely to be affected by court decisions.

We present the estimates in Table 8. The dependent variable in columns (1) and (2) is the natural logarithm of borrowings, and the dependent variable in columns (3) and (4) is the natural logarithm of additions to gross fixed assets. Columns (5) & (6) and columns (7) & (8) presents the results for additions to plant and machinery and sales respectively. The even numbered columns include full set of state-year control variables as explained in section 4. The coefficient on the interaction term $Post \times High_Legal_Expenses_i$ is negative and statistically significant across all columns. Columns (1) and (2) show that borrowing declines for firms in high-exposure industries. The interaction coefficient indicates an 8.16 percent reduction in borrowing, conditional on the full set of controls and fixed effects. Columns (3), (4) and columns (5), (6) show the results for the measures of investment - additions to fixed assets and additions to plant and machinery respectively. The coefficient -0.131 in column (3) suggests that high-legal-exposure firms experience a decline of 12.28% in investment after live streaming adoption. Columns (7) and(8) show that high-legal-exposure firms experience a statistically significant decline in sales of roughly 6.48 percent after live streaming adoption. This decline is consistent with firms curtailing external financing in response to higher perceived enforcement and regulatory risk.

For tests related to borrowing costs, we use loan-level data on borrowing charges filed with the Ministry of Corporate Affairs as described in section 3. Each observation represents a specific loan from a creditor to a firm on a given date. We estimate an analogous specification:

$$InterestRate_{iljt} = \beta_0 + \beta_1 \cdot Post_{jt} \times High_Legal_Expenses_i + \alpha_i + \gamma_{lt} + X_{it} + \delta_{jt} + \epsilon_{iljt} \quad (7)$$

[18] In India, a financial year runs from April 1st of that calendar year to March 31st of the next calendar year

where Interest Rate_{ilt} is the interest rate on a loan from creditor l to firm i in state j on date t. γ_{lt} and δ_{jt} denote creditor-by-year-month and state-by-year-month fixed effects, respectively to control for time-varying lender and state-specific conditions. Other variables carry the same meaning as explained in equation 6. Standard errors are clustered at the state level.

Columns (1) and (2) in Table 9 report the effects on interest rates. Both columns include all fixed effects, while column (2) also includes the time-varying firm-level control variables. In column (1), the interaction term $\text{Post}_{jt} \times \text{High Legal Expenses}_i$ is positive and statistically significant, with a coefficient of 0.309. Since the unconditional mean interest rate of the sample is 9.52 percent, it indicates that high legal-exposure firms faced an additional $0.309 \times 9.52 = 2.95$ percent (compared to the mean) increase in interest rates relative to low legal-exposure firms, reflecting heightened perceived risk and regulatory uncertainty among lenders. The concurrent decline in borrowing and increase in interest rates is consistent with a contraction in credit supply rather than a reduction in credit demand, as lenders adjust their pricing and lending behavior in response to the increased legal and regulatory risk facing these firms.

Taken together, these results demonstrate that increased pro-government judicial bias has significant real effects on firm behavior, affecting firms with more exposure to legal and regulatory risks. The documented declines in borrowing, investment, coupled with increased borrowing costs, are consistent with the hypothesis that a judiciary tilted toward the state increases regulatory and enforcement uncertainty, thereby dampening firm's financial performances.

7 Conclusion

This paper examines whether greater judicial transparency in the form of live streaming of courtroom proceedings affects judicial behavior and firm outcomes. Using the staggered rollout of live streaming across Indian High Courts, we find that transparency systematically alters judicial conduct. Government win rates in cases involving disputes between firms and the state increase significantly following the introduction of live streaming. These shifts in case outcomes are not driven by changes in case composition but rather by a measurable increase in pro-regulation bias in judicial reasoning.

Our analysis of mechanisms shows that live streaming heightens public exposure, as cases heard under live broadcast receive far greater amplification on social media. The main result is strongest in states where incumbent governments enjoy high public support, suggesting that transparency amplifies the influence of prevailing public sentiment. Together, these findings point to an important consequence of transparency: rather than merely improving

accountability, it can reshape judicial incentives in ways that reinforce existing public biases.

Our study has some limitations. First, we cannot definitively establish why judges appear to act in line with popular sentiment. Our evidence is consistent with the idea that even an independent, non-elected judiciary places some weight on public opinion, but the exact causal channel remains unclear. Second, our analysis focuses on High Court decisions, which deal primarily with questions of law and appeals. As such, we underestimate the overall impact of judicial bias, since initial case filings and trial-court proceedings may also be influenced by perceived shifts in judicial behavior. Despite these limitations, our findings are generalizable to other democratic contexts with independent judiciaries. India's institutional structure, combining judicial autonomy with political accountability through public opinion, makes it a valuable setting for understanding how transparency reforms can alter judicial incentives. The results underscore the need for caution in expanding judicial transparency initiatives, especially when governments seek to improve the business environment and encourage private investment. Reforms that increase visibility must be complemented by safeguards that preserve judicial neutrality and prevent transparency from amplifying bias.

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Figure 1: Pre-trend for Government Win

This figure presents event-study estimates examining the dynamic effects of livestreaming adoption on the probability of government victory in commercial disputes between government entities and private firms in Indian High Courts. Given the event study design, we only consider courts that have been treated for at least one year by the end of our sample period (2024) as the treated courts. The analysis is based on a staggered difference-in-differences specification with court and year fixed effects. The horizontal axis represents years relative to livestreaming adoption (year 0 denotes the adoption year), ranging from four years before to three years after adoption. The vertical axis reports the estimated coefficient on each year indicator, representing the change in the probability of government victory (in percentage points) relative to one year before adoption (the omitted baseline period). The coefficients on pre-adoption indicators (years -5 to -1) test for the presence of differential pre-trends between treatment and control courts. The coefficients on the adoption year and post-adoption indicators (years 0 to +3) capture the treatment effect over time. Vertical bars represent 95% confidence intervals based on standard errors clustered at the court level.

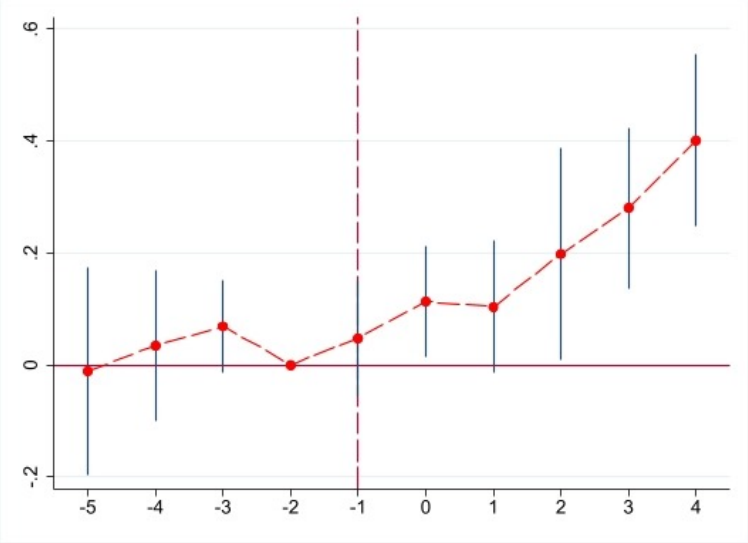


Figure 2: Pre-trend for Judicial Sentiment

This figure presents event-study estimates examining the dynamic effects of livestreaming adoption on the probability of government victory in commercial disputes between government entities and private firms in Indian High Courts. Given the event study design, we only consider courts that have been treated for at least one year by the end of our sample period (2024) as the treated courts. The analysis is based on a staggered difference-in-differences specification with court and year fixed effects. The horizontal axis represents years relative to livestreaming adoption (year 0 denotes the adoption year), ranging from four years before to three years after adoption. The vertical axis reports the estimated coefficient on each year indicator, representing the change in the probability of government victory (in percentage points) relative to one year before adoption (the omitted baseline period). The coefficients on pre-adoption indicators (years -5 to -1) test for the presence of differential pre-trends between treatment and control courts. The coefficients on the adoption year and post-adoption indicators (years 0 to +3) capture the treatment effect over time. Vertical bars represent 95% confidence intervals based on standard errors clustered at the court level.

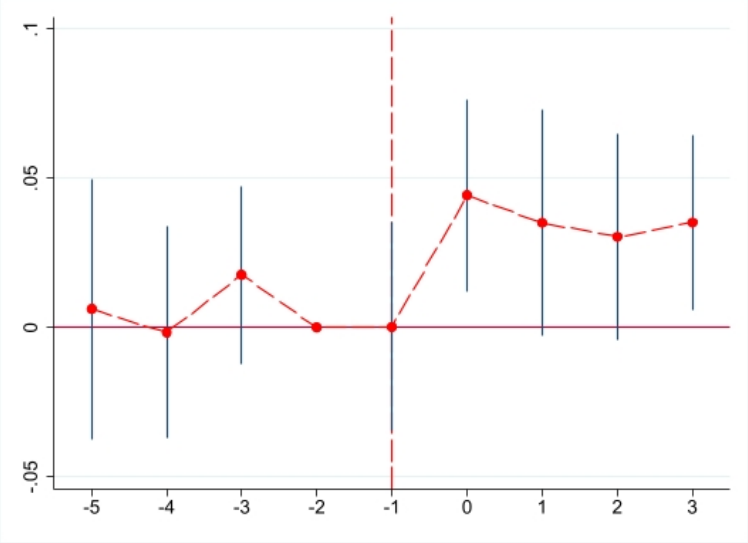


Table 1: Sample Construction

This table presents the construction of the samples used across the empirical analyses in the paper. The overall sample period spans 2016 to 2024. In panels A and B, we summarize the composition of the judicial datasets. Panel A documents the full set of High Court judgments, including the subset of cases in which a government body appears as a litigant against a firm, along with counts of courts and unique judges. Panel B reports the corresponding sample construction for the judgements from District Courts of Delhi and Bangalore, and Income Tax Appellate Tribunals (ITAT). Panel C presents the construction of the social media dataset used to measure online engagement with judicial content. It reports the total number of posts and the number of posts containing media content over the period January 2023 to December 2024. Panel D summarizes the Prowess firm-level dataset, including the number of unique firms, firm-year observations on borrowings and fixed-asset additions. Panel E reports the construction of the loan-level dataset, including the number of unique loans, firms, and lenders.

Sample period	2016 to 2024
Panel A: Judgement Data - All High Courts	
Total number of cases	48,647
Number of government - firm cases	8,005
Number of high courts	25
Number of unique judges	786
Panel B: Judgment Data - Bangalore and Delhi District Courts & Income Tax Tribunals	
Total number of cases from District Courts	18,643
Number of government–firm cases	160
Total number of cases from Income Tax Tribunals	71,684
Number of government-firm cases and the other party a firm	52,105
Number of Tax Tribunals	27
Panel C: Social Media Sample	
Sample Period	January 2023 to December 2024
Total number of posts	73,666
Total number of posts with media (video)	17,052 (331)
Panel D: Firm level Prowess Data	
Number of unique firms	40,672
Number of firm-years with data about borrowings	225,206
Number of firm-years with data about addition to fixed assets	177,619
Number of firm-years observations on addition to plant and machinery	111,604
Number of firm-years observation on sales	223,924
Panel E: Loan Level Data	
Number of unique loans	29,041
Number of unique firms	4,486
Number of unique lenders	198

Table 2: Descriptive Statistics

In this table, we report the descriptive statistics for the key variables used in the empirical analysis of judicial outcomes, credit allocation, state-level characteristics, and social media engagement. Panel A presents summary measures for the High Court case-level dataset. Panel B reports judge-year–level language scores. Panel C provides loan-level and firm-level summary statistics. Panel D presents state-level economic and political indicators, while Panel E reports descriptive statistics for the social media dataset. Variable definitions are provided in Table A6 of the online appendix.

Variable	N	Mean	Standard Deviation	Median	1st Percentile	99th Percentile
Panel A: Case Level						
Gov win	8,005	0.228	0.420	0	0	1
Pro-govt score	7,741	0.353	0.082	0.348	0.168	0.565
Pro-market score	7,741	0.314	0.077	0.310	0.149	0.514
Neutral score	7,741	0.332	0.114	0.335	0.112	0.609
Post	8,005	0.227	0.419	0	0	1
ΔSimilarity	7,384	-0.011	0.232	0	-0.603	0.612
Panel B: Judge-Year Level						
Average Pro-government score	2,106	0.355	0.073	0.349	0.192	0.548
Average Pro-business score	2,106	0.312	0.067	0.310	0.170	0.494
Average Neutral score	2,106	0.332	0.103	0.329	0.124	0.582
Panel C: Social Media Sample						
Bookmarks	70,913	1.408	8.882	0	0	20
Views	70,913	11,134	39,932	4,483	244	109,221
Likes	70,913	49	215	11	0	684
Quotes	70,913	2.190	14.221	0	0	38
Comments	70,913	4.173	18.367	1	0	62
Re-posts	70,913	13.939	67.938	3	0	222
Total Engagements	70,913	11,203	40,140	4,501	246	109,493
Panel D: Loan Level and Firm Level						
Interest rate in %	29,041	9.667	1.902	9.300	7.030	13.900
Borrowings (INR Million)	225,206	5,316	76,114	156	0.100	71,771
Sales (INR Million)	248,773	4,017	53,125	145	0.100	58,383
Gross Fixed Assets (INR Million)	177,619	666	13,493	15	0.100	8,970
Gross Addition to Plant & Machinery (INR Million)	111,604	468	7112	12	0.100	6425
Panel E: State Level						
Credit growth in %	322	12.889	7.992	12.612	-6.841	36.855
Outstanding credit (INR billion)	324	3,058	5,238	826	0.898	25,111
GDP growth	297	6.953	5.115	5.920	-9.503	16.417
GDP at constant prices (INR billion)	297	4,299	4,769	2,806	65	20,588
Political competitiveness	59	0.339	0.221	0.270	0.022	0.940

Table 3: Effect of Livestreaming on Government Win Rates

This table presents difference-in-differences estimates of the impact of livestreaming on the likelihood of a government victory in commercial disputes between government entities and private firms in Indian High Courts, along with placebo estimates examining whether the increase in government win rates observed in High Courts extends to district courts and tribunals that did not adopt live streaming. In panel A, we present the main specification, while in panel B, we present the placebo tests. The data are at a judge-judgment level for High Courts (Columns 1-2) and at a judgment level for district courts and tribunals (Columns 3-6). The dependent variable, *Gov Win*, is a binary indicator equal to one if the government wins and zero otherwise. The key explanatory variable, *Post*, is the staggered treatment indicator variable. For High Courts, it is one for all judgments in the corresponding court after live streaming introduction and zero before that. It takes a value of zero if the corresponding high court is never treated during our sample period. For district courts, *Post* equals one for all judgments in Bengaluru District Court after Karnataka High Court adopted live streaming and zero before that; it is zero for all Delhi District Court judgments since Delhi High Court did not adopt live streaming during our sample period. For Income Tax Appellate Tribunals (ITATs), the sample includes all ITAT judgments involving tax-related disputes between government entities and private firms. In all columns, we include court, year, and judge fixed effects. We also include one-year lagged state-level control variables – credit growth, GDP growth, margin of win by the states' ruling political party, industrial investment, inflation, per-judge caseloads, and unemployment rates – in the even-numbered columns. Standard errors are clustered at the High Court level for Columns (1)-(2) and at the corresponding court levels for Columns (3)-(6), robust and adjusted for heteroskedasticity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Main Result		Panel B: Placebo Tests			
	High Courts		District Courts		Income Tax Tribunals	
			Gov win			
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.087**	0.079**	0.023	0.000	-0.003	-0.020
	(0.037)	(0.037)	(0.012)	(0.000)	(0.013)	(0.016)
Observations	8,685	6,999	157	103	52,105	40,190
R-squared	0.277	0.286	0.085	0.133	0.013	0.009
Control variables	No	Yes	No	Yes	No	Yes
Court F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Judge F.E.	Yes	Yes	No	No	No	No

Table 4: Effects on Judicial Sentiment After Live-Streaming

This table presents a difference-in-differences estimate on the change in judicial sentiment in commercial disputes between government entities and private firms in the Indian High Courts. The sample includes all High Court judgments involving commercial disputes between government entities and private firms. We aggregate the data at a judge-year level. The dependent variables are the judicial sentiments. Columns (1)–(2) report estimates for the Pro Government sentiment score, Columns (3)–(4) for the Pro Market sentiment score, and Columns (5)–(6) for the Neutral sentiment score. The key explanatory variable, *Post*, is the staggered treatment indicator variable. It is one for all judgments in court i after live streaming introduction and zero before that. It takes a value of zero if the high court is never treated during our sample period. We include Court, Judge, and Year fixed effects in all columns. The even-numbered columns include the full set of control variables listed in Table 3. All columns include court, judge, and year fixed effects. The standard errors reported in parentheses are clustered at the High Court level, robust, and adjusted for heteroskedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Pro Govt		Pro Market		Neutral	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.027**	0.025**	0.004	-0.009	-0.031	-0.015
	(0.013)	(0.012)	(0.013)	(0.010)	(0.023)	(0.017)
Observations	1,841	1,456	1,841	1,456	1,841	1,456
R-squared	0.463	0.504	0.448	0.506	0.490	0.562
Control variables	No	Yes	No	Yes	No	Yes
Court F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Judge F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Judicial Narratives, Text Similarity, and Case Outcomes

This table reports estimates examining whether judgments that exhibit greater textual alignment with government submissions are more likely to rule in favor of the government. The data are organized at the judgment level. In panel A, we validate the measure for similarity and limit the sample to 2020 (before the first high court adopted livestreaming). In panel B, we conduct our main test related to the differential change in similarity. In panel B, the sample is until 2024. The variable *Gov Win*, is a binary indicator equal to one if the government prevails in a given case and zero otherwise. The key explanatory variable, ΔSimilarity, measures the relative degree to which the judge's written reasoning is closer to the government's factual narrative than to the corporate litigant's narrative, as constructed in Section 5.2. A higher value of ΔSimilarity indicates that the judge's synthesis of the case facts more closely reflects the government's submissions. All columns include High Court, Judge, and year fixed effects. The even-numbered columns include the full set of control variables listed in Table 3. Standard errors are clustered at the High Court level. The standard errors reported in parentheses are robust and adjusted for heteroskedasticity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: First Stage - Validation		Panel B: Test for change in Similarity	
	Gov Win		ΔSimilarity	
	(1)	(2)	(3)	(4)
ΔSimilarity	0.164**	0.116*		
	(0.077)	(0.061)		
Post			0.104*	0.114*
			(0.051)	(0.051)
Observations	5,250	4,954	5,321	4,762
R-squared	0.083	0.097	0.2250	0.2410
Court F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Judge F.E.	Yes	Yes	Yes	Yes
Control Variables	No	Yes	No	Yes

Table 6: Effect of Media Presence on Total Engagement

This table presents estimates examining whether posts containing video clips of judicial proceedings generate higher public engagement on social media. The sample includes all posts published by the two major legal journalism accounts on the platform *X*, *LiveLaw India* and *Bar & Bench*, between January 1, 2023, and December 31, 2024. The data are organized at the post level. The dependent variable, *Total Engagement*, measures the total number of interactions a post receives, including likes, reposts, and comments. The key explanatory variable, *Media*, is a binary indicator equal to one if the post contains an embedded video or a link to a video, and zero otherwise. Column (1) reports the specification without fixed effects. Column (2) incorporates month fixed effects, which absorb common variation in social media activity, news intensity, and posting patterns across months. Column (3) includes month and hour-of-day fixed effects, thereby additionally controlling for within-day variation in user activity and posting times. The standard errors are clustered at the month level. Since the data in this test are a series of tweets with no identification of the region of origin of the tweets, we can not cluster at the region level. The standard errors reported in parentheses are robust to heteroskedasticity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Engagement		
	(1)	(2)	(3)
Media	16668.30***	16668.30***	16386.14***
	(347.02)	(2028.79)	(2010.44)
Observations	70,911	70,911	70,910
R-squared	0.0462	0.0462	0.0470
Month F.E.	No	Yes	Yes
Hour F.E.	No	No	Yes

Table 7: Effects of Livestreaming on Government Win: Strong vs. Weak Governments

This table presents difference-in-differences estimates of how High Court live streaming affects case outcomes, differentiated by government strength and case type. The data are at a judgment level. The variable *gov win* is as defined in Table 3. Non-Union Case takes a value of one when case i is against the non-central government and zero otherwise. We identify such cases where either of the party names does not contain "Union of India" or "Government of India." The variable *Post* equals one for cases after the corresponding High Court adopted live streaming. The variable *Strong Gov* is the percentage difference between the number of electoral seats won by the ruling party in the state and the number of seats won by the runner-up. Column (2) includes the full set of control variables listed in Table 3. All columns include Court, Year, and Judge fixed effects in their respective specifications. Standard errors are clustered at the High Court level, robust, and adjusted for heteroskedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Gov win	
	(1)	(2)
Post × Non-Union Case × Strong gov	0.235**	0.244**
	(0.106)	(0.101)
Post	0.195***	0.194***
	(0.049)	(0.047)
Strong gov	0.047	0.044
	(0.117)	(0.124)
Post × Strong gov	-0.036	-0.021
	(0.161)	(0.140)
Non-Union Case	-0.033	-0.018
	(0.027)	(0.029)
Post × Non-Union Case	-0.203***	-0.213***
	(0.059)	(0.058)
Non-Union Case × Strong gov	0.062	0.036
	(0.051)	(0.050)
Observations	7,955	7,772
R-squared	0.262	0.261
Control variables	No	Yes
Court F.E.	Yes	Yes
Judge F.E.	Yes	Yes
Year F.E.	Yes	Yes

Table 8: Effects of Livestreaming on Firm Outcomes

This table presents staggered difference-in-differences estimates of the effect of the High Court live streaming on firm-level outcomes. Firms are mapped to High Courts based on the state of their registered office, and the data are organized at the firm–year level. Columns (1)–(2) use log borrowing as the dependent variable, Columns (3)–(4) use log additions to fixed assets, Columns (5)–(6) use log additions to plant and machinery, and Columns (7)–(8) use log sales. The variable *Post* equals one for firm-years after the corresponding High Court adopted live streaming. *High Legal Expenses* is an indicator for industries with an above median value of the ratio between legal expenses and total expenses among all industries. Columns (2), (4), (6), and (8) include the full set of one-year lagged firm-level control variables: total assets, leverage, current ratio, profit margin (PAT/Sales), and return on assets (ROA). All specifications include firm fixed effects and state-by-year fixed effects to control for time-invariant firm characteristics and time-varying state-level shocks. Standard errors are robust, clustered at the corresponding state level, and adjusted for heteroskedasticity. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Log Borrowing		Log Addn. Fixed Assets		Log Addn. Plant & Mach.		Log Sales	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × High Legal Expenses	-0.085*	-0.141***	-0.131**	-0.219***	-0.166***	-0.180***	-0.067**	-0.070***
	(0.046)	(0.021)	(0.061)	(0.030)	(0.040)	(0.041)	(0.030)	(0.020)
Observations	223,294	162,209	174,379	131,578	108,793	93,016	221,982	162,198
R-squared	0.890	0.886	0.759	0.760	0.755	0.758	0.918	0.923
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Effects of Livestreaming on Firms' Borrowing Costs

This table presents staggered difference-in-differences estimates of the effect of High Court live streaming on loan-level interest rates. The data are at the loan level and spans 2016 to 2024. The dependent variable is the interest rate charged by lender j to firm i on date t. The variable *Post* equals one for a loan observation after the High Court with jurisdiction over the firm's registered state adopted live streaming. *High Legal Expenses* is an indicator for industries with an above median value of the ratio between legal expenses and total expenses among all industries. Column (2) includes the full set of one-year lagged firm-year level control variables: total assets, leverage, current ratio, profit margin (PAT/Sales), and return on assets (ROA). All columns include firm, bank-by-year-month, and State-by-year-month fixed effects. Standard errors are robust, clustered at the corresponding state level, and adjusted for heteroskedasticity. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Interest Rate	
	(1)	(2)
Post × High Legal Expenses	0.309***	0.545***
	(0.041)	(0.087)
Observations	25,154	15,411
R-squared	0.846	0.817
Control variables	No	Yes
Firm F.E.	Yes	Yes
State × Year × Month F.E.	Yes	Yes
Bank × Year × Month F.E.	Yes	Yes

Internet Appendix

Figure A1: Screenshot of Live Streaming Cases

This is an example of live streaming cases in one of the high courts.

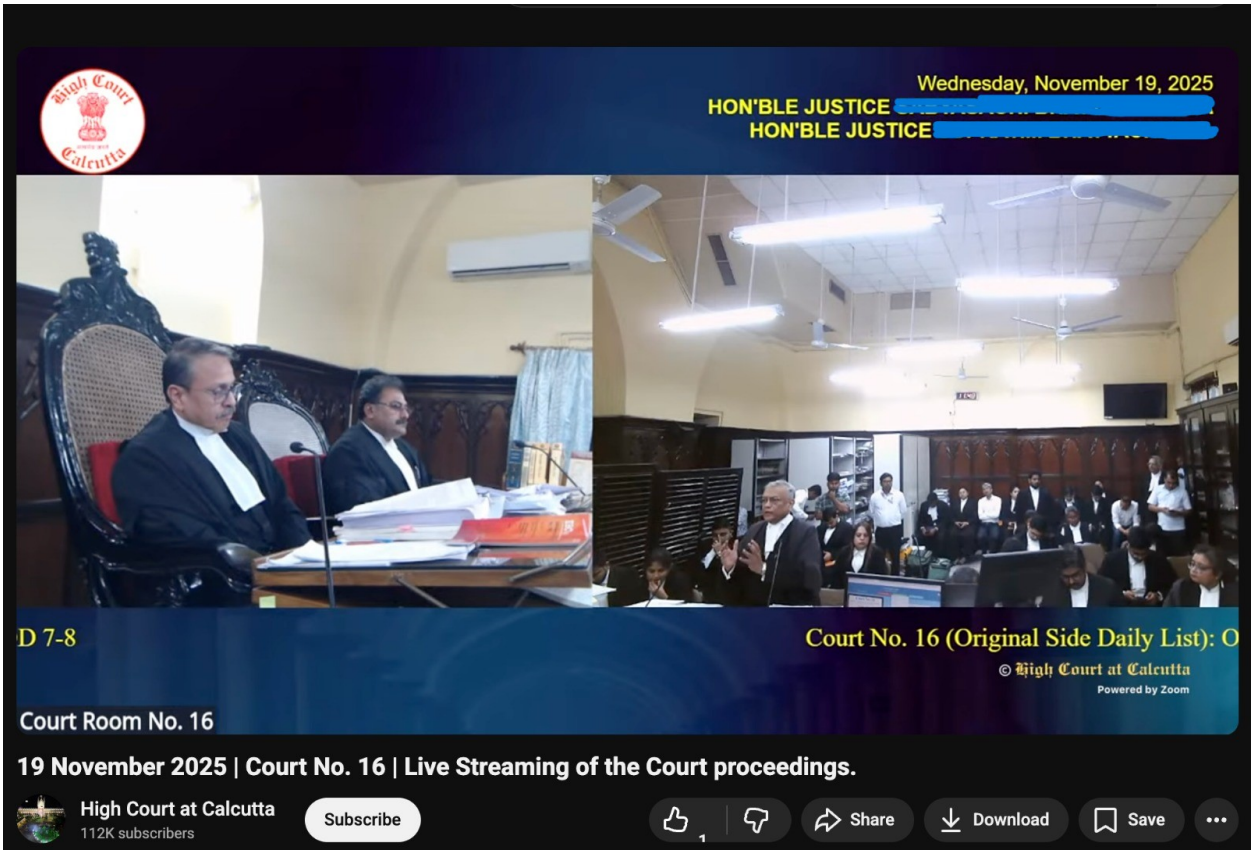
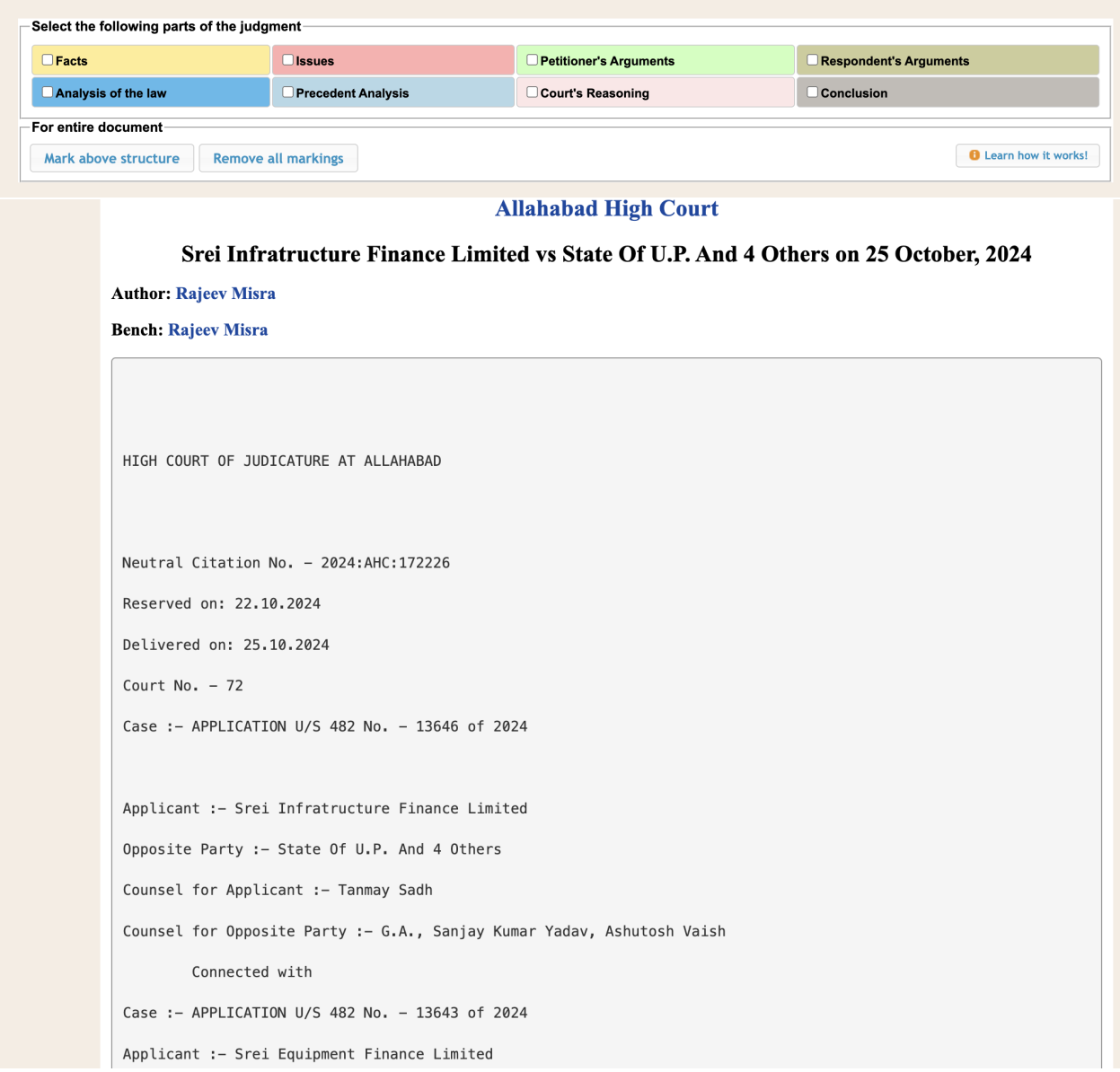


Figure A2: Screenshot of Labeled Judgments

This is an example of a labeled judgment from IndiaKanoon's website.



Case :- APPLICATION U/S 482 No. - 13643 of 2024

Applicant :- Srei Equipment Finance Limited

Opposite Party :- State Of U.P. And 4 Others

Counsel for Applicant :- Tanmay Sadh

Counsel for Opposite Party :- G.A., Sanjay Kumar Yadav, Ashutosh Vaish

Hon'ble Rajeev Misra,J.

1. This application under Section 482 Cr.P.C. has been filed by accused-applicant-Srei Infrastructure Finance Limited challenging the police report/charge sheet no. 13 of 2023 dated 30.12.2023 submitted by the CBI in Case Crime No./FIR No. RCBD12021E0001, under Sections 120-B r/w Section 409, 420 IPC and Sections 13(2) r/w Section 13(1)(d) of Prevention of Corruption Act, 1988, Police Station-CBI, BSFB, New Delhi, the Cognizance Taking Order/Summoning Order dated 14.03.2024 passed by Special Judicial Magistrate (CBI), Ghaziabad in consequential Criminal Case No. 12 of 2024/Registration No. 14248 of 2024 (CBI Vs. M/s SVOGL Oil and Gas Enegry Limited and Others), under Section 120-B IPC read with Sections 420, 471 IPC read with 468 IPC and substantive offence under Section 420 IPC, Police Station-CBI, BSFB, New Delhi as well as the entire proceedings of aforementioned criminal case.

2. Affidavits have been exchanged between the parties. Counsel for the parties agreed that the matter be decided finally at the admission stage on the basis of pleadings of the parties without formally admitting the present application. In view of above and as provided under the Rules of the Court, the present application is being disposed of finally at the admission stage itself. Criminal Misc. Application 13646 of 2024 (Srei Infratructure Finance Limited Vs. State of U.P. and 4 Others) shall be treated as the leading petition. The facts pleaded in the aforesaid petition shall alone be referred to for the sake of convenience.

3. I have heard Mr. Anirban Bhattacharya, Advocate assisted by Mr. Tanmay Sadh, the learned counsel for applicant, the learned A.G.A. representing State-opposite party-1, Mr. Gyan Prakash Srivastava, the learned Deputy Solicitor General of India assisted by Mr. Sanjay Kumar Yadav, the learned Standing Counsel for CBI representing opposite parties 2, 3 and 4 and Mr. Ashutosh Vaish, the learned counsel representing opposite party-5.

5. Record shows that an FIR dated 10.03.2021 was lodged by first informant-opposite party-5 Ms. Mausumi Majundar, DGM, Punjab National Bank, LCB, NOIDA, Branch, U.P. and was registered as FIR No. RCBD12021E0001, under Sections 120-B r/w Section 409, 420 IPC and Sections 13(2) r/w Section 13(1)(d) of Prevention of Corruption Act, 1988, Police Station-CBI, BSFB, New Delhi. In the aforesaid FIR, the following have been nominated as named accused;-

Analysis of the law

(I). M/s SVOGL Oil Gas & Energey Limited, Registered Office at Tower-1, Fifth Floor, NBCC Plaza, Sector V, Pushp Vihar, New Delhi-110017 (Accused No. 1).

(II). Mr. Padam Singhee, S/o Mr. Chimanlal Singhee, Managing Director of SVOGL, resident of House No. 4A, Street C-1, Sainik Farms, New Delhi-110062 also at House No. J-238/3, Lane W-15J, Western Avenue, Sainik Farm, New Delhi-110062 (Accused No.-2).

(III). Mr. Prem Chimanlal Singhee S/o Mr. Chimanlal Singhee, Director of SVOGL, resident of House No. 4A, Street C-1, Sainik Farms, New Delhi-110062 also at House No. J-238/3, Lane W-15J, Western Avenue, Sainik Farm, New Delhi-110062.

Apart from above, the following have also been arraigned as accused (IV) Unknown public servants and others.

It is thus apparent that applicant- SREI Infratructure Finance Limited has not been nominated as a named accused in the aforesaid FIR.

6. After aforementioned FIR was lodged, the CBI proceeded with statutory investigation of aforementioned FIR in terms of Chapter-XII Cr.P.C. On the basis of material collected by CBI, during course of investigation, it came to the conclusion that complicity of various persons is prima-facie apparent in the crime in question. It, accordingly, submitted the police report/charge sheet no. 13 of 2023 dated 30.12.2023 in terms of Section 173(2) Cr.P.C., whereby the following have been charge sheeted;-

I. M/s SVOGL Gas & Oil Exploration Services Ltd., U/s 120-B r/w 420, 471 IPC r/w 468 IPC & Substantive Offence u/s 420 IPC.

II. Shri Prem Singhee, U/s 120-B r/w 420, 471 IPC r/w 468 IPC & substantive offence u/s 420 IPC.

9.3. Subsequent to above, the Reserve Bank of India filed an application before the National Company Law Tribunal, Calcutta Bench, under Section 227 read with Clause (zk) of Sub-Section (2) of Section 239 of the Insolvency and Bankruptcy Code, 2016 read with Rules 5 and 6 of the Insolvency and Bankruptcy (Insolvency and Liquidation Proceedings of Financial Service Providers and Application to Adjudication Authority), Rules, 2019 seeking initiation of Corporate Insolvency Resolution Process of the applicant. The same was registered as CP(IB) No. 295/KB/2021. In the matter of Reserve Bank of India Vs. SREI Infrastructure Finance Limited.

9.4. The National Company Law Tribunal Calcutta Bench, vide order dated 08.10.2021 admitted the aforesaid application and further appointed one Mr. Rajneesh Sharma as the Administrator of applicant. For ready reference, the order dated 08.10.2021 is reproduced herein below;-

"ORDER Per: Rajasekhar V.K., Member (Judicial)

1. The Court convened via video conferencing.

2. This is an application filed by the Reserve Bank of India (Appropriate Regulator) under section 227 read with section 239(2(zk) of the Insolvency and Bankruptcy Code, 2016 (in short "IBC") for initiations of Corporate Insolvency Resolution Process (in short "CIRP") against Srei Infrastructure Finance Limited (in short "SIFL"), the Financial Service Provider.

Fact

3. The respondent/Financial Service Providers (in short "FSP") is a company registered under the Companies Act, 1956, having CIN: L29219WB1985PLC- 055352, and registered with the Registrar of Companies, West Bengal, Kolkata. Therefore, this Bench has jurisdiction to deal with the present petition.

4. Mr. Sudipto Sarkar, Learned Senior Counsel appearing on behalf of the Petitioner/Appropriate Regulator submits as follows :-

These documents demonstrate that the account is in default with the status of "SMA-2", which means that the interest of principal has been overdue and remains unpaid for a period in excess of 60 days calculated in accordance with the RBI Master Circular on Prudential Norms on Income Recognition, Asset Classification and Provisioning pertaining to advances. E-mail communication evidencing classification of SIFL as a Red Flag Account by UCO Bank. The Certificate under the Bankers' Book Evidence Act, 1891 is also attached.

6. The RBI vide its notification dated 04/10/2021, in exercise of its powers under section 45-IE of the Reserve Bank of India Act, 1934 has superseded the Board of Directors of SIFL and appointed Mr. Rajneesh Sharma as the Administrator. It has also constituted a three-member Advisory Committee to assist the Administrator of SIFL in the discharge of its duties. The RBI has proposed the same person to be appointed as the Administrator of the Corporate Debtor.

7. Mr. Sudipto Sarkar, Learned Senior Counsel appearing for the Petitioner/ Appropriate Regulator submits that in view of the huge default committed by the respondent/FSP, there is a need to initiate CIRP against the respondents with speed. He, therefore, urged this Adjudicating Authority to pass appropriate orders expeditiously keeping in view the public interest in the matter.

8. Mr. Sudipto Sarkar, Learned Counsel, further submitted that the challenge to the notification dated 04/10/2021 issued the RBI, in Writ Petition (Lodging) No. 22872/2021, was dismissed by the Hon'ble Bombay High Court vide order dated 07/10/2021.

9. Rule 5(a)(i) of the Insolvency and Bankruptcy (Insolvency and Liquidation Proceedings of Financial Service Providers and Application to Adjudication Authority) Rules, 2019 mandates that no CIRP shall be initiated against an FSP which has committed a default under section 4, except upon an application made by the appropriate regulator in accordance with rule 6. Sub-clause (ii) thereof which specifies that an application under sub-clause (i) shall be dealt with in the same manner as an application by a financial creditor under section 7.

Table A1: Indian States and Union Territories with Their Corresponding High Courts

State	High Court
Andhra Pradesh	Andhra Pradesh High Court
Arunachal Pradesh	Gauhati High Court
Assam	Gauhati High Court
Mizoram	Gauhati High Court
Nagaland	Gauhati High Court
Bihar	Patna High Court
Chhattisgarh	Chhattisgarh High Court
Goa	Bombay High Court
Gujarat	Gujarat High Court
Himachal Pradesh	Himachal Pradesh High Court
Jharkhand	Jharkhand High Court
Karnataka	Karnataka High Court
Kerala	Kerala High Court
Madhya Pradesh	Madhya Pradesh High Court
Maharashtra	Bombay High Court
Manipur	Manipur High Court
Meghalaya	Meghalaya High Court
Odisha	Orissa High Court
Punjab	Punjab and Haryana High Court
Haryana	Punjab and Haryana High Court
Rajasthan	Rajasthan High Court
Sikkim	Sikkim High Court
Tamil Nadu	Madras High Court
Telangana	Telangana High Court
Tripura	Tripura High Court
Uttar Pradesh	Allahabad High Court
Uttarakhand	Uttarakhand High Court
West Bengal	Calcutta High Court
Union Territory	**High Court**
Andaman & Nicobar Islands	Calcutta High Court
Chandigarh	Punjab and Haryana High Court
Dadra & Nagar Haveli	Bombay High Court
Daman & Diu	Bombay High Court
Delhi (NCT)	Delhi High Court
Jammu & Kashmir	High Court of Jammu & Kashmir and Ladakh
Ladakh	High Court of Jammu & Kashmir and Ladakh
Lakshadweep	Kerala High Court
Puducherry	Madras High Court

Table A2: Live Stream Adoption Dates

This table presents the dates of live streaming adoption dates for High Courts in our sample period until December 2024.

High Court	**Livestream Start Date**
Gujarat High Court	1 October 2020
Calcutta High Court	8 October 2022
Gauhati High Court	8 October 2022
Jharkhand High Court	8 October 2022
Karnataka High Court	8 October 2022
Madhya Pradesh High Court	8 October 2022
Orissa High Court	8 October 2022
Patna High Court	8 October 2022
Telangana High Court	8 October 2022
Uttarakhand High Court	8 October 2022
High Court of Meghalaya	10 November 2022
Chhattisgarh High Court	16 August 2023
Kerala High Court	1 August 2024

The following High Courts did not adopt live streaming by Dec 2024: Allahabad, Andhra, Bombay, Delhi, Himachal Pradesh, Jammu & Kashmir, Madras, Manipur, Punjab & Haryana, Rajasthan, Sikkim, and Tripura.

Table A3: Determinants of Failure: Cox Proportional Hazards Model

The table reports results from a Cox proportional hazards model examining the timing of High Court livestream adoption in 2020–2024. The data are organized at the court level. For each High Court, the duration variable measures the number of days from October 1, 2020 until the court adopts livestreaming for the first time. Courts that do not adopt livestreaming by December 31, 2024 contribute time at risk until the end of the observation window. The event of interest is the first adoption of livestreaming by a High Court, and the model estimates hazard ratios that compare the hazard of adoption across courts with different characteristics. The explanatory variables are: Log Amount, which is the logarithm of outstanding credit linked to the court's jurisdiction; Credit Growth, measuring the annual percentage change in credit; GDP Growth, capturing the year-on-year growth in the state economy; GDP Per Capita, reflecting economic conditions in the jurisdiction; Winning Margin, representing the electoral margin in the most recent state election; and Pending Cases per Judge, which measures the pending caseload burden per sitting judge in each High Court. All explanatory variables are measured as of 2020. The standard errors reported in parentheses are the model-based asymptotic standard errors. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1) Hazard: Failure Event
Log Amount	1.077
	(0.288)
Credit Growth	0.000
	(0.001)
GDP Growth	1.083
	(0.151)
GDP Per Capita	0.999
	(0.000)
Winning Margin	1.147
	(1.490)
Pending Cases per Judge	0.999
	(0.000)
Observations	24
Failures	12
Log likelihood	-34.756
LR $\chi^2(6)$	3.52
p-value	0.7418

Table A4: Search Keywords for Commercial Case Identification

Category	**Keywords**
Legal Acts	Companies Act 2013, Companies Act 1956, SARFAESI Act 2002, Insolvency and Bankruptcy Code 2016, IBC, Arbitration and Conciliation Act 1996, Commercial Courts Act 2015, SEBI Act 1992, Competition Act 2002, FEMA
Case Types	Commercial dispute, commercial suit, commercial appeal, commercial arbitration, company petition, winding up petition, oppression and mismanagement, shareholder dispute, director dispute, corporate dispute
Corporate Terms	Company, corporation, private limited, public limited, shareholders, merger, acquisition, amalgamation, liquidation, corporate governance
Financial & Banking	Bank, financial institution, NBFC, loan recovery, debt recovery, secured creditor, unsecured creditor, default, NPA, non-performing asset, mortgage, hypothecation
Contracts	Breach of contract, contractual dispute, supply agreement, distribution agreement, licensing agreement, franchise agreement, tender dispute
Insolvency	CIRP, insolvency resolution, insolvency professional, resolution applicant, committee of creditors, moratorium, fraudulent trading, preferential transaction
Securities	Securities, shares, debentures, investment dispute, insider trading, market manipulation, SEBI order, takeover
Tribunals & Courts	NCLT, NCLAT, National Company Law Tribunal, Debt Recovery Tribunal, DRT, DRAT, Commercial Court, Commercial Division
Specific Provisions	Section 7 IBC, Section 9 IBC, Section 13 SARFAESI, Section 138 NI Act, Section 241 Companies Act, Section 242 Companies Act, cheque dishonor

Table A5: Descriptive Statistics: District and Tax Tribunals

In this table, we report the descriptive statistics for the variables used in placebo test and the control variables. Panel A presents summary measures for the District Court case-level dataset. Panel B presents summary measures for the Tax Tribunals case-level dataset. Panel C reports summary statistics for the High Court-level control variables.

Variable	N	Mean	Standard Deviation	Median	1st Percentile	99th Percentile
Panel A: District Courts						
Gov win	157	0.338	0.474	0	0	1
Panel B: Tax Tribunals						
Gov win	9,238	0.332	0.118	0.341	0.104	0.623
Panel C: Court-level control variables						
GDP growth	199	5.587	5.205	6.408	-8.962	16.692
Credit growth	199	0.123	0.057	0.122	-0.019	0.320
Margin	198	0.341	0.239	0.296	0.022	0.914
Investment (in INR billion)	199	1,987	4,275	518	0	28,100
Inflation	199	4.723	1.699	4.724	0.909	9.160
Cases per judge	196	6,726	5,827	5,875	59	33,891
Unemployment	199	5.298	2.958	4.700	0.800	16.350

Table A6: Variable Definitions: Judge-Level and Social Media Variables

Variable Name	Definition
Judge Experience	It is the number of years since the judge's initial appointment to the High Court.
Judge Tenure	It is the number of years the judge has served in the current High Court.
Judge Age	It is the age of the judge in years at the time of the judgment.
Engagement	It is the total number of likes, reposts, and comments received on a social media post reporting a court proceeding.
Media	It is an indicator variable that takes the value 1 if a social-media post contains a video clip of the proceeding and 0 otherwise.
Total Expenses	It is the sum total of all expenses incurred by a firm in a given year.
LegalExp	It is the share of a firm's total expenses that is spent on legal expenditures.
High Legal Exposure	It is an indicator variable that takes the value 1 if the firm's legal expenditure share in 2016 is above the sample median.
Interest Rate	It is the reported lending rate for a specific loan contract from the MCA database.
Loan Amount	It is the value of the new borrowing undertaken by a firm in a given year, obtained from the Prowess database.
GDP Growth	It is the annual GDP growth rate of the state in which the High Court is located.
Credit Growth	It is the annual growth rate of bank credit outstanding in the state.
Political Competitiveness	It is one minus the vote-share margin of the winning party in the most recent state election.
Number of Firms per Capita	It is the number of registered firms in the state divided by the state's population.
Post	It is an indicator variable that takes the value 1 for all cases heard after a High Court introduces live streaming, and 0 otherwise.
Government Win	It is an indicator variable that takes the value 1 if the judgment concludes in favour of the government and 0 otherwise.
Pro-government Score	It is a text-based semantic score that captures the extent to which the judgment language reflects pro-regulation or pro-government orientation.

Table A6: Variable Definitions: Judge-Level and Social Media Variables

Variable Name	Definition
Pro-market Score	It is a text-based semantic score that captures the extent to which the judgment language reflects pro-market or market-friendly orientation.
Neutral Score	It is a semantic score that reflects neutral orientation in the language of the judgment.
Similarity_Gov	It is a cosine-similarity measure that captures the textual similarity between the judge's reasoning and the government litigant's factual submissions.
Similarity_Firm	It is a cosine-similarity measure that captures the textual similarity between the judge's reasoning and the firm's factual submissions.
ΔSimilarity	It is the difference between Similarity_Gov and Similarity_Firm, and it measures the extent to which the judge's reasoning aligns more closely with the government's narrative relative to the firm's.

B1 Zero-Shot Learning Method

This study employs Zero-Shot Learning (ZSL) for automated text classification of the economic orientation of judicial decisions. Zero-shot learning, formalized by Larochelle et al. (2008) and extended by Lampert et al. (2009), is a machine learning methodology that assigns texts to categories without requiring labeled training examples from those categories. In contrast to supervised learning methods, which require a training dataset where each observation is manually labeled with its correct category, ZSL utilizes the semantic representations encoded in large-scale pretrained language models.

A pretrained language model is a neural network that has been trained on large text corpora to learn statistical patterns and semantic relationships in language. These models encode meaning through high-dimensional vector representations that capture contextual relationships between words and phrases. The core mechanism of zero-shot learning involves evaluating the alignment between a text and descriptive statements. We structure the classification task as follows: each judicial text is assessed against three hypotheses: "This judgment favors government regulation of business," "This judgment favors free-market principles," and "This judgment is neutral in its economic orientation." The model determines the degree to which the textual content supports each hypothesis, expressed as a probability distribution over the three categories. This approach reformulates classification as an assessment of entailment, defined as the probability that a given judgment's content logically supports each economic orientation hypothesis.

For example, consider the following excerpt from a High Court judgment concerning environmental regulation:

"The Court holds that the precautionary principle and the polluter pays principle are essential features of sustainable development. The State has a constitutional obligation to protect the environment and prevent activities that cause ecological degradation, even when complete scientific certainty regarding harm is absent."

The zero-shot classifier assigns probabilities to each hypothesis based on textual content. For this sentence, the model assigns a probability of 0.69 to "pro-regulation," 0.16 to "pro-market," and 0.15 to "neutral." The text is classified as pro-regulation given the substantially higher probability for this hypothesis.

We implement BART-large-mnli (Bidirectional and Auto-Regressive Transformer), a transformer-based neural network architecture developed by Lewis et al. (2020). A transformer is a neural network architecture that processes text using attention mechanisms, which are computational operations that weigh the relevance of different parts of the input when generating representations. BART combines bidirectional encoding, which processes text in both forward and backward directions to capture context from the entire sequence, with autoregressive decoding mechanisms that generate output sequentially. The model is pretrained through a de-noising objective: it learns to reconstruct original text from corrupted versions where portions have been deleted, reordered, or masked. This pretraining process, conducted on large text corpora, enables BART to develop representations of semantic relationships and textual meaning without task-specific supervision.

The specific variant we employ, BART-large-mnli, has been fine-tuned on the Multi-Genre Natural Language Inference (MNLI) dataset (Williams et al., 2018). Fine-tuning refers to additional training on a specific task after initial pretraining, adapting the model's

parameters to perform well on that task. The MNLI dataset contains approximately 433,000 sentence pairs labeled across multiple text genres. Each pair consists of a premise (an initial statement) and a hypothesis (a proposed conclusion), with labels indicating whether the hypothesis is entailed by (logically follows from), contradicts, or is neutral with respect to the premise. Natural language inference (NLI) is the task of determining the logical relationship between these text pairs. This fine-tuning process adapts BART's general language understanding capabilities specifically for assessing logical relationships between text segments.

The connection between BART-large-mnli and zero-shot learning operates through the framework of entailment classification. In zero-shot text classification, each category is represented as a natural language hypothesis expressed in plain language. The model treats the input text (the judicial decision) as a premise and evaluates whether this premise entails each candidate hypothesis (the three economic orientation descriptions). The NLI framework provides a principled probabilistic measure of how strongly a text supports different categorical descriptions. Critically, this evaluation does not require training examples of judicial texts labeled with economic orientations. BART-large-mnli's training on diverse textual entailment tasks across multiple domains enables it to generalize this entailment assessment to new domains and hypotheses not present in its training data, including judicial texts and economic orientation categories. This generalization capacity, defined as the ability to apply learned entailment reasoning to novel category descriptions and text domains, is the mechanism through which zero-shot classification is achieved.

The classification procedure involves segmenting each judgment into chunks of approximately 20 sentences. This segmentation addresses computational constraints, as transformer models have limited input length capacities, and maintains processing efficiency. Each chunk is independently evaluated against the three hypotheses, generating entailment probabilities that sum to one across the three categories. These probabilities are aggregated across all chunks within a judgment using arithmetic averaging to determine its overall economic orientation. The final classification assigns each judgment to the category with the highest average probability.

This methodology offers several advantages for textual analysis in economics research. First, it enables analysis of large judicial datasets without the resource requirements of manual coding, where human annotators read and categorize each text. Second, it applies uniform classification criteria across all observations, removing potential inter-coder reliability concerns. Inter-coder reliability refers to the risk that different human coders may interpret and apply classification rules inconsistently. Third, the probabilistic output provides continuous measures of economic orientation rather than discrete categories, facilitating econometric analysis that can incorporate the degree of confidence in each classification. Fourth, the use of explicit hypotheses stated in natural language maintains methodological transparency and interpretability, allowing researchers to understand and validate the classification logic. These classifications serve as the basis for empirical analysis of patterns in judicial decision-making across economic bias dimensions.