

Data Science for Justice: The Short-Term Effects of a Randomized Judicial Reform in Kenya

By MATTHIEU CHEMIN^{*}, DANIEL L. CHEN[†], VINCENZO DI MARO[‡], PAUL KIMALU[§], MOMANYI
MOKAYA[¶], MANUEL RAMOS-MAQUEDA^{**}

Draft: November 11, 2022

Can data science be used to improve the functioning of courts, and unlock the positive effects of institutions on economic development? In a nationwide randomized experiment in Kenya, we use algorithms to identify the greatest sources of court delay for each court and recommend actions. We randomly assign courts to receive no information, information, or an information and accountability intervention. Information and accountability reduces case duration by 22%. We find an effect on contracting behaviour, with more written labor contracts being signed by firms, and an effect on wage, since jobs with written labor contracts pay more. These results demonstrate a causal relationship between judicial institutions and development outcomes.

^{*} Department of Economics, McGill University; Cireq, Canada; and Cirano, Canada. E-mail: matthieu.chemin@mcgill.ca.

[†] daniel.chen@iast.fr, JD, PhD, Lead Principal Investigator, Data and Evidence for Justice Reform (DE JURE), The World Bank, Directeur de Recherche, Centre National de la Recherche Scientifique (CNRS) Professor, Toulouse School of Economics, Professor, Institute for Advanced Study in Toulouse.

[‡] Development Impact Evaluation (DIME), World Bank. E-mail: vdimaro@worldbank.org

[§] Director, Planning and Organizational Performance Directorate, Judiciary of Kenya. E-mail: paul.kimalu@court.go.ke

[¶] Development Impact Evaluation (DIME), World Bank. E-mail: mmokaya@worldbank.org

^{||} Development Impact Evaluation (DIME), World Bank. E-mail: mramosmaqueda@worldbank.org

^{**} We wish to thank the Judiciary management for the support and endorsement of the project. We particularly thank the Honorable Chief Justice president of the Supreme Court, Hon. Justice Martha K. Koome, the Judiciary's Chief Registrar, Ms. Anne Amadi, the Chair of Administration of Justice and Performance Management Committee, Hon Justice Agnes Murgor, as well as Dr. Paul Kimalu, Director of the Directorate of Planning and Organizational Performance (DPOP) and assistant directors Mr. Fredrick Ombwori, Mr. Dominic Nyambane, Dr. Moses Maranga, Dr. Joseph Osewe, and Gilbert Kirui. Our thanks are also extended to the program officers of DPOP, namely Martin Astiba, Stanford Mwangi, and Solomon Onaya for the generous assistance in the carrying out the project. We would also like to thank World Bank staff Lacey Ramirez, Bilal Siddiqi, and task team leaders Nicholas Menzies and Christine Anyango for the generous guidance through the Judicial Performance Improvement Project (JPIP). Our deepest appreciation goes to Elimu staff Thomas Kokossou, Simon Newman, and Romain Galgani for the tireless research assistance in this project. We gratefully acknowledge financial support from the Social Sciences and Humanities Research Council of Canada, the International Growth Center, the World Bank's Research Support Budget, and the Center for Effective Global Action's Economic Development and Institutions program, funded by the UK Foreign, Commonwealth & Development Office. Chen also acknowledges financial support from the Alfred P. Sloan Foundation (Grant No. 2018-11245), European Research Council (No. 614708), Swiss National Science Foundation (No. 100018-152768), and IAST, TSE-Partnership, and Artificial and Natural Intelligence Toulouse Institute (ANITI) funding from the French National Research Agency (ANR) under the Investments for the Future (Investissements d'Avenir) program, grant ANR-17-EUR-0010. DIME Analytics has verified and approved the reproducibility of the results. The findings, interpretations, and conclusions

I. Introduction

Well-functioning legal systems are associated with economic development (Djankov et al., 2003; Ponticelli and Alencar, 2016; Lichand and Soares, 2014; Visaria, 2009; Chemin, 2020; Kondylis and Stein, 2021). Judicial institutions spur development by enforcing contracts, securing property rights, and increasing investment. This paper uses a randomized judicial reform to assess whether this relationship is causal. Repeated adjournments of cases are a major cause of case backlog in many parts of the world (Muriuki, 2019). When courts are slow, firms and citizens might choose less efficient ways to do business. In a nationwide experiment in Kenya, we use the first digitized daily court records in the Kenyan judiciary and develop an algorithm to identify the greatest sources of court delays. In one treatment arm, we provide actionable information – the sources of court delays. In a second treatment arm, the actionable information is provided to both the courts and the public. The control group receives the status quo – no information. We analyze the effects of information and accountability on courts and economic development. Our results indicate that information and accountability improves the functioning of courts and has positive effects on economic development.

Until 2015, there was no systematic digital data collection in Kenyan courts, with case information written on paper and staying in local courts. It was impossible to measure the key reasons for delays, and no feedback was given to judges on their performance. In October 2015, the Kenyan judiciary began tracking detailed data on every case going through courts. By 2019, the data comprised more than 9 million observations on daily case activities.

We organize and use this dataset to uncover a new set of facts on delays. We document that 14% of all hearings end in an adjournment, i.e., a case delayed to a future hearing. The data provides 38 different reasons for these adjournments. We then document associations in the data between these adjournments and the time it takes to resolve cases. In collaboration with the Kenyan Judiciary, we develop an algorithm that identifies the greatest sources of delays for each court (i.e., the causes for these adjournments in each court). The algorithm predicts the improvements in key indicators of court performance if these sources of delays were addressed. We display the information delivered by the algorithm in a user-friendly way (which we call the “one-pager”). Our intervention is the first to provide actionable information, tailored to each individual court, to the courts and to the public.

To measure the effects, we implement a nationwide randomized experiment across the 124 court

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stations in Kenya. In one treatment arm, we send the information to the presiding judge or the head of the court station. In a second treatment arm, we provide the same information, but with additional instructions to share the information with the quarterly Court User Committee (CUC) meeting. Members of this meeting include presiding judges or heads of court stations, as well as representatives of lawyers, police, prosecutors, prisons, probation officers, public security agencies and civil society. The function of the CUC meeting is to discuss issues arising in courts and suggest solutions.

We find that this second intervention, sending data and actionable information both to courts and to the CUC, is particularly effective in reducing adjournments and delays in courts. We find a 20% reduction in adjournments, which results in a 22% reduction in case duration. The effect is smaller and not statistically significant for the first intervention (information without public accountability).

To understand the mechanisms, we assess which particular adjournments are reduced. We find a reduction in external adjournments, and less of an effect on internal adjournments. This last finding suggests that the main barrier to court efficiency is not a lack of effort on the judges' side, but comes from external actors.

We find no evidence that greater speed comes at the expense of quality. To assess quality, we scrape and assemble a dataset on publicly available decisions for roughly 160,000 cases from 1976 to 2020 in the superior courts. We find no negative effects of the reform on the probability of the case to be appealed, the length of the judgements, the number of laws or jurisprudence cited in the text, the subsequent citations of the case, or the case outcome. In fact, we find evidence of an increase in court quality according to court satisfaction surveys collected by the Kenyan judiciary. Specifically, we find a reduction in the number of complaints (and suggestions to address them) about the speed of courts. We interpret this as evidence that the reform's beneficial effects are not only found in administrative data through a reduction in adjournments, but also experienced by the wider population.

We also measure economic effects. A strong empirical literature has found that faster courts lead to greater investment by firms. The literature highlights various mechanisms: less fear of expropriation by investors (Kondylis and Stein, 2021; Mehmood, 2022), more reliance on contracts benefitting contract-intensive industries (Boehm and Oberfield, 2020; Amirapu, 2021), and more credit availability (Jappelli et al., 2005; Visaria, 2009; Lilienfeld-Toal et al., 2012; Ponticelli and Alencar, 2016; Rao, 2022). We contribute to this literature by providing the first randomized experiment on the topic. We look at the effects of faster courts on investment, business creation,

access to credit, consumption, and contracting behavior; all outcomes specified in our pre-analysis plan. We find little effect on investment, business creation, access to credit, and consumption, which is probably due to the short-term nature of the intervention, with only one wave of the one-pagers sent in February 2019. We do find a short-term effect on contracts, with more written labor contracts being signed. Since written contracts are associated with higher wages, we also find an effect on wages. In a decomposition exercise, we document that a large share of the increase in wages that we detect in the data comes from these written contracts. These results demonstrate a causal relationship between judicial institutions and development outcomes and suggest that contract enforcement is a key mechanism for law and development.

We also contribute to a burgeoning literature on the personnel economics of the state (Finan et al., 2017). We show that reducing information frictions and providing accountability to the public motivates stronger judiciaries. Other studies of judicial reforms focus on procedure (imposing time limits in Kondylis and Stein, 2021); presidential appointment of judges in Mehmood (2022); and infrastructure (setting up special civil tribunals in Lichand and Soares (2014) or debt recovery tribunals in Lilienfeld-Toal et al. (2012)). Our study focuses on another problem: the recurrence of adjournments, which contributes to the slow resolution of cases. Indeed, some parties benefit from court delays, asking for unnecessary and frivolous adjournments to delay cases as much as possible (Moog, 1997; Blue and Berg, 2008). We implement a cost-effective intervention that leverages existing data to provide information and accountability to judges and civil society. Our results demonstrate that greater transparency and accountability can substantially improve the efficiency and effectiveness of courts.

The rest of the paper is organized as follows. Section II presents the judicial reform. Section III presents the experimental design. Section IV presents the data and methodology, while section V discusses the results. Section VI concludes.

II. The Judicial Reform

A. Background

In October 2015, the Kenyan judiciary began collecting a dataset called the Daily Court Return Template (DCRT). The DCRT dataset contains detailed data on every case going through Kenyan courts, with more than 9 million observations at the case-activity level. It includes information on the exact charge leveled against the defendant, the precise outcome of each appearance, the name

of the presiding judge(s)¹, the number of plaintiffs/appellants, the number of defendants/accused, whether any of the parties has legal representation, how many accused were remanded in custody, and whether a witness has testified.

The DCRT dataset allows us to shed new light on the sources of delays in courts. It contains data on the sources of cases, what happened in court, and next steps. In particular, hearings can result in an “adjournment”, i.e., a postponement of the case to a future time, which are important sources of delay. When adjournments are too frequent, litigants get frustrated, files get lost, memories fade and witnesses disappear, such that both the speed and quality of legal processes may be affected (Messick, 2015). Adjournments also cause delayed punishment, discounting its net present value (or severity), which encourages opportunistic behavior.

Prior to 2015, there was no verifiable data on adjournments, or on their link with court performance. It was impossible to measure them or to give feedback to judges; in other words, there were few incentives for judges to resolve cases faster and no accountability. Cases were frequently adjourned.

Table 1 below shows the descriptive statistics of key variables in the DCRT before 2019, i.e., before our randomized intervention. First, it shows that the probability that any case coming to court ends up in an adjournment is 14 percent. This is a large number considering that the mean number of hearings per case is 4.63.

The DCRT also shows the precise reason for the adjournment (of 38 different types). Some adjournments may be necessary (“death of a party”) or even desirable (“parties to negotiate”), but these only represent a tiny fraction of all adjournments (0.01 percent for “death of a party”, 0.6 percent for “parties to negotiate”). Other adjournments are caused by the court itself, which we call “internal” adjournments. Examples are “court not sitting” or “judgment not ready”. They represent 26 percent of all the adjournments. These adjournments mean that litigants are coming to court but were not warned ahead of time that the court was not sitting, which can be a very frustrating experience.

Other adjournments are caused by other actors, which we call “external” adjournments. We display the main categories in Table 1: “parties not ready” (13% of all adjournments), “parties not present” (13%), “lawyer not ready” (9%), “witness not present” (17%), “police”² (1%), and “prosecutor not ready or not present” (9%)³. These adjournments may be valid or strategic. Kenya’s

¹The Kenyan judiciary consists of: Supreme Court, High Court, Employment and Labour Relations Court and Environment and Land Court (the superior courts) and Magistrate Courts (the lower-level courts). The superior courts have judges, and the lower-level courts have magistrates or judicial officers. For the sake of brevity, we use the word “judges” throughout the paper, but technically it should be “judges and judicial officers”.

²“Faulty Charge Sheet” or “Police file not availed”

³Both adjournments from the police or the prosecutor can only happen for criminal cases. The denominator in the proportion

TABLE 1—DESCRIPTIVE STATISTICS BEFORE 2019

	Mean	SD	N
Probability that the hearing ends in an adjournment	0.144	0.351	5245230
Conditional on being adjourned, reason of adjournment:			
Death Party	0.00	0.02	757419
To Negotiate	0.00	0.07	757419
Court	0.26	0.44	757419
Parties not ready	0.13	0.34	757419
Parties not present	0.13	0.34	757419
Advocate	0.09	0.29	757419
Witness	0.17	0.38	757419
Police	0.01	0.10	757419
Prosecutor	0.09	0.28	757419
Other	0.06	0.23	757419
Probability that the hearing ends in an:			
Adjournment External	0.10	0.30	5426222
Adjournment Internal	0.02	0.14	5426222
Probability that the hearing is/has:			
Resolved	0.142	0.349	5426222
Filed	0.140	0.347	5426222
Appealed	0.02	0.15	5426222
Convicted	0.05	0.23	5426222
Frivolous	0.04	0.19	5426222
Legal Representation	0.40	0.49	5426222
Witness Plaintiff	0.06	0.51	5426222
Witness Defendant	0.02	0.23	5426222
Court-level Data			
Clearance Rate	165.06	514.90	6791
Clearance Rate (trim 95)	93.98	64.24	6351
Case-level Data			
Time to Disposition	854.02	1703.64	609666
Time to Disposition (trim 95)	487.00	798.12	570226

Criminal and Civil Procedure Rules provide very clear remedies to avoid these adjournments, such as active case management strategies and the use of pre-trial conferences to clarify schedules and avoid adjournments down the line (Chemin and Newman, 2020). We can see that there are more external adjournments than internal ones (10 percent of all hearings end with an external adjournment while only 2 percent of all hearings end with an internal adjournment). Thus, a large share of adjournments are avoidable. The rest of the table presents basic descriptive statistics on the courts. We use these variables as controls after we present the results in raw form. Appendix A shows descriptive statistics on the type of cases in court.

B. Link between adjournment and court performance

In collaboration with the Kenyan judiciary, we constructed an index of court performance. We calculate the clearance rate at the court level, which is the number of cases resolved in the month divided by the number of cases filed in the month. It measures the extent to which the court system is able to cope with its caseload. A target of 100% has been established by the Kenyan judiciary. The case clearance rate (CCR) is one of the most important indicators of court efficiency, and is used in all evaluation of courts within the Kenyan judiciary.

There are clear outliers when calculating this index, simply because some courts are small and file few cases (the denominator), which makes the clearance rate large. For example, the highest clearance rate in the data is 15100%. We thus trim the data at the 95th percentile (which corresponds to a clearance rate of 375%). The untrimmed mean clearance rate is 165%, but the trimmed mean clearance rate is 94%, and the median clearance rate is 73%. For courts with a clearance rate below 100%, the backlog of pending cases is growing.

This data can be used to measure the link between adjournments and court performance. We use the following specification:

$$CCR_{cm} = \beta_0 + \beta_{adj} Adj_{cm} + \alpha_c + \delta_m + \varepsilon_{cm} \quad (1)$$

where c is for court c , m for month m , CCR_{cm} is the CCR of court c in month m , Adj_{cm} is the proportion of cases seen in the month ending with an adjournment, α_c court fixed effects, δ_m month-year fixed effects, and ε_c is the disturbance term.

We estimate this relationship separately for civil and criminal cases. Based on data on and before 2018, we find a statistically significant coefficient β_{adj} of -5 for civil cases (and -1 for criminal given is defined for all cases, civil and criminal).

cases), i.e., a 1 percentage point reduction in the proportion of adjourned cases would result in a 5 percentage point increase in the case clearance rate. The logic is simple: if there are less adjournments, more cases get resolved, which increases the CCR.

These estimates are quantitatively large since the average proportion of cases ending with an adjournment is 14 percent, and the average clearance rate is $M=94$ ($SD=64$). Thus reducing adjournments from 14 to 0 percent, i.e. eradicating adjournments, would be associated with a $[14 \times 5 =]$ 70 percentage point increase in the clearance rate.

C. The “One-Pager”

The goal of the intervention is to display key metrics for each court, such as their CCR (CCR_{cm}), the proportion of adjournments (Adj_{cm}), the top three reasons for these adjournments, as well as the predicted improvement in court performance if the adjournment reason had been addressed. For this purpose, we develop the “One-Pager” (see Figure 1 below for an example).

The first section of the One-Pager shows basic numbers of cases filed, cases resolved, rulings, and adjournments during the month. The goal is to start with a section easy to understand for any judge.

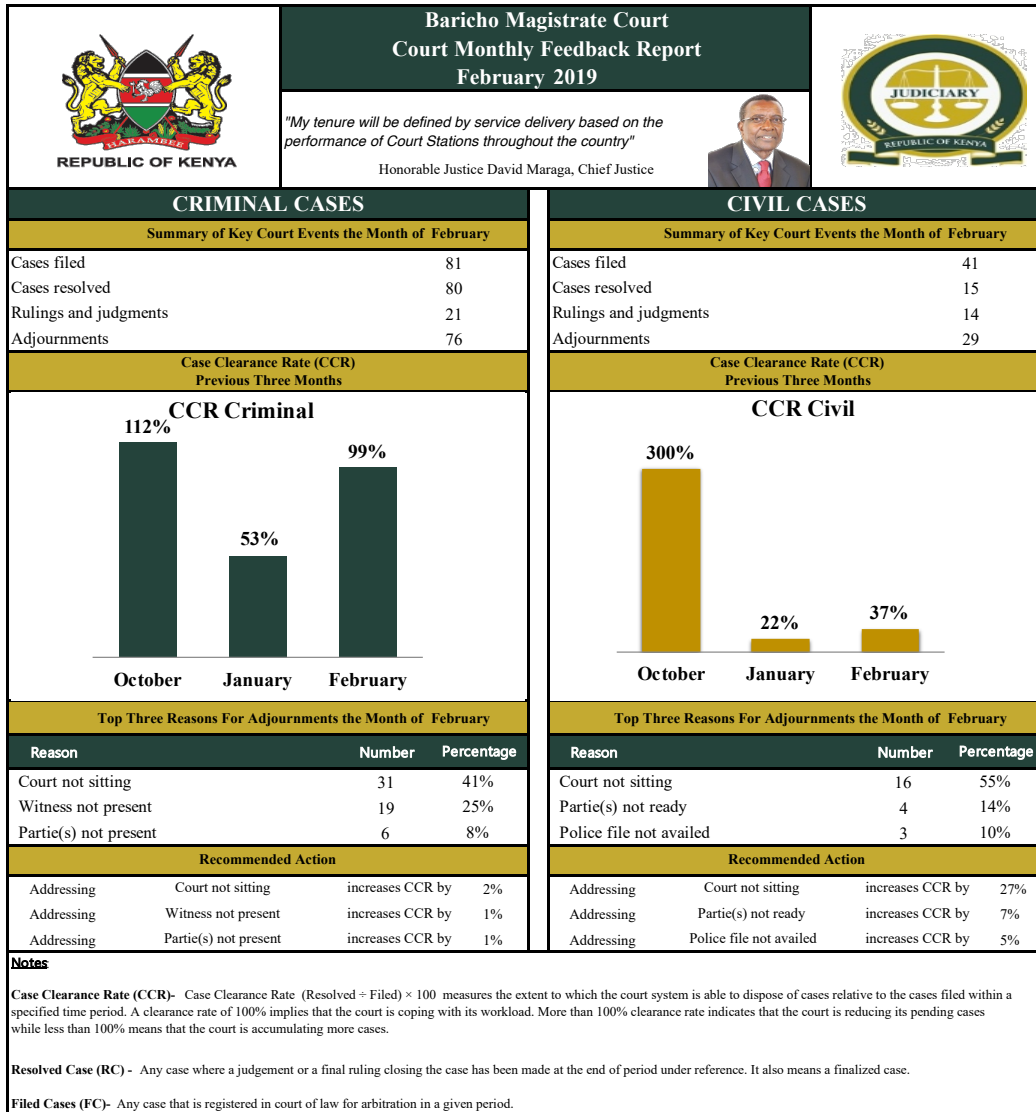
The second section shows the CCR. The third section shows the number of monthly adjournments in the court. In particular, the feedback report shows the top three reasons for adjournments for each specific court. (For this particular court, for example, the main reason for adjournments is “court not sitting”.)

The fourth section shows the link between adjournments and performance (measured by the CCR). The goal is to provide actionable information to that particular court. We use the estimate β_{adj} obtained above. We take the absolute value since β_{adj} is negative (more adjournments mean less CCR). One can then simply predict the impact on CCR if the top reason for adjournments was reduced from their current level in month m (i.e., $AdjTop1_{cm}$) to zero with the formula:

$$PredictionCCR_{cm}AdjTop1 = |\beta_{adj}| \times AdjTop1_{cm}$$

The interpretation is: a reduction in the top reason for adjournment from current levels (i.e., $AdjTop1_{cm}$) to zero is associated with an increase in CCR by $PredictionCCR_{cm}AdjTop1$. After extensive piloting with officials in the Kenyan judiciary and judges, this sentence was judged slightly difficult to understand and simplified to: “Addressing [the top reason for adjournment] increases CCR by $[PredictionCCR_{cm}AdjTop1]$ ”. This sentence is added on the One-Pager (see Figure 1

FIGURE 1. EXAMPLE OF A ONE-PAGER



for an example). We predict the impact on CCR if the top three reasons of adjournments were addressed. These three sentences constitute the actionable information presented to the judge or to the judge and the public.

D. The Intervention

We implement two different treatments:

1. Actionable information: Providing judges this One-Pager that shows them, as explained above, 1) the CCR, 2) the number of adjournments and their top three reasons, and 3) the predicted impact of reducing adjournments on the CCR.

2. Actionable information with accountability: As above, but also sharing the One-Pager with Court User Committees (CUCs), which includes court actors such as lawyers, prosecutors, the police, as well as representatives from local communities, to focus discussion around performance, create bottom-up accountability, and collectively arrive at ways to remove the bottlenecks.

The One-Pagers may work because they significantly increase the costs of granting or requesting adjournments. To see this, it is important to understand the nature and reasons of adjournments. As discussed above, adjournments can essentially be grouped in the data into two categories: internal (judges) and external (other actors). Internal adjournments can be granted when the judge is not present (despite a hearing date having been given to all parties) or when the judgement is not ready (among other reasons). External adjournments are granted when the lawyer or other parties are not ready (among other reasons) as indicated in Table 1.

The One-Pagers may affect the costs of both types of adjournment. Regarding “internal” adjournments, the One-Pagers are the first official document showing explicitly the number of adjournments, disaggregated by source. Regarding “external” adjournments, the One-Pagers, especially when shared with the CUCs, may discourage these other parties from requesting adjournments.

The relative effects on either internal or external adjournments thus provide a test to identify which mechanism the One-Pagers are working through. If internal adjournments are reduced by the One-Pagers, this indicates that internal processes involving judges and their staff required streamlining and the One-Pagers significantly increased the costs of this lack of efficiency. On the other hand, if external adjournments are reduced by the One-Pagers, this indicates that judges were subject to the pressure of other parties and the One-Pagers gave them the tools to resist such pressure. The differential effect of the One-Pagers on internal or external adjournments can thus shed light on the constraints faced by judges.

III. Experimental design

The unit of randomization is a court station, since one court station has one CUC. If a court station is randomized into the treatment “One-Pager”, then all the courts within that court station receive a one-pager. If a court station is randomized into the treatment “One-Pager + CUC”, then all the courts within that court station receive a one-pager, and the one-pagers must also be distributed to all members of the CUC such that the one-pager is discussed in their quarterly meetings.

There are 124 court stations in Kenya. To achieve balance, we follow (Bruhn and McKenzie, 2009) and use a stratification technique. We stratify based on geographical variables, since the effect may be different in different places. In practice, we established a list of 8 regions in Kenya to make sure that there was an approximately equal number of control and treated court stations in each of these 8 regions. Appendix B provides more details on how we determined these 8 regions.

We also stratify based on fast versus slow court stations, since the effects could be different across fast and slow courts. One may expect a large effect of the interventions on slow courts, and maybe less effect on fast courts (since these courts are already performing well). Thus, it will be important to look at heterogenous effects of the one-pager across fast and slow courts. The proper way to do this is to stratify on initial speed such that the sample is balanced across fast and slow courts. Appendix B provides more details on how we created these indicators of fast or slow courts.

We obtained ethical approval for this project,⁴ and filed a pre-analysis plan.⁵

IV. Data and Methodology

ADJOURNMENTS:

The primary outcome specified in our pre-analysis plan was a reduction in adjournments. To evaluate the effect on adjournments, we use the DCRT data set (described in section II.A).

The main empirical question we ask is: Do the One-Pagers successfully reduce the number of adjournments that are granted during trials? To test this proposition, we estimate the following specification:

⁴McGill REB 20-06-027

⁵AEARCTR-0006228

$$\begin{aligned}
Adjournment_{ictjk} = & \beta_0 + \beta_1 OnePager_c \times Feb2019_t + \beta_2 OnePagerCUC_c \times Feb2019_t \\
& + \beta_3 OnePager_c \times Mar2019_t + \beta_4 OnePagerCUC_c \times Mar2019_t \\
& + \beta_5 OnePager_c \times Apr2019_t + \beta_6 OnePagerCUC_c \times Apr2019_t \\
& + \beta_7 OnePager_c \times May2019_t + \beta_8 OnePagerCUC_c \times May2019_t \\
& + \beta_9 OnePager_c \times AfterJune2019_t + \beta_{10} OnePagerCUC_c \times AfterJune2019_t \\
& + \beta_{11} OnePager_c \times Jan2019_t + \beta_{12} OnePagerCUC_c \times Jan2019_t \\
& + \alpha_c + \gamma_t + \beta_4 X_{ictjk} + \delta_j + \theta_k + \epsilon_{ictjk}
\end{aligned}$$

$Adjournment_{ictjk}$ is a dichotomous variable equal to 1 if the outcome of a hearing is adjournment, 0 otherwise; such that the regression is predicting the average probability that a hearing will be adjourned. The subscript i corresponds to each individual court appearance. c refers to court c , t refers to the time period (a month-year). The variable $Feb2019_t$ takes on a value of 1 if the observation is in February of 2019, 0 otherwise, similarly for the other months. $OnePager_c$ is a dichotomous variable equal to 1 for courts receiving the One-Pager, 0 otherwise. $OnePagerCUC_c$ is a dichotomous variable equal to 1 for courts receiving the One-Pager that is disseminated to the CUC meeting, 0 otherwise.

The key variable of interest to determine the impact of the One-Pagers is: $OnePager_c \times Feb2019_t$, which estimates the short-run effect (the month of the implementation). $OnePager_c \times Mar2019_t$, $OnePager_c \times Apr2019_t$, $OnePager_c \times May2019_t$ measure the effect in the following months. $OnePager_c \times AfterJune2019_t$ measures the long-run effects.

To check for common time trends, we look at the variable $OnePager_c \times Jan2019_t$. The coefficient β_{11} checks for an effect of the One-Pagers in a period before the intervention had started. If we find that the pilot has an impact in January 2019, this will suggest that the treatment and control groups were on divergent time trends before the pilot so the results we obtain from the difference-in-differences regression could be driven by something other than the intervention itself. If, on the other hand, β_{11} is not significantly different from zero, we can be more confident that the treatment and control groups were on the same pre-trends.

(α_c) are court fixed effects and (γ_t) are month-year fixed effects. X_{ictjk} is a vector of controls which includes: legal representation of the defendant, accused or plaintiff; whether the defense produced a witness; whether the prosecution produced a witness. Moreover, we include judge fixed

effects (δ_j), and detailed case code fixed effects (θ_k).⁶ ϵ_{ictjk} is a stochastic error term. Standard errors are robust, clustered at the level of courts.

QUALITY OF DECISIONS:

To explore effects on quality, we use two different datasets. First, we assemble a database of the written decisions on the Judiciary of Kenya’s publicly available search engine for higher courts (<http://kenyalaw.org/caselaw/>). This dataset contains roughly 160,000 cases from 1976 to 2020 from the higher courts. We build this dataset by scraping both the metadata associated with each case and the full text of the decision. This allows us to explore if the “One-Pager” had an effect not only on the efficiency of judicial decisions, but also on the quality of written decisions, particularly in higher courts. In contrast to the DCRT, in this dataset we can extract proxies for the quality of judicial decisions, such as the length of the judgement, the number of laws or cases cited in a decision, or whether a specific decision was appealed to higher courts.

The data comprises cases which were appeals against the decisions of lower courts. Such cases are determined from the case history variable present in the metadata scraped from a search engine. In our dataset, we have roughly 33,000 appeals. We then match these appeals with their original cases by using the case numbers and date of delivery extracted from the case history of appeals, and matching them with the case numbers and date of delivery of their respective original cases. In addition to case numbers, we also use the names of judges who presided over the original case (which was appealed against) extracted from the case history variable to match them with the judges of the respective original cases to make sure the cases are indeed the same.

As a measure of quality of judgements, we also determine the length of the judgement, using the text of judgements of the decisions scraped from the website. We also calculate the number of judgements, laws and acts cited by each judgement. To further measure the quality of the judgement, we determined how many times a judgement in our dataset has been cited by the other judgements present in our dataset.

COURT USER SATISFACTION:

Our second measure of quality comes from citizen perceptions. We use Court User Satisfaction Surveys (CUSS) collected by the Kenyan judiciary to gauge the response of court users to the treatment. These surveys were collected in 2015, 2017, and 2019 and ask questions to court users about their satisfaction with multiple aspects of court processes.

⁶Case codes are used for administrative purposes to categorize the 42 different types of cases.

To determine the effect of the One-Pagers on court user satisfaction, we estimate the following specification:

$$\begin{aligned}
Y_{ict} = & \beta_0 + \beta_1 \text{OnePager}_c \times 2019_t + \beta_2 \text{OnePagerCUC}_c \times 2019_t \\
& + \beta_3 \text{OnePager}_c \times 2015_t + \beta_4 \text{OnePagerCUC}_c \times 2015_t \\
& + \alpha_c + \gamma_t + \epsilon_{ict}
\end{aligned}$$

Where Y_{ict} is the answer to a question on the CUSS. The subscript i corresponds to individual i , interviewed in court station⁷ c , in year t . The variable $\text{OnePager}_c \times 2019_t$ takes on a value of 1 if the observation is in the treatment group One-Pager, and observed in 2019; 0 otherwise. $\text{OnePagerCUC}_c \times 2019_t$ is defined similarly for the treatment group One-pager sent to CUCs. The coefficients of interest are thus β_1 and β_2 .

The variable $\text{OnePager}_c \times 2015_t$ takes on a value of 1 if the observation is in the treatment group One-Pager, and observed in 2015; 0 otherwise. This represents a test of the balance before the one-pagers were sent out. Ideally, this coefficient is not significantly different from zero.

α_c are court station fixed effects, γ_t are year fixed effects, and ϵ_{ict} is the error term. Standard errors are clustered at the level of the court station.

ECONOMIC EFFECTS:

In our pre-analysis plan, we had specified to look at investment, business creation, access to credit, consumption, and contracting behavior.

Suppose an entrepreneur (or a farmer, investor, firm) decides to invest in a certain factor of production to produce more. The final output can be expropriated by a powerful individual (or local powerful elites or predatory government). The entrepreneur can sue in court. In that case, he/she only recovers a fraction of the original amount since the net present value of the recovery decreases with the time the proceedings take in court. This depresses the incentives to invest in the first place.

There is strong non-experimental empirical support for this channel in the literature (Kondylis and Stein, 2021; Mehmood, 2022; Chemin, 2009*b,a*, 2012, see Ramos Maqueda and Chen, 2021 for a review). Our paper contributes to this literature by providing the first randomized experiment

⁷The CUSS dataset only has information on the “court station”, the geographical compound that may host multiple courts in populous areas, such as both a high court and a magistrate court. Thus, for this analysis, it is not possible to distinguish high courts from magistrate courts.

on the topic.

This explanation for the effect of slow courts is centered on the security of property rights, but a similar explanation could center on contract enforcement. Suppose a firm contracts with a supplier to produce a customized good (which only has value for the firm, not any other firms). Once the supplier has sunk the investment costs to produce the customized good, the buyer can renegotiate prices down since there are no other buyers for this customized good. The supplier can sue in court. Once again, slow courts lower the amount recovered. This depresses the incentives to produce the customized good, and potentially its quality. This has implications for the firm (the buyer of the customized good). If the customized good is defective, the firm needs to use some of its labor force to correct these deficiencies. As in Boehm and Oberfield (2020), this introduces a “wedge” in labor, which depends on the defectiveness of the customized input. Therefore, with a more effective judiciary, the wedge would be reduced. The marginal product of labor, and therefore wages, would increase, as shown formally in Appendix C. There is ample support for this hypothesis in the literature (Boehm and Oberfield, 2020; Amirapu, 2021). Our paper contributes to this literature by looking at the incentives to enter into contracts with a randomized experiment.

Overall, fast courts are thus key to secure property rights and enforce contracts, which themselves shape the incentives to start a business. An entrepreneur might be more willing to start a business if he/she knows efficient courts will secure their output from expropriation and enforce their contracts. We had thus pre-specified business creation as an outcome of interest.

Another literature has focused on the effect of slow courts on access to credit. A borrower borrows from a lender with collateral. The collateral mitigates the well-known moral hazard and adverse selection issues. Indeed, the potential loss of the collateral in case of non-repayment motivates the borrower to work hard and repay (moral hazard) and in fact selects safe borrowers in the first place (adverse selection). Suppose the borrower chooses not to repay, the lender can sue in court to recover the collateral. Slow courts impede this process and discourage lenders from lending in the first place. Once again, there is very strong empirical support for this channel (Jappelli et al., 2005; Visaria, 2009; Lilienfeld-Toal et al., 2012; Ponticelli and Alencar, 2016; Rao, 2022).

Overall, through these channels (contracting behavior, investment, business creation, and access to credit), there might be an overall effect of faster courts on welfare and consumption levels.

To determine the effect of the intervention on these outcomes, we use the Kenya Continuous Household Survey Programme (KCHSP). The continuous data collection was implemented all throughout 2019 by the Kenyan National Bureau of Statistics (KNBS) which allows us to look at the effects of the intervention before and after the treatment. This data is a representative sam-

ple of Kenya. It includes individual-level data with basic sociodemographics presented in greater detail below, a labor force survey with measures of entrepreneurship, investment and access to credit, as well as some variables on contracting behavior. We estimate the following specification:

$$Y_{ict} = \beta_0 + \beta_1 \text{FracOnePager}_c \times \text{Post}_t + \beta_2 \text{FracOnePagerCUC}_c \times \text{Post}_t + \alpha_c + \gamma_t + \epsilon_{ict}$$

where Y_{ict} is the outcome specified in our pre-analysis plan for individual i , interviewed in county c , in quarter t in 2019.

The variable FracOnePager_c is the fraction of court stations in a county that received the One-Pagers.⁸ For example, the county of Mombasa has 5 court stations, two of which received the One-Pagers; a fraction of $(2/5=)$ 0.4. This fraction varies between 0 and 1, such that there are some counties with no court stations receiving One-Pagers and other counties where all court stations receive One-Pagers.

This fraction is further interacted with the variable Post_t , equal to 1 in the quarters 2, 3, and 4, and equal to 0 in quarter 1. We define Post_t this way since the One-Pagers were sent in February. It is thus reasonable to expect no effect in quarter 1 (January - March) and an effect in later quarters. We sent the one-pagers in February. To the extent that some of the effect is felt instantaneously, this would serve to bias down the estimates found.

The variable FracOnePagerCUC_c is defined similarly for the other treatment of One-Pagers sent to the CUC. It also varies between 0 and 1 across counties.

α_c are county fixed effects, γ_t are quarter fixed effects, and ϵ_{ict} is the error term. Standard errors are clustered at the level of the county.

A. Check for Balance and Pre-Trends

Overall, the sample is balanced across the treatment groups and control groups. In Table 2, we restrict the sample to the period before 2019 and regress the case outcome of interest and the two treatment dummies. None of the coefficients in this table are statistically significant. For example, there were 0.5 percentage points more adjournments in the treatment group “One-Pager + CUC”. There are no differences in the proportion of internal or external adjournments.

Table B1 in Appendix B shows that there are similar proportions of resolved cases, filed cases,

⁸The KCHSP data’s most disaggregated geographical variable is at the county level.

TABLE 2—BALANCE BEFORE THE INTERVENTION

	(1)	(2)	(3)
	Adjournment	Adjournment External	Adjournment Internal
OnePager	0.014 (0.021)	0.015 (0.012)	-0.00032 (0.0040)
OnePager CUC	0.0050 (0.018)	0.017 (0.013)	-0.0017 (0.0035)
Observations	5240381	5421368	5421368

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. The sample is restricted to the period before 2019. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment, 0 otherwise. In Column (2), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment and the reason given for adjournment was classified as Internal (those under the control of the judge), 0 otherwise. In Column (3), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment and the reason given for adjournment was classified as External (requested by lawyers or prosecutors), 0 otherwise. The variable “OnePager” takes on a value of 1 if the observation is in a court which received a One-Pager, 0 otherwise. The variable “OnePager CUC” takes on a value of 1 if the observation is in a court which received a One-Pager and that OnePager was sent to the CUC, 0 otherwise. The regressions include the stratification dummies (the 8 region dummies and the Slow/Fast dummy) as well as a dummy for whether the court is a magistrate court or a high court.

appeals, convictions, frivolous cases, legal representation, number of witnesses for plaintiff, number of witnesses for defendants across treatment and control groups. The composition of case types is also balanced.

Next, we present a check for pre-trends between the treatment and control groups in the KCHSP, focusing on the first quarter of 2019. Table 3 below restricts the sample to quarter 1, and simply regresses the outcome on $FracOnePager_c$ and $FracOnePagerCUC_c$.⁹

In Column (1), the constant term shows that 50 percent of the individuals are male in the counties with no treated court stations.¹⁰ This proportion is not significantly different in counties with more treated courts, as indicated by the insignificant coefficients of $FracOnePager_c$ and $FracOnePagerCUC_c$. Thus, the sample is well balanced across treatment and control groups as far as this variable is concerned.

The average age is 25 years old, number of years on the job is 8.5 years (for those with a job), 49 percent of the sample went to primary school, 20 percent went to secondary school, and the average

⁹We cannot include the stratification dummies in these regressions (the 8 region dummies and the Slow/Fast dummy) since these stratification variables are defined at the court level, whereas the KCHSP is at the individual level, with county being the most disaggregated geographical variable. For the 8 region dummies, the Kenyan judiciary established their own list at the court level that does not correspond exactly to the official counties but that make sense distance-wise to organize potential future regional meetings to debrief court stations about the interventions. For example, Thika court is in Central province but it is easier and cheaper for them to travel to Nairobi for the meeting. Therefore, Thika was classified in the Nairobi region, not Central. Thus, there is no exact correspondence between an individual living in a certain county and the region created by the Kenyan judiciary. The Slow/Fast dummy is similarly defined at the court level, it is thus impossible to assign a specific individual to a Slow/Fast dummy since one does not know exactly which the individual would file a case were he to do so.

¹⁰In this table, we display the constant term and not the mean dependent variable as in all other tables since they are the same in this particular table. There are no variables in this model other than $FracOnePager_c$ and $FracOnePagerCUC_c$, therefore the constant term is also the mean of the dependent variable in the control group.

household size is 3.3. The proportion of the sample with primary education is slightly lower for the treatment arm one-pagers, but not for the other treatment arm of one-pagers sent to CUC.

TABLE 3—BALANCE TEST (QUARTER 1 OF 2019)

	(1)	(2)	(3)	(4)	(5)	(6)
	Gender	Age	Years on Job	Primary	Secondary	HH Size
FracOnePager	-0.02 (0.01)	-1.59 (1.59)	0.37 (1.63)	-0.09* (0.05)	-0.05 (0.04)	0.22 (0.31)
FracOnePager_CUC	0.00 (0.01)	-0.06 (1.40)	0.81 (1.49)	-0.08 (0.05)	-0.00 (0.04)	0.15 (0.28)
Constant	0.50*** (0.01)	24.89*** (1.02)	8.46*** (0.93)	0.49*** (0.02)	0.20*** (0.02)	3.30*** (0.17)
Observations	22,732	22,732	5,409	22,732	22,732	22,732

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1) the dependent variable is gender, a dichotomous variable equal to 1 for males, 0 for females. The variable “FracOnePager” is the fraction of court stations in a county that received the One-Pagers. In Column (2), the dependent variable is age in years. In Column (3), the dependent variable is the number of years on the job. In Column (4), the dependent variable is equal to 1 if the individual has completed any years of primary school, 0 otherwise. In Column (5), the dependent variable is equal to 1 if the individual has completed any years of secondary school, 0 otherwise. In Column (6), the dependent variable is the size of the household.

There is also good balance on the outcomes of interest specified in our pre-analysis plan: investment, business creation, access to credit, consumption, and contracting behavior; as shown in Appendix D.

We also present other balance tests in Appendices E and F. Table E1 shows the balance test using County GDP collected between 2013 and 2017 by the Kenya National Bureau of Statistics. Table F1 presents the balance test using the Kenya Integrated Household Budget Survey (KIHBS) 2015-2016. All of these tests show good balance between the treatment and control groups.

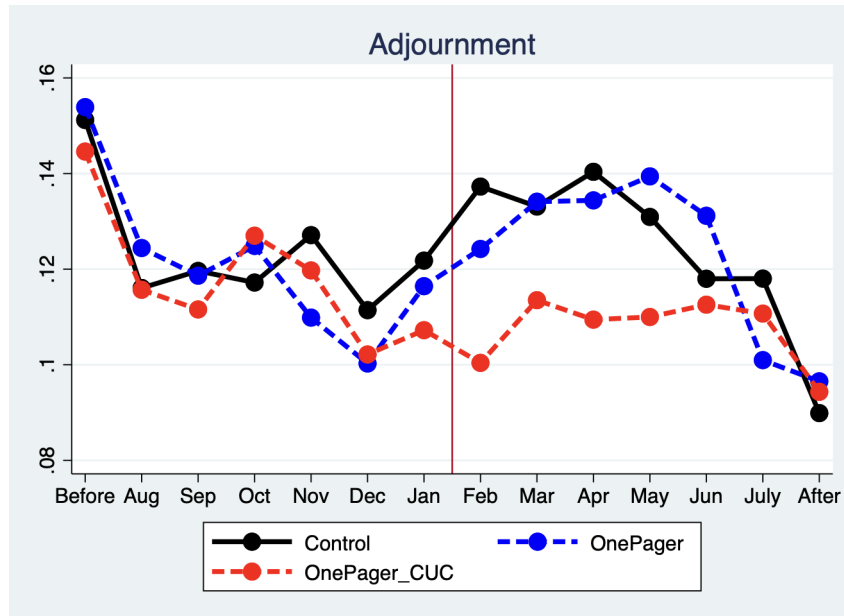
V. Results

A. Effects on Adjournments

Before turning to regression results, we show the raw data on adjournments in Figure 2. This figure displays the proportion of hearings ending in an adjournment every month. Before the intervention implemented in February 2019, the three groups are quite comparable. The situation changes after February 2019: the treatment group OnePager CUC is now below the control group, and even the treatment group OnePager. While the control group is around 14% in that period,

the treatment group OnePager CUC is around 11%, indicating a three percentage points difference between the two groups. The effect fades away in June 2019.

FIGURE 2. EFFECTS ON ADJOURNMENT



One could argue from Figure 2 that the treatment effect is driven by the control group increasing, not the treatment group decreasing. However, the slight increase in the control group before and after February 2019 is not statistically significant.¹¹ The only significant effect (detected in the regression) is between the control group and the treatment group OnePager CUC. This figure is thus best considered as a relatively stable control group, and a treatment group OnePager CUC very similar until February 2019, but significantly lower after February 2019.

Table 4 shows the regression results estimating the impact of the One-Pagers on adjournments. Column (1) shows the main result of this paper: the One-Pagers reduced the probability of adjournment by 1.3 percentage points in the month of February 2019. The effect is greater for the one-pagers sent to the CUC meeting: this intervention reduced the probability of adjournment by 2.8 percentage points, exactly in line with Figure 2 above. The effect is significantly different from zero. This is a large effect considering that the probability of adjournment for the treatment and control groups combined was 14 percent prior to 2019. It thus corresponds to a $[2.8/14=]$ 20 percent reduction in adjournments. The effect persists in March and April (with reductions of 1.5 and 2.4 percentage points, albeit less significantly), but drops after June 2019.

¹¹The time fixed effects for these months are not significantly different from zero in the main regression below.

TABLE 4—EFFECT ON ADJOURNMENTS

	(1)	(2)	(3)	(4)	(5)	(6)
					Same as on One-Pager	Different as on One-Pager
OnePager * February 2019	-0.013 (0.012)	-0.012 (0.012)	-0.012 (0.012)	-0.0040 (0.012)	-0.015* (0.0085)	0.0026 (0.0092)
OnePager CUC * February 2019	-0.028** (0.014)	-0.028** (0.014)	-0.028** (0.014)	-0.023 (0.014)	-0.018** (0.0091)	-0.0066 (0.010)
OnePager * March 2019	0.0012 (0.013)	0.0016 (0.013)	0.0016 (0.013)	0.013 (0.014)	-0.0046 (0.0081)	0.0091 (0.0098)
OnePager CUC * March 2019	-0.015 (0.014)	-0.017 (0.015)	-0.017 (0.015)	-0.016 (0.014)	-0.014* (0.0078)	-0.0018 (0.010)
OnePager * April 2019	-0.012 (0.014)	-0.011 (0.014)	-0.011 (0.014)	-0.0030 (0.013)	-0.010 (0.010)	0.00078 (0.011)
OnePager CUC * April 2019	-0.024 (0.015)	-0.024 (0.016)	-0.024 (0.016)	-0.032** (0.014)	-0.019* (0.010)	-0.0058 (0.011)
OnePager * May 2019	0.0099 (0.017)	0.010 (0.017)	0.010 (0.017)	0.0023 (0.015)	-0.0030 (0.014)	0.027** (0.014)
OnePager CUC * May 2019	-0.014 (0.017)	-0.018 (0.017)	-0.018 (0.017)	-0.021 (0.015)	-0.013 (0.014)	0.0041 (0.012)
OnePager * After June 2019	0.0028 (0.017)	0.0035 (0.016)	0.0035 (0.016)	-0.0015 (0.011)	0.0012 (0.0066)	0.0044 (0.013)
OnePager CUC * After June 2019	-0.00027 (0.019)	-0.0030 (0.019)	-0.0030 (0.019)	-0.020 (0.015)	-0.0050 (0.0077)	0.00035 (0.014)
OnePager * Month Before	-0.0090 (0.013)	-0.0082 (0.013)	-0.0082 (0.013)	-0.0018 (0.013)	-0.0031 (0.0083)	-0.0027 (0.0099)
OnePager CUC * Month Before	-0.0063 (0.013)	-0.0065 (0.013)	-0.0065 (0.013)	-0.0050 (0.014)	-0.0100 (0.0094)	0.0046 (0.011)
Case Code Fixed Effects		Yes	Yes	Yes		
Controls			Yes	Yes		
Judge Fixed Effects				Yes		
Observations	8641819	8464456	8464456	7074897	9047041	9047041

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment, 0 otherwise. Column (2) includes judge fixed effects. Column (3) include case code fixed effects. Column (4) includes control variables for the presence of legal representation and number of witnesses. In Column (5), the dependent variable is a dichotomous variable equal to 1 if the reason for the adjournment is the same as the top three adjournments displayed on the one-pagers, 0 otherwise. In Column (6), the dependent variable is a dichotomous variable equal to 1 if the reason for the adjournment is different from the top three adjournments displayed on the one-pagers, 0 otherwise. The variable “OnePager*February2019” takes on a value of 1 if the observation is in “February of 2019” and in a court which received a One-Pager, 0 otherwise.

Of course, an immediate concern with these results is that judges may have responded due to experimenter demand or simply manipulated the data to reduce their adjournments in the treatment group. This is unlikely to be the case for three reasons. First, we find no effect in the treatment group OnePager, where experimenter demand is the same as in the treatment group OnePager CUC. If judges were motivated to manipulate their data, an effect should have been found there. Second, the data is not entered by judges themselves, but by court clerks following public processes. Third, data quality is of paramount concern to DPOP. Large teams of DPOP statistical officers constantly engage the courts to do back checks on the data. They train local court staff on data quality. They also make field visits in every court of the country, where they randomly sample some cases from the paper registers and track the data in the DCRT to make sure all the information is accurate.

The result remains significant when controlling for case code fixed effects in Column (2), and control variables for the presence of legal representation and number of witnesses in Column (3). Controlling for judge fixed effects in Column (4) hardly changes the results.

In Column (5), we define a variable equal to 1 if the reason for the adjournment is the same as the top three adjournments displayed on the one-pagers for that particular court, 0 otherwise. The results show that the one-pagers sent to the CUC meeting reduce those types of adjournment. In contrast, in Column (6), we define a variable equal to 1 if the reason for the adjournment is different from the top three adjournments displayed on the one-pagers for that particular court, 0 otherwise. There are no effects there. This confirms the mechanism of the effect: the One-Pagers display the top three reasons for adjournment, and the effect is concentrated among those top 3 reasons that are shown in the One-Pager.

A reduction in adjournments can be converted into time saved. In fact, adjournments generate delays that compound over time. If each hearing faces a certain probability of adjournment, then that adjourned hearing can itself be adjourned at the next stage. Our estimates show that a 20% decrease in adjournments translate into a reduction of 107 days in trial length, or $(107/487*100=)$ 22%.¹²

¹²Suppose p is the probability of an adjournment. On the first hearing, the probability that the case is closed is $1 - p$. With probability p , the case is adjourned to the next time available, say after d days. At that time, the case is resolved with probability $1 - p$, and adjourned with probability p to a next time after another d days, $2d$ days after the start of the case. At that time, reached with probability p^2 , the case closes with probability $1 - p$. Overall the total case length is:

$$(1 - p) * 0 + p(1 - p)d + p^2(1 - p)2 * d + p^3(1 - p)3 * d + \dots$$

Basic algebra can simplify this expression. We can factor by $p(1 - p)d$:

$$p(1 - p)d(1 + 2p + 3p^2 + \dots)$$

We note that the last term can be rewritten in the following way:
 $1 + 2p + 3p^2 + 4p^3 + \dots = (1 + p + p^2 + \dots) + (p + p^2 + p^3 + \dots) + (p^2 + p^3 + p^4 + \dots) + \dots = (1 + p + p^2 + \dots) * (1 + p + p^2 + \dots) = (\text{sum of the terms of a geometric series of reason } p)^2 = (1/(1 - p))^2 = (1 - p)^{-2}$

Therefore the total case length is: $p/(1 - p) * d$

The new total case length under a lower p' would be: $p'/(1 - p') * d = p'/(1 - p')/[p/(1 - p)] * \text{total case length}$

Plugging in $p = 0.14$, $p' = 0.11$, total case length=487 (trimmed at 95%), we get the new total case length of 370 days.

Table 5 disaggregates adjournments by their main cause, internal or external. Column (1) replicates the main result of the paper on adjournments. Column (2) shows a reduction in external adjournments, while Column (3) shows no effect on internal adjournments. This result is notable because it sheds light on the mechanisms through which the intervention works, and even on the underlying reasons for delays in the judiciary. The One-Pagers do not work because they motivate judges to work faster. This is corroborated by the fact that internal adjournments are at baseline much less than external adjournments, indicating that lack of effort on the judge's part is not the entire story. Rather, we find an effect on delays caused by external actors. The One-Pagers work because judges grant fewer adjournments to other parties, or other parties ask for fewer adjournments in the first place. These other parties are involved in the CUC meetings where the One-Pagers are discussed and actionable information is provided to avoid them.

This corresponds to a reduction of 107 days in trial length, or $(107/487*100=)$ 22%.

TABLE 5—EFFECT ON INTERNAL VERSUS EXTERNAL ADJOURNMENTS

	(1) Adjournment	(2) External Adjournment	(3) Internal Adjournment
OnePager * February 2019	-0.013 (0.012)	-0.017 (0.011)	0.0000067 (0.0043)
OnePager CUC * February 2019	-0.028** (0.014)	-0.030** (0.012)	-0.0033 (0.0042)
OnePager * March 2019	0.0012 (0.013)	0.0027 (0.011)	-0.00024 (0.0041)
OnePager CUC * March 2019	-0.015 (0.014)	-0.021* (0.011)	0.0015 (0.0040)
OnePager * April 2019	-0.012 (0.014)	-0.0044 (0.011)	-0.0076 (0.0063)
OnePager CUC * April 2019	-0.024 (0.015)	-0.022* (0.012)	-0.0072 (0.0062)
OnePager * May 2019	0.0099 (0.017)	0.016 (0.015)	-0.0022 (0.0053)
OnePager CUC * May 2019	-0.014 (0.017)	-0.012 (0.015)	-0.0027 (0.0049)
OnePager * After June 2019	0.0028 (0.017)	-0.0013 (0.012)	0.00011 (0.0033)
OnePager CUC * After June 2019	-0.00027 (0.019)	-0.014 (0.014)	0.0043 (0.0039)
OnePager * Month Before	-0.0090 (0.013)	-0.0039 (0.0092)	-0.0069 (0.0052)
OnePager CUC * Month Before	-0.0063 (0.013)	-0.011 (0.011)	-0.0081 (0.0053)
Observations	8641819	9047041	9047041

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment, 0 otherwise. In Column (2), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment and the reason given for adjournment was classified as Internal (those under the control of the judge), 0 otherwise. In Column (3), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in adjournment and the reason given for adjournment was classified as External (requested by lawyers or prosecutors), 0 otherwise.

Table 6 shows that the effect is much stronger in High Courts in Column (1), consistent with a hypothesis that cases are more complex at the high court level, and thus the temptation to grant adjournments is stronger, which is countered by the One-pagers. The results are weaker at the level of Magistrate Courts, where cases are simpler, as can be seen in Table G1 in Appendix G.

We then present heterogeneous effects on slow versus fast courts as specified in our pre-analysis plan. The idea is to check whether the effect is concentrated in slow courts in need of improvement.

Column (2) shows that the effect is stronger in initially slow courts, versus fast courts in Column (3).¹³ A court is classified as slow if its average time to disposition is above the Kenyan average at baseline. Thus, the One-Pagers work better in slower courts. This is confirmed in Columns (4) and (5), which shows the differential response in courts above or below the median level of adjournments: once again, we see that the One-Pagers work better in courts with a high number of adjournments at baseline.

Table H1 in Appendix H shows the effect on other outcomes of speed. We find an increase in cases resolved and no effect on cases filed, it implies a positive effect on the CCR. This result is policy-relevant because the CCR is one of the most important indicators of court efficiency, and is used in all evaluation of courts within the Kenyan judiciary for promotion and transfers.

A criticism against increased speed due to the One-Pagers may come from “judges closing cases too quickly”, however, we find no evidence for this phenomenon in Table I1 of Appendix I: we find no effect on appeals, convictions or dismissals on the grounds that a case is frivolous. In the next section, we look at the quality of decisions in greater detail by analyzing the text of judgments.

B. Effects on Quality of Decisions

Table 7 below uses the same specification as above, with various measures of quality. We find no negative effects of the One-Pagers on the length of the judgements in Column (1), the number of other cases cited in the text in Column (2), the number of laws cited in the text in Column (3), and the number of citations in Column (4). Overall, we thus find no detrimental effects of the One-Pagers on these measures of the quality of legal processes.

¹³There is an effect on fast courts in April, yet there is also a violation of the pre-trend in this regression, such that this result must be taken with caution.

TABLE 6—EFFECT ON ADJOURNMENTS IN HIGH COURTS

	(1)	(2) Slow	(3) Fast	(4) Above Median Adj.	(5) Below Median Adj.
OnePager * February 2019	-0.059** (0.023)	-0.068** (0.025)	0.021 (0.044)	-0.10* (0.053)	-0.044** (0.019)
OnePager CUC * February 2019	-0.053*** (0.016)	-0.060*** (0.017)	0.0089 (0.045)	-0.093*** (0.021)	-0.036* (0.019)
OnePager * March 2019	0.0080 (0.018)	0.0058 (0.020)	-0.0068 (0.031)	0.043 (0.043)	-0.011 (0.011)
OnePager CUC * March 2019	-0.012 (0.015)	-0.013 (0.015)	-0.034 (0.043)	0.011 (0.030)	-0.00013 (0.012)
OnePager * April 2019	-0.044* (0.022)	-0.043* (0.024)	-0.073* (0.039)	-0.078 (0.054)	-0.031* (0.018)
OnePager CUC * April 2019	-0.035** (0.017)	-0.031 (0.018)	-0.088** (0.034)	-0.068* (0.035)	-0.010 (0.017)
OnePager * May 2019	-0.011 (0.023)	-0.014 (0.024)	-0.0046 (0.040)	-0.055 (0.035)	-0.020 (0.016)
OnePager CUC * May 2019	-0.024 (0.019)	-0.022 (0.021)	-0.030 (0.039)	-0.040 (0.028)	-0.035** (0.014)
OnePager * After June 2019	-0.021 (0.023)	-0.035 (0.025)	0.092* (0.045)	-0.028 (0.057)	-0.026 (0.018)
OnePager CUC * After June 2019	-0.0052 (0.020)	0.0026 (0.022)	-0.040* (0.020)	0.0090 (0.030)	-0.023 (0.016)
OnePager * Month Before	-0.018 (0.023)	-0.024 (0.020)	-0.15 (0.088)	0.0062 (0.046)	-0.022 (0.013)
OnePager CUC * Month Before	0.0035 (0.022)	0.014 (0.021)	-0.23** (0.083)	0.037 (0.027)	0.0045 (0.032)
Observations	1238950	1100117	138027	623156	535775

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing in the High courts ends in adjournment, 0 otherwise. In Column (2), the sample is restricted to slow courts, i.e., with a baseline average time to disposition above the Kenyan average. In Column (2), the sample is restricted to fast courts, i.e., with a baseline average time to disposition below the Kenyan average. In Column (4), the sample is restricted to courts with baseline adjournments above the median level. In Column (5), the sample is restricted to courts with baseline adjournments below the median level.

TABLE 7—EFFECTS ON QUALITY

	(1)	(2)	(3)	(4)
	Judgement Length	Cases in text	Laws in text	Number citations
OnePager * February 2019	-2.75 (160.75)	-0.87 (0.66)	0.23 (0.55)	-0.01 (0.09)
OnePager CUC * February 2019	-38.67 (179.62)	-0.07 (0.82)	0.06 (0.54)	-0.10 (0.10)
OnePager * March 2019	194.00 (142.12)	0.09 (0.38)	0.32 (0.50)	0.05 (0.05)
OnePager CUC * March 2019	107.30 (179.59)	0.54 (0.52)	0.67 (0.60)	0.22 (0.25)
OnePager * April 2019	186.91 (193.18)	0.73 (0.68)	0.56 (0.73)	0.13* (0.07)
OnePager CUC * April 2019	-29.20 (229.49)	0.89 (0.60)	0.49 (0.82)	-0.07 (0.09)
OnePager * May 2019	-4.81 (221.05)	-0.76 (0.67)	0.51 (0.69)	0.08 (0.07)
OnePager CUC * May 2019	-92.43 (236.63)	0.17 (0.78)	0.86 (0.80)	-0.11 (0.09)
OnePager * After June 2019	143.04 (151.46)	-0.04 (0.75)	0.36 (0.69)	0.08 (0.07)
OnePager CUC * After June 2019	70.80 (194.39)	0.82 (0.87)	0.07 (0.66)	-0.05 (0.09)
OnePager * Month Before	-4.36 (172.62)	0.24 (0.45)	-0.26 (0.72)	0.08 (0.07)
OnePager CUC * Month Before	206.14 (194.22)	1.45** (0.61)	0.35 (0.68)	0.14 (0.14)
Observations	137,376	137,376	137,376	137,231
R-squared	0.111	0.141	0.126	0.034
Mean Dep Var	2023	3.273	5.128	1.350
(SD)	2643	6.558	13.51	12.82

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable contains the length of the judgements from the Kenya law dataset. In Column (2) the dependent variable contains the number of other cases cited in the text of the judgement. In Column (3) the dependent variable has the number of laws cited in the text of the judgement. In Column (4) the dependent variable contains the number of times the judgement has been cited.

C. Effects on Court User Satisfaction

In Table 8 shown below, we start with “The judge/magistrate was neutral in his/her decision” (on a 1 to 4 scale: Strongly Disagree, Disagree, Agree, Strongly Agree). Column (1) shows no negative effect of the One-Pagers on this particular outcome. This is reassuring, in the sense that this focus on speed did not come at the detriment of perceptions of the neutrality of the judge.

TABLE 8—EFFECT ON QUALITY

	(1) Judge neutral	(2) Judge led proceedings well	(3) Suggestion Speed	(4) Suggestion Quality
OnePager * 2019	0.04 (0.07)	0.00 (0.07)	-0.06* (0.03)	-0.06*** (0.02)
OnePager_CUC * 2019	-0.09 (0.07)	-0.04 (0.06)	-0.04 (0.04)	-0.05*** (0.02)
OnePager * 2015	0.29 (0.27)	0.33 (0.32)	-0.05 (0.03)	0.01 (0.04)
OnePager_CUC * 2015	0.26 (0.26)	0.31 (0.30)	-0.00 (0.03)	0.02 (0.04)
Observations	12,612	13,847	15,199	15,199
R-squared	0.875	0.903	0.227	0.176

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1) the dependent variable “Judge Neutral” is measured on a 1 to 4 scale: Strongly Disagree, Disagree, Agree, Strongly Agree. In Column (2), the dependent variable “Judge Led Hearing Well” is measured on the same 1 to 4 scale. In Column (3) the dependent variable “Suggestion Speed” is a dichotomous variable equal to 1 if the respondent made a suggestion associated with speed, 0 otherwise. In Column (4), the dependent variable “Suggestion Quality” is a dichotomous variable equal to 1 if the respondent made a suggestion to improve quality, 0 otherwise. The variable “OnePager*2019” is a dichotomous variable which takes on a value of 1 if the survey was conducted after 2019 and in a court which received the One-Pagers, 0 otherwise.

In Column (2), the variable is: “The judge/magistrate listened and led the hearing well”. Once again, there are no negative effects.

We run the same specification on all the variables in this questionnaire and find no effects on any other variables which relate to the quality of the court infrastructure, the court cells, the customer care desk, the court service delivery charter, or the court registry. These null results are expected since the One-Pagers did not change any of those factors.

We then look at the open-ended text question: “What suggestions do you have for improving court facilities and services?”. We read all the answers and establish a list of keywords associated with speed.¹⁴ We define a dichotomous variable equal to 1 if the individual made a suggestion

¹⁴The full list of keywords is: time, speed, efficient, fast, track, postpone (this captures any words starting with postpone),

containing one of these keywords associated with speed, 0 otherwise.

Column (3) shows that these suggestions on speed decrease with the One-Pager and the One-pager sent to CUCS (albeit not significantly so). We interpret a decrease in suggestions about speed as evidence that people are more satisfied with the speed of courts.

In column (4), the variable is “Suggestion Quality”. We search for keywords associated quality.¹⁵ The hypothesis is that if the courts are getting worse, suggestions on how to improve quality should increase, however they decrease as shown in Column (4).

D. Effects on Economic Outcomes

We follow the pre-analysis plan and look at the effects of faster courts on investment, business creation, access to credit, consumption, and contracting behavior.

We first look at a measure of agricultural investment. Column (1) of Table 9 shows no effect on the purchase of farm inputs for crop production.

There is no measure of investment in business in the KCHSP.¹⁶ Still, we proxy business investment by income from self employment (for both working employers and own account workers). The two are related since investment generally results in greater income for the business. Column (2) shows no effect on this measure.

We then look at business creation. Column (3) shows no effect on applications to permit to start businesses. One issue with this variable is that it is only asked to unemployed persons and persons not in the labour force since it is the answer to the question on actions taken to look for a job or start any kind of business/income generating activity. We propose another proxy for business creation exploiting the full sample in Column (4): the transitions to entrepreneurship (both working employers and own account workers) from being employed, unemployed or out of the labour force a year ago. There, we find a small effect of the one-pagers, not statistically different from the effect of the one-pagers sent to CUCs. Thus, there appears to be a small effect of faster courts on entrepreneurship.

Our next outcome specified in the pre-analysis plan was access to credit. There is no such measure in the KCHSP data (as opposed to the KIHBS). We again use the question on actions to look for a

shorter, early, long, typed (because this was in a sentence associated with speed), prompt, delay, expedite, slow, immediately, quick, duration, timing, adjournment, unnecessary, settlement, more, work, adequate, notice, backlog, dates, case, management, late, earlier, start, expeditious, punctua, absenteeism, dragging, efficiency, performance, adjou, short, overwhelmed, puntual (with this particular typo), congestion, drag, expeditions, expeditious, hasten, have, afternoon, sessions, scheduling.

¹⁵The full list of keywords is: expertise, quality, file lost, file missing, communication, administration, neutral, skill, assist, competent, service, delivery, charter, friendly, inform, collaboration, cooperation, witness refund, training, fair, fact, properly investigated, justice, transparent, train, motivate, ethic, accuracy, rude, polite, knowledgeable, accurate, understanding, courtesy, arrogant, filing, audible, bias, courteous, transparency, honesty, witness, bribe, corrupt, integrity

¹⁶When we wrote our pre-analysis plan, we thought another wave of the Kenya Integrated Household Budget Survey (KIHBS) would become available, the 2015 wave contained a measure of investment in businesses. The Kenyan National Bureau of Statistics collected instead the KCHSP, with no such measure.

job or start any kind of business/income generating activity, but this time we focus on the answer: “Applied for a loan from a bank”. Column (5) shows no effect.¹⁷

Finally, we had pre-specified to look at contracting behavior of firms. No data on firms in Kenya has become available yet for this period. We thus present the only variable in the KCHSP dataset related to contracting behavior. The survey asks the type of employment contract: written contract, verbal agreement, implied contract, or no contract. Column (6) shows an effect of the one-pagers sent to CUCs on the prevalence of written contracts. This indicates greater reliance on contracts as a result of the information and accountability intervention, and is important because jobs with such contracts pay more, as shown in Appendix J. This partially explains the effect on wages detected in Column (7), as shown in greater detail in a decomposition exercise in Appendix J. It is important to keep in mind, however, that wage was not an outcome specified in our pre-analysis plan.¹⁸ This result thus has to be taken with caution, yet we present it since it is naturally linked with written labor contracts.

In Appendix K, we dig deeper into this effect on wages and find that the wage was balanced before the experiment between the treatment and control groups, that the effect on wages is stronger in the short-run and fades away with time, consistent with the short-run effect on the speed of courts. We also classify industries by contract intensity and find that the wage effect is concentrated on contract-intensive sectors. It is important to keep in mind that this analysis was not specified in our pre-analysis plan¹⁹, yet they tend to show that there is a pure productivity effect of faster courts on contract-intensive industries on top of the move towards written contracts documented above. We also find little effect on investment, business creation and access to credit, probably because the reform has very short-term effects, with only one wave of the one-pagers sent in February 2019. In an on-going project, we are sending multiple waves of the one-pagers over the years 2021 and 2022.

¹⁷There is no measure of consumption in the KCHSP, another variable specified in our pre-analysis plan when we thought we would have access to another wave of the Kenya Integrated Household Budget Survey (KIHBS).

¹⁸Consumption was, but there is no measure of consumption in the KCHSP, only in the KIHBS that was not collected after the intervention.

¹⁹We could not have pre-specified it since we thought we would have access to another wave of the KIHBS and the KIHBS does not contain industry data. The KCHSP contains industry data. Even though this analysis was not specified, it is standard in the literature (see Boehm and Oberfield (2020); Amirapu (2021)).

TABLE 9—EFFECTS ON ECONOMIC OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Agri. Inv.	Income Self Emp.	Permit Busi.	Transition Entrepre.	Apply Loan	Contract	Not in PAP Wage
FracOnePager * Post	-0.01 (0.03)	43.34 (32.88)	-0.00 (0.00)	0.03* (0.02)	0.00 (0.00)	0.03 (0.02)	58.50 (36.98)
FracOnePagerCUC * Post	-0.04 (0.02)	36.17 (44.58)	-0.00 (0.00)	0.01 (0.02)	0.00 (0.00)	0.04* (0.02)	98.37** (41.77)
Observations	86,647	25,020	40,508	74,617	40,508	35,078	7,457
County fixed effects	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES
Mean control group	0.00809	260.9	0.000349	0.141	0.000174	0.119	247.4
SD control group	0.108	560.3	0.0187	0.348	0.0132	0.324	307.8

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is the answer to the question: “Did the household purchase farm inputs for crop production during the last month (Yes/No)”. This question is asked for each and every crop produced. The dependent variable is the sum of all answers at the household level. Results are similar if we take a dummy taking the value 1 if the household answers yes for any crop produced by the household, 0 otherwise. The variable “FracOnePager” is the fraction of court stations in a county that received the One-Pagers. The variable “Post” is equal to 1 in the quarters 2, 3, and 4, and equal to 0 in quarter 1. In Column (2), the dependent variable is the earnings after expenses for both worker employers and own account workers, otherwise called income from self-employment in the dataset. In Column (3), the dependent variable is equal to 1 if the individual answered: “Applied for permit to start business” to the question: “In the past 4 weeks what actions has ... taken to look for a job or start any kind of business/income generating activity? rank the three main ones”. This question is only asked to unemployed persons and persons not in the labour force. In Column (4), the dependent variable is equal to 1 if the individual is a working employer or an own-account worker, 0 otherwise, conditional on being a year ago employed, unemployed, student, housewife, retired, family worker, incapacitated, discouraged worker. In Column (5), the dependent variable is equal to 1 if the individual answered: “Applied for a loan from a bank” to the question: “In the past 4 weeks what actions has ... taken to look for a job or start any kind of business/income generating activity?”. In Column (6), the dependent variable is equal to 1 if the individual answers “a written contract” to the question “Is ... employed on the basis of”. Other answers are verbal agreement, implied contract, no contract. In Column (7), the dependent variable is payment for wages and gross salary in the last one month, trimmed at the 5 percent level.

VI. Conclusion

This paper is the first randomized nationwide experiment on reforming courts. A large literature documents that institutions are key drivers of economic growth. Ours is the first randomized reform that demonstrates the causal impact of judicial institutions on economic development.

This project is the result of collaboration with the Kenyan judiciary and the World Bank to use a novel administrative dataset on all cases going through the Kenyan courts. We develop an algorithm able to identify the reasons for delays in each court and predict the increase in performance that would result from the elimination of such delays. Court performance is important because judges and courts are evaluated regularly on these indicators for promotions and transfers. We present the information in an easily digestible “One-Pager” and send it to a randomized set of courts. Other courts receive the One-Pagers and must share them with CUC meetings.

We find that this latter intervention has beneficial effects on the reduction of delays specifically displayed in the One-Pagers. This result is easily explained by a simple principal-agent model. The principal (the Chief Justice, CJ) wishes the agents (the judges) to exert effort and resolve cases quickly. Absent the one-pagers, the agents’ effort is unobservable, and thus provided at low levels. Increasing the monitoring of agents through the one-pagers (which measure and reveal judges’ effort) thus increases judges’ effort.

This is not the entire story, however, since the one-pagers have less of an effect than the one-pagers sent to CUCs. This latter treatment group introduces a new principal: civil society. The general population wants faster justice, and is represented in CUC meetings. In that treatment group, civil society groups receive the one-pagers and can directly monitor the productivity of judges.

In fact, the treatment group with the CUC meeting introduces another set of agents (such as lawyers, police, and prosecutors) who can also affect the duration of proceedings. Lawyers can ask for adjournments to strategically delay cases; police and prosecutors may also delay cases through lack of effort and insufficient preparation. The one-pagers display the top three reasons for adjournment, which can feature these groups. The one-pagers are the first set of hard evidence showing whether these groups are asking for excessive adjournments and delaying cases. These CUC meetings can thus act as forums whereby monitoring of all groups happens and pressure can be applied on specific groups creating delays. Therefore, the one-pagers sent to CUCs feature not only one but two principals: CJ and civil society groups. It also features two sets of agents exerting effort on cases: judges and other court users, i.e., lawyers, police, and prosecutors. This explains why the one-pagers sent to CUCs have more of an effect than one-pagers sent to judges alone, which feature only one principal (CJ) and one set of agents (the judges).

We find no significant effect on internal adjournments, but an effect on external adjournments. The lack of effect on internal adjournments tends to show that lack of effort on judges' part is not the mechanism at play. The effect on external adjournments suggests that having civil society as principals and courts users as agents is the important channel through which we see an effect.

Finally, we find downstream economic effects. We find an increase in written labor contracts, in line with the view that faster courts increase the incentives to enter into contracts. This effect is important because jobs with such contracts pay more; in addition, it indicates greater reliance on contracts as a result of the intervention, which the literature has shown to be an important mechanism through which courts affect economic development. We find that this increase in written contracts drives an increase in wages. We find little effects on investment, business creation and access to credit, probably because of the short-term nature of the reform, with only one wave of the one-pagers sent in February 2019. A direction for future research is to look at the longer-run effects of this reform on investment, business creation, access to credit and overall welfare.²⁰

In much of the world, courts have excessive delays, and adjournments are a key reason behind court delays. This paper explores how data science can identify the main sources of delay and present them in a manner that improves development outcomes. Information alone is insufficient to increase court efficiency. Information and accountability led to measurable impacts on judicial outcomes and economic development. Court users benefited from faster courts. Firms signed more contracts and wages improved.

²⁰This will be addressed by another experiment implemented before writing this paper and discovering these positive results, where we sent four additional waves of one-pagers every quarter over the years 2021/2022.

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ONLINE APPENDIX (Not For Publication)

APPENDIX A: DESCRIPTIVE STATISTICS ON TYPE OF CASES

There are 33 percent civil cases, the rest being criminal cases. Among civil cases, cases can be personal injury (11% of all cases), family (4%), succession (7%), commercial (5%), or other (8%). Among criminal cases, cases can be about property (15% of all cases), violent (12%), state regulations (7%), disturbance (2%), drugs (3%), sexual (3%), fraud (1%), other (17%).

TABLE A1—DESCRIPTIVE STATISTICS

Type of case	Mean	SD	N
Civil	0.33	0.47	5426222
Personal Injury	0.11	0.31	5192017
Family	0.04	0.20	5192017
Succession	0.07	0.25	5192017
Commercial	0.05	0.21	5192017
Other Civil	0.08	0.27	5237056
Property	0.15	0.36	5192017
Violent	0.12	0.33	5192017
State Regulations	0.07	0.25	5192017
Disturbance	0.02	0.12	5192017
Drugs	0.03	0.16	5192017
Sexual	0.03	0.17	5192017
Fraud	0.01	0.12	5192017
Other Criminal	0.17	0.38	5282718

APPENDIX B: SAMPLING FOR EXPERIMENTAL DESIGN

To achieve balance, we stratify on geographical variables and on a slow/fast court dummy.

For the geographical variables, we established a list of 8 regions that do not correspond exactly to the official regions but that make sense distance-wise to organize potential future regional meetings to debrief court stations about the interventions. For example, Thika court is in Central province but it is easier and cheaper for them to travel to Nairobi for the meeting. Therefore, Thika was classified in Nairobi, not Central.

We also stratify on a slow/fast court dummy. To build this dummy, we use average time to disposition at the station level. We compute the median of time to disposition, and define a dichotomous variable equal to 1 if the court station is above the median time to disposition, 0 otherwise.

We then stratify on 1) regions, and 2) time to disposition. This means creating 8 (regions)*2 (above median time to disposition, i.e., slow stations, or below median time to disposition, i.e., fast stations) = 16 strata of court stations. Within each strata, we then split the court stations into three groups: control, “One-Pager” and “One-Pager + CUC”. This produces a sampling plan with 41 stations in the control group, 41 in the “One-Pager”, and 41 in the “One-Pager + CUC”.²¹

This procedure ensures that the treatment is balanced on time to disposition. In fact, one can regress time to disposition on control, “One-Pager” and “One-Pager + CUC”, and we find a t-statistic of -0.38 and -0.29 respectively.

This technique does not ensure that the treatment and control groups will be balanced on other variables. To check this, we regress treatment on four other variables: number of cases filed at the station level, number of adjournments civil, number of adjournment criminal, and due process.²² The number of cases filed at the station level is a proxy for court size. Ideally, one would like to have a balance of small and big courts in each treatment group. The number of adjournments is an important intermediate variable in this project since the one-pager aims at reducing adjournments. Finally, due process will be an important outcome of this project since one would expect the one-pagers to increase speed, but not at the detriment of due process.

²¹The size of the strata can vary: for example, strata1 has 8 stations. The issue is that 8 cannot be neatly divided by 3 (for Control/OnePager/OnePager_CUC). The sampling plan starts by assigning 2 stations to control, 3 to “One-Pager”, and 3 in the “One-Pager + CUC”. To make sure that the control group does not always get less stations, we rotated the order of the treatments. This achieves a 44/40/39 split. We then randomly select three stations from the Control group and assign one of them to OnePager, and two of them to OnePager_CUC. This ensures a 41/41/41 split. All of this is done randomly, such that balance is achieved in the end.

²²To get an estimate of due process, we used the 2017 Court User Satisfaction Survey and calculated the average of answers to the section “court room experience”. Question 19.1 The judge/magistrate was courteous 19.2 My matter took the time I was expecting 19.3 The judge/magistrate listened and led the hearing well 19.4 My matter was started in time 19.5 The judge/magistrate made decision in a timely manner 19.6 The judge/magistrate was neutral in his/her decision. Average: 70%, as in “COURT USER SATISFACTION SURVEY, REPORT BY PERFORMANCE MANAGEMENT DIRECTORATE, JUNE, 2017”

The maximum t-statistic across all these variables is 1.84.

To achieve even better balance, this process can be repeated by rerandomizing: we draw 10,000 allocations to treatment and control, and chose the one that shows best balance on the observable variables. In that winning iteration, the “minimum maximum” t-stat is 0.57.

In particular, this plan achieves balance on the number of cases filed per station. When regressing number of cases filed per station on control, “One-Pager” and “One-Pager + CUC”, we find a t-statistic of 0.15 and 0.32 respectively.

Table B1 below shows the balance test with respect to other outcomes than adjournments. Column (1) shows that the likelihood that a case gets resolved is not significantly different in the treatment groups before 2019. Similarly, there are no significant differences in the proportion of cases filed, appealed, convicted, or frivolous. There is a small difference in the proportion of cases with legal representation. We control for this factor in all regressions of the paper. There are no differences in the number of witnesses for either the plaintiff or the defendant.

Columns (9) to (21) show the balance test for the make-up of cases. There are few differences overall, with slightly more commercial cases and and less property and violent cases in treatment areas.

TABLE B1—BALANCE ON OTHER OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Resolved	Filed	Appeal	Convicted	Frivolous	Legal Rep	Witness Plaintiff	Witness Defendant
OnePager	0.0044 (0.0096)	-0.0049 (0.0084)	0.00090 (0.0035)	-0.0037 (0.0089)	-0.0016 (0.0032)	0.010 (0.039)	0.0041 (0.0058)	0.0020 (0.0021)
OnePager CUC	0.0049 (0.012)	-0.0073 (0.012)	-0.0033 (0.0048)	-0.00095 (0.011)	0.0038 (0.0042)	0.089* (0.047)	0.0022 (0.0058)	-0.00081 (0.0026)
Observations	5421368	5421368	5421368	5421368	5421368	5421368	5421368	5421368

	(9)	(10)	(11)	(12)	(13)
	Personal injury	Family	Succession	Commercial	Other Civil
OnePager	-0.0051 (0.027)	0.0023 (0.010)	-0.0072 (0.0097)	0.011 (0.012)	-0.00068 (0.011)
OnePager CUC	0.033 (0.032)	0.031 (0.019)	-0.0067 (0.014)	0.022* (0.013)	0.024 (0.016)
Observations	5187245	5187245	5187245	5187245	5232282

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
	Property	Violent	State Regulations	Disturbance	Drugs	Sexual	Fraud	Other Criminal
OnePager	-0.00086 (0.015)	-0.0016 (0.015)	-0.0035 (0.0073)	0.0011 (0.0026)	-0.0045 (0.0040)	-0.000078 (0.0052)	0.0016 (0.0020)	-0.0080 (0.016)
OnePager CUC	-0.035** (0.016)	-0.024** (0.011)	-0.012 (0.014)	-0.0043* (0.0022)	-0.013** (0.0050)	-0.0028 (0.0042)	0.0027 (0.0044)	-0.016 (0.015)
Observations	5187245	5187245	5187245	5187245	5187245	5187245	5187245	5277934

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. The sample is restricted to the period before 2019. The variable “OnePager” takes on a value of 1 if the observation is in a court which received a One-Pager, 0 otherwise. The variable “OnePager CUC” takes on a value of 1 if the observation is in a court which received a One-Pager and that OnePager was sent to the CUC, 0 otherwise. The regressions include the stratification dummies (the 8 region dummies and the Slow/Fast dummy) as well as a dummy for whether the court is a magistrate court or a high court.

APPENDIX C: MODEL

Suppose a firm contracts with a supplier to produce a customized good (which has value only for the firm). The supplier exerts effort $e \in [0, 1]$, of which he has an endowment \bar{e} . Effort e is observable, there is perfect information. This yields output A with probability \sqrt{e} , and 0 with probability $1 - \sqrt{e}$. Thus, output produced is $A\sqrt{e}$. For simplicity, the utility function u of the seller is linear in consumption c and leisure l , $u(c, l) = c + l$, such that there is no risk-aversion effects. The buyer promises in a contract to pay $A\sqrt{e}$. The seller chooses e to maximize utility:

$$\begin{aligned} \max_e \quad & A\sqrt{e} + \bar{e} - e \\ \text{s.t.} \quad & e \leq \bar{e} \end{aligned}$$

The first-order condition for an interior solution leads to equilibrium effort level $e^* = \left[\frac{A}{2}\right]^2$. Output is $y^* = \frac{A^2}{2}$.

Once this effort level has been sunk and output has been produced, the buyer can renegotiate prices down to offer a minimal amount $\varepsilon > 0$. Since there are no other buyers for this customized good, the seller is “held up”.

The seller can sue in court. To model the judiciary in a simple way, we assume that a judgment is made in favor of the seller with probability p , after time T , and with legal costs l (proportional to the value of the cause). The seller thus recovers a fraction $p\beta^T - l$ of its output.

The production function of the seller becomes: $(p\beta^T - l)A\sqrt{e} - e$. The first order condition yields: $e^* = \left[(p\beta^T - l)\frac{A}{2}\right]^2$.

This has implications for the firm (the buyer of the customized good). Effort is lower than in the optimal case with no contractual difficulties. The output associated with this effort is $A\sqrt{e} = A\sqrt{\left[(p\beta^T - l)\frac{A}{2}\right]^2} = \frac{A^2}{2}(p\beta^T - l)$, less than $\frac{A^2}{2}$ since $p\beta^T - l < 1$ (the judiciary is less than perfect $p < 1$, slow (high T), and costly to access (high l)).

One can construe this lesser output as a defective customized good, or not fully customized, caused by contractual difficulties, in a similar way as in Boehm and Oberfield (2020). In that case, the firm needs to hire extra labor or use some of its labor force to correct these deficiencies. Suppose the firm faces the choice for each worker of outsourcing their work to an outside supplier or using this worker to produce the output, in a more vertically integrated way. Then each worker must spend a fraction of their time $1 - (p\beta^T - l)$ correcting the defective output. For each unit of labor, the firm only has a fraction available $(p\beta^T - l)$, the rest must be spent on correcting the defective inputs. The labor force is therefore diminished: instead of L , the firm only gets $(p\beta^T - l)L$.

The production function of firm i at time t is:

$$Y_i(t) = F(K_i(t), (p\beta^T - l)L_i(t))$$

The term $(p\beta^T - l)$ can also be construed as a labor-augmenting productivity term (usually called A). If $(p\beta^T - l)$ increases (the judiciary is improving), then there is more labor at the disposal of the firm, because less labor needs to be allocated to the customization of defective inputs. This paper thus opens the black box of A and models it specifically as being derived from contractual issues.

We now follow the political economy model developed in Acemoglu (2012). The only difference is to incorporate specifically the functioning of the judicial system $p\beta^T - l$ within the model.

There are three groups: the workers, entrepreneurs and the elite. Considering the elite is important to understand the motivations to set $(p\beta^T - l)$ at a certain level (potentially suboptimal as far as economic growth is concerned). The elite makes political decisions and engage as well in economic activities. The political system is an oligarchy dominated by the elite. The workers supply their labor inelastically and are of mass 1. There are θ^e elites and θ^m entrepreneurs (m for middle class), such that total population is $1 + \theta^e + \theta^m$.

Agent i maximizes their discounted flow of consumption, assuming risk-neutrality: $U_i = \sum_{t=0}^{\infty} c_i(t)$. ■

Entrepreneurs produce according to the production function explicated above. \bar{L} is the maximum size of firms (otherwise one firm holds all the labor due to constant returns to scale), which can be justified by a limited span of control for each entrepreneur. Thus, $\theta^e\bar{L} + \theta^m\bar{L}$ is the total number of jobs created. If $\theta^e\bar{L} + \theta^m\bar{L} < 1$, there is unemployment and equilibrium wage $w = 0$. Suppose $\theta^e\bar{L} < 1$, such that there are not enough elites to hire the entire population.

There is a linear tax on output $\tau(t)$ which serves to finance lump-sum transfers to each of the three groups: T^w , T^m , and T^e . The government budget constraint is:

$$T^w + T^m + T^e \leq \Phi \int_i \tau_i(t) F(K_i, L_i) di$$

$\Phi \in [0, 1]$ is a measure of state capacity, in other words the ability to collect resources from the economy. If $\Phi = 0$, all the revenue collected is wasted. In that case, the elite does not care about revenue extraction and only cares about the economic competition with entrepreneurs.

The political process announces $\tau(t+1)$. Given this, entrepreneurs decide their production:

$$U_i = \sum_{t=0}^{\infty} c_i(t)$$

$$s.t. \quad K_i(t+1) = (1-\delta)K_i(t) + I_i(t)$$

Where δ is the depreciation rate and I is investment. Given investment is: $I_i(t) = (1 - \tau(t))F(K_i(t), (p\beta^T - l)L_i(t)) - c_i(t) - wL_i(t) + T^m(t)$ (where w is the wage). Dividing by $L_i(t) = 1$ and rearranging leads to: $c_i(t) = (1 - \tau(t))f(k_i(t)) - (k_i(t+1) - (1 - \delta)k_i(t)) - w + T^m$, where k is capital stock per worker and $f(\cdot)$, the production function per worker.

To make progress, one can use basic elements of dynamic programming. The consumption Euler equation is: $\frac{\partial U}{\partial y} + \beta V'(y) = 0$, where U is the instantaneous utility function, V the continuation value, x is the state variable $k_i(t)$, and y is the control variable $k_i(t+1)$. Thus, in this case: $\frac{\partial U}{\partial y} = -1$ (since U is $c_i(t)$, and $k_i(t+1)$ appears with the negative sign in the formulation of $c_i(t)$).

The envelope theorem delivers: $V'(x) = \frac{\partial U}{\partial x} = (1 - \tau(t))f'(k(t)) + (1 - \delta)$.

Putting the two parts together yields:

$$(C1) \quad -1 = \beta(1 - \tau(t+1))f'(k^*(t+1)) + (1 - \delta)$$

Given $\tau(t+1)$, this expression delivers the $k_i^*(t+1)$ that will be chosen by entrepreneurs.

Suppose the production function is Cobb-Douglas: $Y_i(t) = \frac{1}{\alpha}K_i(t)^\alpha ((p\beta^T - l)L_i(t))^{1-\alpha}$. $\frac{1}{\alpha}$ is added as a convenient normalization. Suppose also $\delta = 1$, depreciation does not play a role.

Output per worker is: $\frac{Y_i}{L_i} = \frac{1}{\alpha} (p\beta^T - l)^{1-\alpha} k_i^\alpha = f(k_i)$.

In this case, equation (1) becomes:

$$k_i^*(t+1) = [\beta(1 - \tau(t+1))]^{\frac{1}{1-\alpha}} (p\beta^T - l)$$

Importantly, one can see from this expression that capital stock per worker is an increasing function of the judiciary's efficiency summarized in $p\beta^T - l$.

Entrepreneurs' profit is then: $\Pi_i = (1 - \tau)F(K_i, L_i) - RK_i - wL_i$. Output per worker is: $\frac{\Pi_i}{L_i} = (1 - \tau)(f(k_i) - k_i f'(k_i)) - w$ (since the return to capital $R = (1 - \tau)f'(k_i)$ from profit maximization with respect to K).

Replacing f by its Cobb-Douglas expression leads to:

$$\frac{\Pi_i}{L_i} = (1 - \tau)^{\frac{1}{1-\alpha}} (p\beta^T - l)^{\frac{1-\alpha}{\alpha}} \beta^{\frac{\alpha}{1-\alpha}} - w$$

The first term is the net marginal product (profitability) of labor: MPL_i , net of the costs of investment RK_i . If the wage is above this MPL_i , then the firm hires $L_i = 0$. If the wage is below this MPL_i , then the firm hires $L_i = \bar{L}$.

Suppose we are in the full employment case such that the number of jobs created is: $\theta^e \bar{L} + \theta^m \bar{L} > 1$. Otherwise, there are fewer jobs than workers and $w = 0$.

What is the equilibrium wage under these circumstances?

Suppose the quality of the judiciary faced by the elite is different from the one face by entrepreneurs. In the extreme, suppose: $(p\beta^T - l)^e = 1$. In other words, the elites through their personal connections have access to a perfect judiciary that will always rule for them ($p = 1$), fast ($T = 0$), and with no legal fees associated ($l = 0$). Suppose moreover that the elite does not levy a tax on itself since they decide the rules of the game: $\tau^e = 0$. Under those circumstances: $MPL^e > MPL^m$. Notice that businesses of entrepreneurs are not less productive per se, they are less productive because they face a lower $p\beta^T - l$ and a greater tax rate.

To find the equilibrium wage, start with $w = 0$. One firm can increase w by a small amount, still make a profit, and attract all the workers. Thus, w increases until it reaches $\min(MPL^e, MPL^m) = MPL^m$. Above this level, the entrepreneurs cannot make a profit. The elite does not need to raise wages any further since $\theta^e \bar{L} < 1$: every firm managed by the elite can find workers. Therefore, the equilibrium wage is $w = MPL^m$. At this wage, the elite can hire \bar{L} . The entrepreneurs get the rest: $1 - \theta^e \bar{L}$.

What will the elite decide, in terms of τ and $p\beta^T - l$? The goal of the elite is to maximize their transfers, thus they will set: $T^w = T^m = 0$ and $\tau^e = 0$. The government budget constraint thus becomes:

$$\theta^e T^e = \Phi \tau^m(t) \int_{i \in S^m} F(K_i, L_i) di$$

with S^m the set of entrepreneurs. Replacing $F(K_i, L_i)$ by $L_i f(k_i)$ leads to: $T^e = \frac{1}{\theta^e} \Phi \tau^m(t) f(k^*(t)) \theta^m L^m$. ■

Thus, the maximization problem of the elite is:

$$V^e(\tau(t), K_i(t)) = \max_{\tau^m} [(MPL^e - w)L^e + T^e(t) + \beta V^e[\tau(t+1), K_i(t+1)]]$$

V^e is the continuation value for the elite. The first term $(MPL^e - w)L^e$ is the profit made from the elite's businesses. The equilibrium wage being $w = MPL^m$, this term exemplifies the economic competition between the elite and entrepreneurs. The elite will want to depress the equilibrium wage to maximize their own profits. They can do so using two levers. First they can increase the taxation rate τ^m on the entrepreneurs which will reduce the marginal product of labor since

$MPL^m = (1 - \tau^m)^{\frac{1}{1-\alpha}} (p\beta^T - l)^{\frac{1-\alpha}{\alpha}} \beta^{\frac{\alpha}{1-\alpha}}$. The downside is that this will also reduce tax revenues in $T^e(t)$. Second, they can decrease the efficiency of the judiciary: $p\beta^T - l$.

The second term is transfers obtained from taxation $T^e(t) = \frac{1}{\theta^e} \Phi \tau^m(t) f(k^*(t)) \theta^m L^m$. With the Cobb-Douglas specification: $f(k_i^*) = \frac{1}{\alpha} (p\beta^T - l)^{1-\alpha} k_i^{*\alpha} = \frac{1}{\alpha} (p\beta^T - l) [\beta(1 - \tau)]^{\frac{\alpha}{1-\alpha}}$.

The third term V^e is the continuation value at time $t + 1$ discounted to the present.

The elite pursues two objectives (which may conflict with each other): maximizing their businesses' profits (first term) and maximizing transfers from taxing entrepreneurs (second term).

Replacing MPL^e , w , and $T^e(t)$ by their expressions leads to:

$$(C2) \quad \begin{aligned} V^e(\tau(t), K_i(t)) = \max_{\tau^m} & \left[\left[\frac{1-\alpha}{\alpha} \beta^{\frac{\alpha}{1-\alpha}} - (1 - \tau^m)^{\frac{1}{1-\alpha}} (p\beta^T - l)^{\frac{1-\alpha}{\alpha}} \beta^{\frac{\alpha}{1-\alpha}} \right] L^e \right] \\ & + \frac{1-\theta^e \bar{L}}{\theta^e} \Phi \tau^m(t) \frac{1}{\alpha} (p\beta^T - l) [\beta(1 - \tau)]^{\frac{\alpha}{1-\alpha}} \\ & \beta V^e[\tau(t+1), K_i(t+1)] \end{aligned}$$

where the first term on the first line is economic competition, the second term on the second line is revenue extraction, and the third term on the third line is the continuation value.

We can apply dynamic programming once more to solve for the equilibrium. The consumption Euler equation is: $\frac{\partial U}{\partial y} + \beta V'(y) = 0$, where U is the instantaneous utility function, V the continuation value, x is the state variable $\tau(t)$, and y is the control variable $\tau(t+1)$. The instantaneous utility function U does not depend on the future, thus $\frac{\partial U}{\partial y} = 0$, and $V'(y) = 0$. The envelope theorem gives: $V'(x) = \frac{\partial U}{\partial x}$. Thus, in this particular case, maximizing the elite's utility function is equivalent to maximizing its instantaneous utility function.

The maximization leads to an optimal $\tau^m = \frac{\kappa}{1+\kappa}$, with $\kappa = \frac{1-\alpha}{\alpha} \left(1 + \frac{\theta^e \bar{L}}{\Phi(1-\theta^e \bar{L})} \right)$. It can be shown that $\tau < 1$.

Suppose now that the elite can also choose $p\beta^T - l$. What is the optimal amount they will choose? Consider equation (2). If the only motive is revenue extraction, then the first term representing the economic competition disappears. The only term of interest is the second term representing extraction from the entrepreneurs. In that case, $p\beta^T - l$ should be set at its maximum level of 1 to increase the output of entrepreneurs. A better judiciary will lead to more revenue extraction.

In contrast, suppose there is economic competition between the elites and entrepreneurs and no revenue extraction. In the extreme, suppose $\Phi = 0$, such that the second term disappears. In that case, the elite wishes to decrease w to increase their profit. $p\beta^T - l$ should be set at its lower level possible to depress wages.

Overall, there are two implications of this model:

1. The equilibrium wage level is an increasing function of the judiciary's effectiveness: $p\beta^T - l$.

This is obvious from its expression: $w = \min(MPL^e, MPL^m) = MPL^m = (1-\tau^m)^{\frac{1}{1-\alpha}} (p\beta^T - l)^{\frac{1-\alpha}{\alpha}} \beta^{\frac{\alpha}{1-\alpha}}$; with $\tau^m = \frac{\kappa}{1+\kappa}$ and $\kappa = \frac{1-\alpha}{\alpha} \left(1 + \frac{\theta^e \bar{L}}{\Phi(1-\theta^e \bar{L})}\right)$.

The intuition is that each unit of labor spends less time correcting defective customized inputs and more time producing output. Thus when $p\beta^T - l$ increases, the net marginal product (profitability) of labor increases.

This is only true for contract-intensive industries, which was the starting point of this model (a firm contracts with a supplier which leads to contractual issues). This argument is not valid for firms not contracting with suppliers for relationship-specific investments. We test this empirical implication in the data.

2. The elite has incentives to lower $p\beta^T - l$ under certain conditions, i.e., there is economic competition between the elite and entrepreneurs, which dominates the revenue extraction motive. In the extreme case, $\Phi = 0$ such that the elite does not care about revenue extraction. In that case, the only motive of the elite is to lower wages to maximize their profits.

This explains why we might observe low-quality judiciaries around the world. If revenue extraction was the main channel, there would be incentives for the elite to provide the best possible judiciary.

The conclusion of this model is that the elites can block the development of contract-intensive industries through a sub-par judiciary if they compete economically with this sector. This may explain the small size of the contract-intensive sector in developing countries which usually face this situation of an oligarchy dominated by an elite, themselves engaged in business ventures possibly in contract-intensive sectors. This has welfare implications since the model shows that wages, and therefore living standards, of workers in that sector are negatively affected.

APPENDIX D: BALANCE TEST WITH ECONOMIC OUTCOMES

Table D1 below shows the balance test with the following economic outcomes: investment (purchase of farm inputs for crop production in Column (1) and income from self employment in Column (2)), business creation (applications to permit to start businesses in Column (3) and transitions to entrepreneurship in Column (4)), access to credit (applied for a loan from a bank to look for a job or start any kind of business/income generating activity in Column (5)), contracting behavior (written labor contract in Column (6)), and wage in Column (7)).

All the coefficients are not statistically significant, except for contract for the one-pager intervention, significant at the 10 percent level. (but not for the one-pager sent to CUC intervention). Getting one significant coefficient out of 14 in this table (7 outcomes * 2 interventions) is expected at the 10 percent level.

TABLE D1—BALANCE TEST WITH ECONOMIC OUTCOMES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Agri. Inv.	Income Self Emp.	Permit Business	Transition Entrepreneur	Applied Loan	Contract	No PAP Wage
FracOnePager	0.01 (0.01)	-23.51 (31.77)	0.00 (0.00)	0.02 (0.03)	-0.00 (0.00)	-0.04* (0.02)	-19.31 (37.94)
FracOnePagerCUC	0.01 (0.01)	25.96 (52.84)	0.00 (0.00)	0.01 (0.02)	0.00 (0.00)	-0.01 (0.04)	-28.83 (43.87)
Constant	0.00 (0.00)	260.12*** (25.04)	-0.00 (0.00)	0.13*** (0.02)	0.00 (0.00)	0.14*** (0.01)	263.06*** (26.51)
Observations	22,732	5,456	11,465	19,504	11,465	8,271	2,154

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is the answer to the question: “Did the household purchase farm inputs for crop production during the last month (Yes/No)”. This questions is asked for each and every crop produced. The dependent variable is the sum of all answers at the household level. Results are similar if we take takes a dummy taking the value 1 if the household answers yes for any crop produced by the household, 0 otherwise. The variable “FracOnePager” is the fraction of court stations in a county that received the One-Pagers. The variable “Post” is equal to 1 in the quarters 2, 3, and 4, and equal to 0 in quarter 1. In Column (2), the dependent variable is the earnings after expenses for both worker employers and own account workers, otherwise called income from self-employment in the dataset. In Column (3), the dependent variable is equal to 1 if the individual answered: “Applied for permit to start business” to the question: “In the past 4 weeks what actions has ... taken to look for a job or start any kind of business/income generating activity? rank the three main ones”. This questions is only asked to unemployed persons and persons not in the labour force. In Column (4), the dependent variable is equal to 1 if the individual is a working employer or an own-account worker, 0 otherwise, conditional on being a year ago employed, unemployed, student, housewife, retired, family worker, incapacitated, discouraged worker. In Column (5), the dependent variable is equal to 1 if the individual answered: “Applied for a loan from a bank” to the question: “In the past 4 weeks what actions has ... taken to look for a job or start any kind of business/income generating activity?”. In Column (6), the dependent variable is equal to 1 if the individual answers “a written contract” to the question “Is ... employed on the basis of”. Other answers are verbal agreement, implied contract, no contract. In Column (7), the dependent variable is payment for wages and gross salary in the last one month, trimmed at the 5 percent level.

APPENDIX E: BALANCE TEST WITH COUNTY GDP

Table E1 below shows the balance test using County GDP collected between 2013 and 2017 by the Kenya National Bureau of Statistics (all figures are in Million USD PPP). There is no significant association between county GDP and the fraction of court stations treated with either the OnePager or the OnePager_CUC.

TABLE E1—BALANCE TEST WITH COUNTY GDP

	(1)	(2)	(3)	(4)	(5)
	CGDP2013	CGDP2014	CGDP2015	CGDP2016	CGDP2017
Frac. OnePager	-466.66 (448.76)	-493.80 (515.86)	-557.23 (623.72)	-473.94 (753.35)	-476.21 (886.56)
Frac. OnePager_CUC	857.06 (1,783.93)	977.13 (1,973.39)	994.50 (2,190.73)	1,150.76 (2,460.23)	1,189.46 (2,667.47)
Observations	47	47	47	47	47
Mean control group	2062	2062	2062	2062	2062
SD control group	3298	3658	4083	4618	5038

Note: Robust standard errors, clustered at the county level. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is the 2013 county GDP, expressed in Million USD PPP. The variable “OnePager” is the fraction of court stations in a county that received the One-Pagers.

APPENDIX F: BALANCE TEST WITH KIHBS

This section presents the balance test using the Kenya Integrated Household Budget Survey (KIHBS) 2015-2016. Column (1) of Table F1 shows a regression of gender (1 for males, 0 for females) on the fraction of court stations in the county treated with the OnePager or OnePager_CUC. There is no significant association there. Columns (2), (3), and (4) show no significant relationship between age, highest grade completed and wage in 2015.

TABLE F1—BALANCE TEST WITH KIHBS

	(1) Gender	(2) Age	(3) Highest Grade Completed	(4) Wage
Frac. OnePager	0.01 (0.01)	-1.75 (1.52)	-0.10 (0.13)	-18.26 (27.01)
Frac. OnePager_CUC	-0.00 (0.01)	-0.98 (1.41)	-0.11 (0.09)	51.98 (40.48)
Observations	92,846	92,846	69,353	38,681
Mean Dep Var	0.494	23.50	4.144	174.9
SD	0.500	30.76	2.352	394.3

Note: Robust standard errors, clustered at the county level. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1) the dependent variable is gender, a dichotomous variable equal to 1 for males, 0 for males. In Column (2), the dependent variable is age in years. In Column (3), the dependent variable is equal to the highest grade completed. In Column (4), the dependent variable is the wage, defined as the basic salary in last month. The variable “Frac. OnePager” is the fraction of court stations in a county that received the One-Pagers.

APPENDIX G: EFFECTS ON MAGISTRATE COURTS

TABLE G1—EFFECT ON ADJOURNMENTS IN MAGISTRATE COURTS

	(1)	(2) Slow	(3) Fast	(4) Above Median Adj.	(5) Below Median Adj.
OnePager * February 2019	-0.0078 (0.014)	-0.013 (0.015)	0.0097 (0.029)	0.011 (0.023)	-0.0034 (0.017)
OnePager CUC * February 2019	-0.025 (0.018)	-0.0054 (0.015)	-0.063 (0.040)	-0.016 (0.018)	-0.0067 (0.023)
OnePager * March 2019	0.0033 (0.016)	-0.0022 (0.020)	0.018 (0.024)	0.025 (0.030)	-0.0026 (0.019)
OnePager CUC * March 2019	-0.0097 (0.018)	0.0038 (0.019)	-0.038 (0.039)	-0.0055 (0.024)	0.018 (0.030)
OnePager * April 2019	-0.0080 (0.016)	-0.022 (0.019)	0.023 (0.025)	0.022 (0.028)	-0.025 (0.019)
OnePager CUC * April 2019	-0.020 (0.019)	-0.0096 (0.019)	-0.039 (0.038)	-0.023 (0.020)	0.012 (0.030)
OnePager * May 2019	0.014 (0.019)	0.00018 (0.022)	0.048 (0.031)	0.067* (0.035)	0.0017 (0.017)
OnePager CUC * May 2019	-0.011 (0.020)	0.00046 (0.021)	-0.037 (0.045)	-0.018 (0.027)	0.023 (0.026)
OnePager * After June 2019	0.0048 (0.018)	0.0067 (0.024)	0.0071 (0.020)	0.063* (0.033)	-0.010 (0.014)
OnePager CUC * After June 2019	-0.0041 (0.022)	0.031 (0.023)	-0.073* (0.040)	0.046 (0.034)	-0.0063 (0.014)
OnePager * Month Before	-0.0078 (0.014)	-0.015 (0.016)	0.015 (0.026)	0.024 (0.022)	-0.014 (0.017)
OnePager CUC * Month Before	-0.0062 (0.016)	0.0076 (0.019)	-0.034 (0.027)	0.0059 (0.020)	-0.020 (0.028)
Observations	7014231	4736841	2257886	3162403	3000988

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing in the Magistrate courts ends in adjournment, 0 otherwise. In Column (2), the sample is restricted to slow courts, i.e., with a baseline average time to disposition above the Kenyan average. In Column (3), the sample is restricted to fast courts, i.e., with a baseline average time to disposition below the Kenyan average. In Column (4), the sample is restricted to courts with baseline adjournments above the median level. In Column (5), the sample is restricted to courts with baseline adjournments below the median level.

APPENDIX H: EFFECTS ON OTHER OUTCOMES

Table H1 shows the effect on other outcomes of speed. Column (1) shows that more of the cases are resolved in February 2019 for both interventions, although less significantly so for the OnePager CUC intervention. Column (2) indicates that there are no more cases filed. This translates into an increased case clearance rate (CCR), which is the ratio of cases resolved over cases filed.

TABLE H1—EFFECT ON OTHER OUTCOMES

	(1) Resolved	(2) Filed	(3) CCR
OnePager * February 2019	0.042* (0.025)	-0.0014 (0.0086)	14.0 (13.1)
OnePager CUC * February 2019	0.0056 (0.013)	-0.011 (0.011)	19.4 (11.9)
OnePager * March 2019	0.024* (0.014)	0.00058 (0.0099)	15.3 (12.6)
OnePager CUC * March 2019	0.0034 (0.015)	-0.012 (0.011)	33.8** (13.8)
OnePager * April 2019	0.0100 (0.014)	0.0047 (0.011)	9.39 (12.7)
OnePager CUC * April 2019	0.024 (0.016)	-0.017 (0.014)	23.6* (12.7)
OnePager * May 2019	0.015 (0.015)	0.011 (0.013)	4.87 (16.5)
OnePager CUC * May 2019	0.034* (0.020)	-0.0088 (0.010)	7.27 (15.6)
OnePager * After June 2019	0.0075 (0.0096)	0.0025 (0.011)	-0.32 (4.77)
OnePager CUC * After June 2019	-0.014 (0.011)	0.019 (0.014)	-1.66 (4.92)
OnePager * Month Before	0.0073 (0.017)	-0.0079 (0.012)	5.50 (11.5)
OnePager CUC * Month Before	-0.0100 (0.014)	-0.0060 (0.015)	5.60 (10.7)
Observations	9047041	9047041	10512

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if a hearing ends in a resolution of the case, 0 otherwise. In Column (2), the dependent variable is a dichotomous variable equal to 1 if a case is filed, 0 otherwise. In Column (3), the dependent variable is the case clearance rate (CCR), which is the ratio of cases resolved during the month divided by the number of cases filed during the month (multiplied by 100), defined at the court level.

APPENDIX I: EFFECTS ON QUALITY

A criticism against increased speed due to the One-Pagers may come from “judges closing cases too quickly”, however, we find no evidence for this phenomenon: we find no effect on appeals, convictions or dismissals on the grounds that a case is frivolous.

Table I1 shows the regression results for these variables. Column (1) shows the impact on the probability that a case is an appeal (in the High Courts). This variable is a proxy for quality since lower quality decisions in Magistrate courts may lead to more appeals at the High Courts. There is no significant impact in February 2019.

Column (2) shows the impact on the probability of conviction. If cases are closed too early because of a desire to reduce delays, we might expect judges to rush their judgements and convict felons more often. There is no evidence of this in the data in February 2019, but there is a positive effect in March 2019 for the One-Pagers intervention.

Column (3) shows cases that are either terminated, dismissed, struck out, or case closed. We call these cases “frivolous” since they were dismissed by the judge without a judgement. Here the impact is a reduction in dismissals which suggests that judges were being more careful and not simply throwing out cases to increase speed.

TABLE II—EFFECT ON QUALITY

	(1) Appeal	(2) Convicted	(3) Frivolous
OnePager * February 2019	0.027 (0.024)	0.047 (0.031)	0.0026 (0.0067)
OnePager CUC * February 2019	-0.011 (0.024)	0.011 (0.0088)	-0.0019 (0.0057)
OnePager * March 2019	0.047 (0.029)	0.027** (0.013)	0.0020 (0.0034)
OnePager CUC * March 2019	-0.0095 (0.037)	0.017 (0.012)	-0.0015 (0.0051)
OnePager * April 2019	0.066 (0.051)	0.0079 (0.011)	-0.0045 (0.0040)
OnePager CUC * April 2019	-0.00031 (0.031)	0.020 (0.014)	-0.0036 (0.0079)
OnePager * May 2019	0.011 (0.037)	0.015 (0.013)	-0.0023 (0.0037)
OnePager CUC * May 2019	-0.021 (0.033)	0.016 (0.011)	0.0053 (0.0073)
OnePager * After June 2019	0.016 (0.048)	0.015* (0.0076)	-0.0018 (0.0041)
OnePager CUC * After June 2019	0.042 (0.039)	0.0064 (0.010)	-0.0098 (0.0061)
OnePager * Month Before	0.017 (0.036)	0.0037 (0.012)	-0.0022 (0.0051)
OnePager CUC * Month Before	-0.00094 (0.037)	0.0061 (0.011)	-0.0087 (0.0059)
Observations	1321777	9047041	9047041

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), the dependent variable is a dichotomous variable equal to 1 if the case is an appeal, 0 otherwise. This is defined only in the High Courts, hence the smaller sample. In Column (2), the dependent variable is a dichotomous variable equal to 1 if the hearing ends in a conviction, 0 otherwise. In column (3), the dependent variable is a dichotomous variable equal to 1 if the hearing ends in the case being either terminated, dismissed, struck out, or case closed; 0 otherwise. We call these cases “frivolous” since they were dismissed by the judge without a judgement.

APPENDIX J: DECOMPOSITION OF THE WAGE EFFECT

Column (1) replicates the effect on wage, from Column (7) of Table 9. When we include the contract variable as an additional regressor in Column (2), the coefficient OnePager sent to CUC drops dramatically. This lets on the idea that the effect on wage is partially due to this mechanism. Indeed, individuals with a written contract are paid more, significantly so (by a coefficient of 333 in Column (2)).

The intervention increases the probability to have a written contract by 4 percentage points as can be seen in Column (3), which themselves increase wages by 333. Thus, the intervention increase wages by $0.04 \times 333 = 13.32$ USD by that channel. This effect is significant at the 10 percent level.

This represents (Indirect effect = $13.32 / (\text{Direct Effect} = 66.68 + \text{Indirect effect} = 13.32) = 17$ percent of the total effect. Therefore, 17 percent of the increase in wages is due to the higher prevalence of written contracts.

TABLE J1—DECOMPOSITION OF THE EFFECT ON WAGES

VARIABLES	(1) Wage	(2) Wage	(3) Contract
Frac. OnePager * Post	58.50 (36.98)	39.47 (31.45)	0.03 (0.02)
Frac. OnePagerCUC * Post	98.37** (41.77)	66.58** (31.99)	0.04* (0.02)
Contract		332.96*** (12.48)	
Constant	357.06*** (8.14)	203.45*** (8.78)	0.36*** (0.00)
Observations	7,457	7,283	35,078
R-squared	0.065	0.324	0.045
County fixed effects	YES	YES	YES
Quarter FE	YES	YES	YES

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. The variable “Frac. OnePager” is the fraction of court stations in a county that received the One-Pagers. The variable “Post” is equal to 1 in the quarters 2, 3, and 4, and equal to 0 in quarter 1.

As a robustness check, we also use the sequential g-estimator and find that the proportion mediated is 22 percent, very similar to the decomposition exercise above.

APPENDIX K: EFFECT ON WAGE

Figure K1 below shows a binscatter of the relationship between the proportion of a county with the information and accountability treatments and wages of individuals in the county, controlling for the proportion of a county with only the information treatment. In the post period after treatment on the right-hand side, there is a clear positive relationship between the fraction of courts treated and the wage. There is no such relationship before the treatment on the left-hand side, which acts as a balance test.

FIGURE K1. EFFECTS ON WAGES

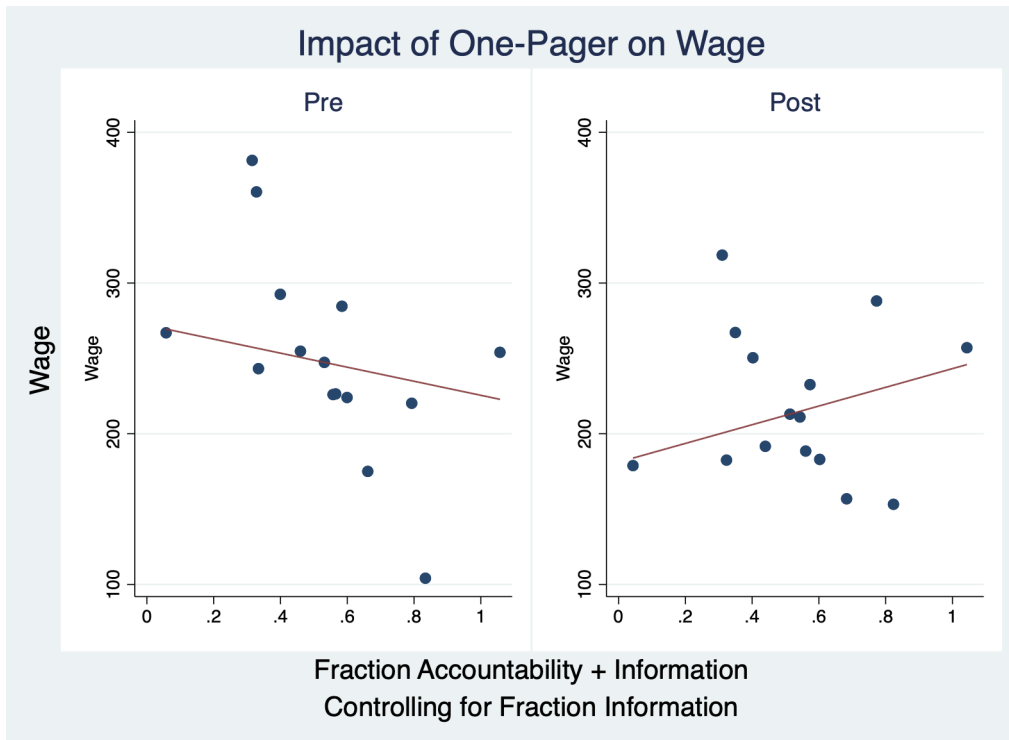
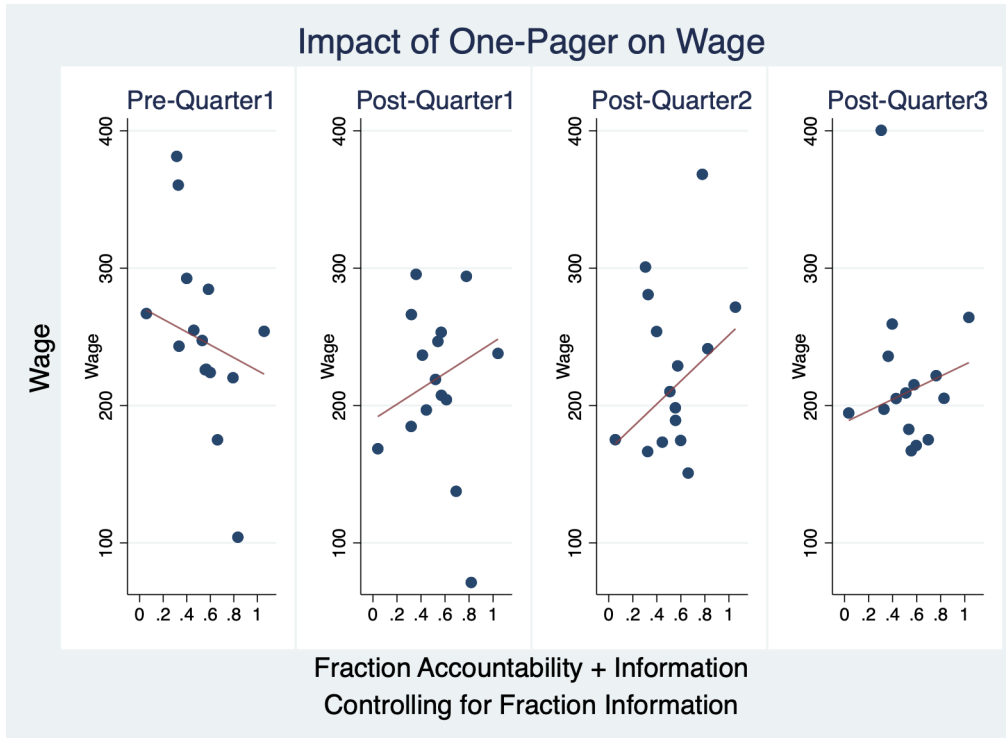


Figure K2 shows the effect per quarter. The effect is present in all quarters, and slightly weaker in the last quarter, in line with the effect on adjournment fading away after several months. We now dig deeper into the effect on wage by focusing on contract-intensive industries. Firms enter in contract with suppliers to acquire customized inputs. A more effective judiciary may foster these arrangements, incentivizing suppliers to produce quality inputs. Each worker in the downstream firm can spend less time correcting defective customized inputs and more time producing the output of the firm, which increases the marginal product of labor, and therefore wages, as shown formally in Appendix C.

We use the Kenya Continuous Household Survey Programme (KCHSP) to evaluate the economic

FIGURE K2. EFFECTS ON WAGES



effects on contract-intensive industries. Notably, the KCHSP also contains data on the industry in which the individual is working (using the International Standard Industrial Classification Revision 4, ISIC Rev 4). We thus classify each industry according to its reliance on contracts. We use an index of input complexity, which can be construed as a measure of the reliance on contract enforcement mechanisms. The intuition is that a more complex input mix will increase the dependence on contract enforcement mechanisms.

To measure input complexity, a large body of work pioneered by Levchenko (2007) uses 1 minus the Herfindahl index, calculated as the sum of the share of inputs from each supplier (squared).

If an industry has only one supplier (the input mix is not complex), the share of all inputs from this supplier is 1, and $1-1=0$. On the other hand, if an industry has numerous small suppliers, the sum of the share (squared) is close to zero, and $1-0=1$. The input mix is more complex, and the industry relies more on contracts with all of their suppliers.

We thus call this measure CI (contract intensiveness of the industry). To calculate it, we use the US Input-Output table available at the OECD.²³ We use this table since the goal is to measure the technological reliance of sectors on a complex input mix under a near-perfect judiciary. We calculate for each industry the Herfindahl index. The advantage of this methodology over others also used in

²³Available at: https://stats.oecd.org/Index.aspx?DataSetCode=IOTSI4_2018

robustness checks in this paper is that it uses the ISIC Rev 4 (such that no correspondence between sectors is needed) and it can be calculated for all firms, not just those in, say, the manufacturing sector.

In our sample, the mean of CI is 82 out of 100 (SD=11, median=86%). For ease of interpretation, we standardize CI in all the regressions below.

Figure K3 shows the effect on contract-intensive industries. Firms are classified as being contract intensive according to the median of the indicator used above (which was 86% for CI). The left hand side shows that the effect is present in such industries, not so in other industries, in line with the theory that faster courts disproportionately benefit firms in contract intensive sectors.

FIGURE K3. EFFECTS ON WAGES IN CONTRACT INTENSIVE INDUSTRIES

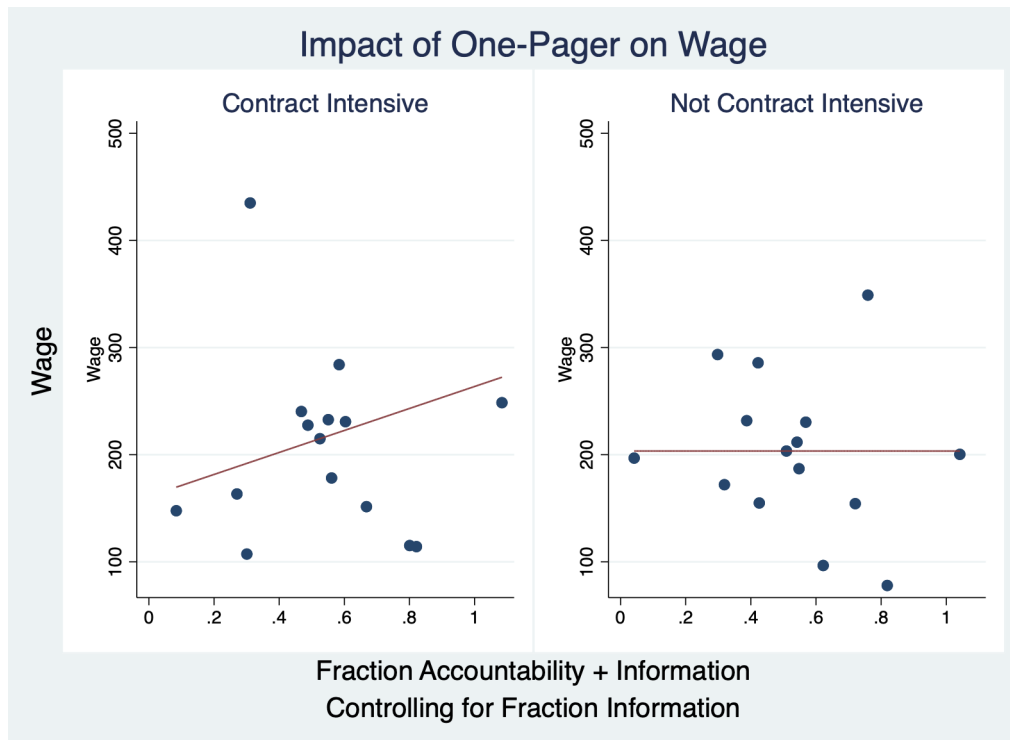


Table K1 presents the regression results. The dependent variable in this table is the wage. Column (1) shows that the wage increases in those counties which had a greater share of courts treated by the intervention, in particular the One-Pagers sent to the CUCs, in line with our earlier results showing greater effect on the judicial speed in those courts.

Column (1) shows the average impact on wages to be 98.4 over a mean of 261. This translates to a 37% increase in wages. The magnitude of this association is in the ballpark of cross-country correlations on the association between case speed and GDP per capita. The cross-country cor-

relation between case duration (Data from Doing Business project, time to enforce a contract) and GDP per capita is -0.5, indicating that a 20% decrease in case duration is associated with a $(20 \times 0.5 =)$ 10 percent increase in GDP per capita. We find a 37% increase in wages, yet this is only for people reporting a wage (7,457 from column (1) Table K1 out of 34,887 individuals in the labor force from column 5 Table K3, which represents $7,457/34,887 = 21\%$ of the population). Thus, the overall effect is $(37\% \times 0.21 =)$ 8%, very similar to the cross-country correlation. In summary, we find that cross-sectional and experimental variation all yield roughly similar estimates. These results support the notion that speed of justice causally impacts economic growth.

The effect is observed only in Quarter 3, and becomes less significant in Quarter 4, as shown in Column (2). Thus, the effect appears strongest in the short-run, in line with the short-term effect of the one-pagers observed above.

The effect is primary driven by contract-intensive industries, as shown in Column (3). The coefficient of the interaction “Frac. OnePager_CUC * Post * CI” is 76, statistically significant. This means that a one standard deviation increase in the Contract Intensiveness measure increases the treatment effect by 76 USD PPP. The average wage being 263 USD PPP, this corresponds to a 29 percent increase in the wage.

Columns (4) and (5) confirm that there is no significant effect in industries below the median of the CI index, there statistically significant effect appears in industries above the median of the Herfindahl index.

The results are the same if we use different measures of contract intensity. Our preferred measure in Table K1 uses the US Input-Output table from the OECD. The advantage is that these tables uses the ISIC Rev 4, the same code as in the KCHSP, such that no correspondence between sectors is needed. Thus, we are able to assign a value to each observation in the KCHSP. The downside is that the OECD tables are only at the 2 digit level, a relatively coarse classification.

In Table K2 below, we thus use the US Input/Output table from the Bureau of Economic Analysis.²⁴ The advantage is that these tables are much more disaggregated, at the 6 digit level. In fact, the inputs are at the commodity level, the most disaggregated level of analysis. The downside is that this table uses the BEA codes, which must be converted into the North American Industry Classification System (NAICS), which must be themselves converted into ISIC Rev4. We use the official correspondence tables (available at: <https://unstats.un.org/unsd/classifications/Econ/isic>), yet the link is not 1 to 1, such that some industries in the BEA table have multiple ISIC codes, and vice versa. Some observations in the KCHSP have also no natural match in the data. Still, we

²⁴available at: <https://www.bea.gov/industry/input-output-accounts-data>

TABLE K1—EFFECTS ON CONTRACT-INTENSIVE INDUSTRIES

	(1)	(2)	(3)	(4)	(5)
	Wage	Wage	Wage	Above Median CI	Below Median CI
Frac. OnePager * Post * CI			61.61 (46.95)		
Frac. OnePagerCUC * Post * CI			76.18** (34.96)		
Frac. OnePager * Post	58.50 (36.98)		52.40 (36.93)	93.36 (67.34)	39.02 (40.60)
Frac. OnePagerCUC * Post	98.37** (41.77)		106.88** (44.29)	177.71** (81.57)	66.28 (48.04)
Frac. OnePager * Quarter 2		61.67 (45.16)			
Frac. OnePagerCUC * Quarter 2		73.25 (48.16)			
Frac. OnePager * Quarter 3		71.74** (34.70)			
Frac. OnePagerCUC * Quarter 3		139.61*** (43.15)			
Frac. OnePager * Quarter 4		35.97 (46.34)			
Frac. OnePagerCUC * Quarter 4		82.97 (51.31)			
Observations	7,457	7,457	6,857	2,189	4,668
County fixed effects	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES
CI	NO	NO	YES	NO	NO
Mean control group	261	261	261	261	261
SD control group	319.3	319.3	319.3	319.3	319.3

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In all columns, the dependent variable is the wage, defined as the basic salary in last month. The variable “Frac. OnePager” is the fraction of court stations in a county that received the One-Pagers. The variable “Post” is equal to 1 in the quarters 2, 3, and 4, and equal to 0 in quarter 1. The variable CI is the standardized measure of the reliance on contracts of a certain industry. The variable “Frac. OnePager * Post * CI” is the variable of interest, and measure the effect of the reform in contract-intensive sectors.

compute the CI index of each BEA code, and take the average of those indices per ISIC codes.

Column (2) presents the results, with a significant coefficient for $Frac.OnePagerCUC_c \times Post_t \times CIBEA_j$. This is all the more remarkable in that the sample is very different, in fact much smaller, due to the imperfect match. Our main result is thus robust to using a much more disaggregated measure of contract intensity, in a different sample.

TABLE K2—OTHER MEASURES OF CONTRACT INTENSITY

	(1)	(2)	(3)	(4)
		Wage		
Frac. OnePager * Post * CI	61.61 (46.95)			
Frac. OnePagerCUC * Post * CI	76.18** (34.96)			
Frac. OnePager * Post	52.40 (36.93)	56.18 (63.25)	24.64 (41.85)	27.78 (46.97)
Frac. OnePagerCUC * Post	106.88** (44.29)	94.39 (60.38)	34.66 (47.52)	31.84 (46.14)
Frac. OnePager * Post * CI BEA		-2.95 (18.46)		
Frac. OnePagerCUC * Post * CI BEA		42.79* (21.42)		
Frac. OnePager * Post * CI WBES			-13.43 (23.41)	
Frac. OnePagerCUC * Post * CI WBES			60.93** (28.42)	
Frac. OnePager * Post * CI I/O WBES				-14.52 (50.64)
Frac. OnePagerCUC * Post * CI I/O WBES				73.08** (32.69)
Observations	6,857	3,513	2,582	2,582
County fixed effects	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Contract-Intensity	YES	YES	YES	YES
Mean control group	261	261	261	261
SD control group	319.3	319.3	319.3	319.3

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In all columns, the dependent variable is the wage, defined as the basic salary in last month. In Column (1), the variable CI is the standardized measure of the reliance on contracts of a certain industry, using the US Input/Output table from the OECD. In Column (2), the variable CI BEA uses the US Input/Output table from the Bureau of Economic Analysis. In Column (3), the variable CI WBES uses the World Bank Enterprise Surveys. In Column (4), the variable CI I/O WBES is calculating the ratio of inputs to output using the World Bank Enterprise Surveys.

In Column (3), we use a completely different source of data for contract intensity: the World

Bank Enterprise Surveys (WBES). We restrict the sample to the wealthiest countries in that sample (Belgium, Denmark, Ireland, Italy, Luxembourg, Netherlands, Portugal, Sweden). For each firm in these surveys, we compute the Herfindahl index based on the inputs disaggregated into nine categories in the Enterprise surveys (labor, raw materials and intermediate inputs, electricity, communications services, fuel, transport for inputs, water, rental of land/buildings, equipment, furniture). We then average at the four digit industry code. The issue is that the World Bank Enterprise Surveys use ISIC Rev3.1. We thus use the correspondence tables to match these codes to revision 4. The matches are imperfect, which explain the smaller sample size when using this methodology.

Column (3) shows that the interaction term $Frac.OnePagerCUC_c \times Post_t \times CIWBES_j$ is statistically significant when using this completely different measure.

In Column (4), we use a completely different measure of contract intensity. Rather than the concentration of input use, it may be the total value of inputs with respect to output that makes firms dependent on the judiciary. In other words, firms using more inputs into their production rely more on contracts. Thus, we use the total input to output value ratio as an alternative measure. If the index is zero, the firm is not using any inputs and is not relying on any contracts with suppliers. As the index increases, the firm relies more on contracts and on contract enforcement mechanisms.

Column (4) of Table K2 shows that firms in sectors with a higher total input to output ratio benefit more from this judicial reform.²⁵

Table K3 shows that the result stays the same with different trimming of the wages (3 standard deviation, Column (2)), or using the log of wages (Column (3)), or using another measure of wage in the dataset (Total Gross Pay including Allowances (house, medical, transport and other allowances received), Column (4)). Column (5) shows no effect at the extensive margin of receiving a wage (a dummy equal to 1 if the individual receives a wage, 0 otherwise).

Overall, we find that contract intensive industries benefit from this judicial reform. A natural explanation for these findings is that firms in contract intensive industries can rely more on contracts and have greater confidence in their capacity to resolve disputes.

Table K4 shows that the effect on other outcomes. There is a slight increase in non-farm activities (Column (1)), in “white collar” occupations (in Column (2) or compared to “blue collar”

²⁵Another measure suggested by Nunn (2007) is to use the proportion of inputs sold on internationally organized exchanges. The intuition is that inputs sold on internationally organized exchanges are generic, while inputs not sold on internationally organized exchanges are specific, and thereby necessitates relationship-specific investments. The issue is that this data uses ISIC Rev 2, for which there is no existing correspondence with ISIC Rev4. We attempted a manual match between ISIC Rev2 and Rev4, and the resulting sample size was only 355 observations. The sample is small because the match is not perfect between ISIC Rev 2 and ISIC Rev4. Moreover, the methodology is only available the manufacturing sector, which is small in Kenya. This is why our preferred estimate is using the Input/Output tables which includes all sectors of the economy.

TABLE K3—OTHER MEASURES OF WAGE

	(1)	(2)	(3)	(4)	(5)
	Wage	Wage Trim 3 sd	Log Wage	Total Gross Pay	Extensive Margin Wages
Frac. OnePager * Post * CI	61.61 (46.95)	63.25 (45.94)	0.37 (0.32)	59.99 (59.51)	0.022 (0.033)
Frac. OnePagerCUC * Post * CI	76.18** (34.96)	74.91** (35.45)	0.33* (0.18)	110.21* (57.14)	0.005 (0.026)
Frac. OnePager * Post	52.40 (36.93)	45.80 (37.56)	0.26 (0.35)	69.39 (64.07)	0.016 (0.037)
Frac. OnePagerCUC * Post	106.88** (44.29)	103.29** (44.23)	0.55 (0.35)	173.95** (67.44)	-0.008 (0.029)
Observations	6,857	6,827	6,857	3,574	34,887
County fixed effects	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES
CI	YES	YES	YES	YES	YES
Mean control group	261	261	8.225	436.4	0.0921
SD control group	319.3	319.3	1.819	462.4	0.289

Note: Robust standard errors, clustered at the level of the court. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent.

occupations in Column (3)), a slight increase in the number of months worked. Overall, these results paint a picture of a growing formal sector, in line with a structural change.

TABLE K4—OTHER OUTCOMES

	(1)	(2)	(3)	(4)
	Non-farm	White Col.	White vs Blue	Months worked
OnePager * Quarter 2	0.05 (0.06)	0.01 (0.01)	0.05 (0.04)	-0.06 (0.25)
OnePager_CUC * Quarter 2	0.10* (0.06)	0.03** (0.01)	0.11* (0.06)	0.43 (0.25)
OnePager * Quarter 3	0.03 (0.08)	0.02** (0.01)	0.13*** (0.05)	-0.04 (0.32)
OnePagerCUC * Quarter 3	0.03 (0.06)	0.04*** (0.01)	0.18*** (0.06)	0.45 (0.28)
OnePager * Quarter 4	-0.05 (0.07)	0.01 (0.01)	0.09* (0.05)	0.22 (0.39)
OnePagerCUC * Quarter 4	0.07 (0.05)	0.04*** (0.01)	0.19*** (0.06)	0.73* (0.37)
Observations	34,894	86,647	15,878	19,947
County fixed effects	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES
Mean control group	0.398	0.0569	0.326	9.431
SD control group	0.490	0.232	0.469	3.152

Note: Robust standard errors, clustered at the level of the county. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In all columns, the dependent variable is the wage, defined as the basic salary in last month. In Column (2), tenure is the number of years on the job. In Column (3), gender is a dichotomous variable equal to 1 if male, 0 if female. In Column (4), age is in years. In Column (5), tenure is the number of years on the job. In Column (6), education is a set of dummies for: junior_secondary senior_secondary certificate undergrad grad adult_ed vocational madrassa. Primary school is the omitted category. In Column (7), household size is the number of individuals in the household.

It is important to keep in mind that this analysis on contract-intensive industries and these other outcomes are merely suggestive because they were not pre-specified in the pre-analysis plan.

APPENDIX L: FALSIFICATION EXERCISE WITH WAGES OF TEACHERS

Wages of teachers are set nationally in Kenya. Thus, these wages should not differ in the treatment group versus control group. This is what we find in Table L1. We use various definitions of teachers. In Column (1), we define an individual as a teacher if their Kenya National Occupational Classification Standard (KNOCS) corresponds to code 250: Teaching Professionals (see the table footnotes for the exact definition). There are no differences between the control group and the OnePager or OnePager_CUC treatment groups, as expected.

In Column (2), we adopt a more restrictive definition to focus solely on primary and secondary school teachers (KNOCS codes 252 and 371).

In Column (3), we use the International Standard Industrial Classification Revision 4 (ISIC Rev 4) instead of the KNOCS to define teachers. In Column (4), we adopt a more restrictive definition to focus solely on primary and secondary school teachers (ISIC4 codes 851, 8510, 852, 8521).

Not all teachers are in the public sector. In Column (5), we use an entirely different question (Who was the main employer for primary job / business? Code 5: Teachers Service Commission).

All of these tests show no significant differences between the control group and the OnePager or OnePager_CUC treatment groups. This is as expected since teachers wages are set nationally and should thus not vary across geographical areas.

TABLE L1—WAGES OF TEACHERS

	(1)	(2)	(3)	(4)	(5)
Definition of Teacher:	KNOCS	KNOCS Reduced	ISIC4	ISIC4 Reduced	TSC
Frac. OnePager * Post	63.86 (77.62)	98.67 (78.00)	83.38 (69.71)	67.42 (70.86)	107.86 (93.71)
Frac. OnePagerCUC * Post	55.65 (102.08)	-14.71 (102.26)	26.84 (100.52)	15.43 (101.72)	44.25 (107.25)
Observations	771	612	988	918	417
County fixed effects	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES
Mean control group	483.8	527.2	419.3	420.7	671.5
SD control group	360.9	366.3	352.4	354.4	349.8

Note: Robust standard errors, clustered at the county level. *** Significant at 99 percent confidence-interval, ** Significant at 95 percent confidence-interval, * Significant at 90 percent. In Column (1), we restrict the sample to teachers defined as such if their Kenya National Occupational Classification Standard (KNOCS) is: 250: Teaching Professionals, 251: University and Post-Secondary Teachers/Lecturers, 252: Secondary and Technical Institute Teachers and Instructors, 253: Special Education Teaching Professionals, 254: Education Methods Advisers and Assessors, 259: Other Teaching Professionals, 370: Primary and Pre-primary education and Other Teachers, 371: Primary Education Teachers, 372: Pre-primary Education Teachers, 373: Other Teachers and Instructors. Column (1) restricts the sample to these individuals only. In Column (2), we restrict the sample to primary and secondary school teachers (KNOCS 252 and 371). In Column (3), we define an individual as a teacher if their ISIC4 codes are: 85 Education, 851 8510 Pre-primary and primary education, 852 Secondary education, 8521 General secondary education, 8522 Technical and vocational secondary education Higher education, 853 8530 Higher education, 854 Other education, 8541 Sports and recreation education, 8542 Cultural education, 8549 Other education n.e.c., 855 8550 Educational support activities. In Column (4), we adopt a more restrictive definition to focus solely on primary and secondary school teachers (ISIC4 codes 851, 8510, 852, 8521). In Column (5), we use an entirely different question (Who was the main employer for primary job / business? Code 5: Teachers Service Commission). The variable “Frac. OnePager” is the fraction of court stations in a county that received the One-Pagers.