Illicit Assignments of Cases to Judges in Ecuador

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Abstract

I develop tools to detect illicit assignments of cases to judges and apply them to Ecuador's judicial system. I construct a database of over 2 million case assignments in Ecuador's district courts from 2016 to 2020 and I find that at least 2.9% of assignments are inconsistent with existing Ecuadorian regulations. The bulk of such assignments concentrate on a handful of judges and courts. These lower bounds are sharp. I obtain aggregate, regional and temporal variation in illicit assignments using novel instrumental variables that are excluded from a single counterfactual outcome. Concrete knowledge of the distribution of the case assignments that would be observed, had they been consistent with existing regulations, yields tighter bounds as well as informative judge-specific measures of illicit assignments. In any case, the upper bound on the extent of illicit assignments is uninformative.

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Strict regulations of judicial case assignments to judges are widespread nowadays and go back, at least, to the 4th century BCE in Athens.[1] Such regulations often mandate random assignment and aim to abolish the market for judges, in which judicial decisions are biased towards the party with a higher willingness to pay for a favorable decision, the party that files the case and, hence, has a first-mover advantage, or the party that knows more about the set of available judges (Egan, Matvos, and Seru 2021). A successful implementation of such regulations requires enforcement resources, and such resources may be limited in judiciaries of low and middle income countries. In these contexts, a non-trivial amount of actual assignments could be *illicit*, meaning that they are inconsistent with existing regulations.[2]

How many case assignments are illicit? How does the share of illicit assignments vary across courts? Across judges? This paper develops tools to address these questions in any given judiciary, and answers them in the context of Ecuador's district courts.[3] I construct a novel database that contains information on over 2 million case assignments made in district courts between March, 2016 and February, 2020, and I find that at least 2.9% of case assignments are illicit, or inconsistent with existing Ecuadorian regulations. The illicit assignments that I detect are concentrated in few courts. I conclude that at least 111 judges (out of 1568) received cases with illicit assignments in this period.

At the heart of these measurements is knowledge of the existing case assignment regulations, which may be open to interpretation. On one end of the spectrum, we might infer from the regulations a probability distribution of the judge that a case should be assigned to.[4] On the other end, we might only infer that certain judicial case characteristics do not influence the judge that the case should be assigned to, such as the plaintiff's friendly ties with government officials, or the amount of

[1] During the 4th century BCE, athenian jurors were randomly selected to participate in a given trial using a random, multi-stage selection process that involved an allotment machine called a *kleroterion*. See Dow (1937) p.198.

[2] This situation contrasts with that of countries like Norway or certain judiciaries in the United States, where random assignment of cases to judges is not a topic of concern, and heterogeneity in judge leniency underpins judge leniency instrumental variable designs (e.g. Kling 2006 in the United States, or Dahl, Kostøl, and Mogstad 2014 in Norway).

[3] District courts are Ecuador's courts of first instance, the lowest-ranking courts in Ecuador's judicial system.

[4] Conditional on the set of jurors of each tribe that showed up for a given trial and the jury size required by the trial, Athenian regulations presumably implied a uniform distribution over the set of possible juror combinations of the given jury size that satisfied a fixed ratio of tribal representation.

money claimed in a payment dispute. Each interpretation implies a separate identification assumption that, paired with observed assignments, informs the probability that a case's assignment is illicit. However, the more precise interpretation of the regulations is more informative and, in particular, allows one to measure a second parameter of interest: the probability that a case's assignment is illicit, conditional on a given judge. This parameter gives a granular view on the structure of illicit assignments and is a valuable input to guide the allocation of regulatory enforcement resources.

The tools developed in this paper are relevant for a variety of settings, beyond the detection of illicit assignments of cases to judges. Auctions have well defined allocation rules that need not be consistent with observed allocations. Government hiring schemes may be inconsistent with actual hiring decisions. Lottery winners may not be randomly selected. These situations involve a mechanism that allocates individuals to a finite number of categories and is (partially) known to the researcher. Does the mechanism generate the allocations that we observe? More broadly, the framework fits situations where the researcher is interested in the mixing weight of a discrete, two-component mixture model and knows about one of the mixture components, either in the form of a known distribution, or in terms of an individual characteristic that is arguably excluded from that component, but is not necessarily excluded from the other.

I begin by casting the measurement problem as a potential outcomes model that relates the judge that a case is assigned to with the judge that the case would have been assigned to, had its assignment been illicit, and the judge that the case would have been assigned to, had its assignment been licit (or in accordance with existing regulations). The counterfactual assignment that is observed will depend on whether the case's assignment is illicit or not. Unlike program evaluation models, where the treatment status is observed, we do not observe any case's illicit assignment status. Indeed, the distribution of the case's illicit assignment status is the object of interest. Thus, our model involves a discrete, two-component mixture.

I then study two identification assumptions. The first assumption corresponds to the less precise interpretation of the regulations: we observe a case characteristic that is statistically independent of counterfactual licit assignments only. I call such an instrumental variable a *one-sided instrument*. One-sided instruments are weaker than traditional instrumental variables (e.g. Imbens and Angrist 1994), which require exclusion from both counterfactual outcomes, and their identification power has not been studied in the context of mixture models. They differ from the instrumental variables studied by Henry, Kitamura, and Salanié (2014), which are excluded from observed outcomes, conditional on the unobserved state – the case's illicit assignment status.[5] The second assumption I consider corresponds to the stronger interpretation of the regulations: the probability mass function of counterfactual licit assignments is known.

For each assumption, I obtain analytical solutions for the sharp bounds on our parameters of interest. In either case, this is a two step process. First, I show that the parameters of interest are examples of linear and scalar parameters whose identified sets are obtained by solving two linear programming problems. Related characterizations can be traced back to Balke and Pearl (1997) in program evaluation models, and our characterization can be seen as a special case of Lafférs (2019), who shows that the identified set of a given discrete data-generating process under arbitrary linear restrictions can be recovered with standard linear programming tools. Then, I reformulate the linear programs that define the lower bounds for our parameters of interest in terms of optimal transport problems with convenient graphical interpretations and obtain their closed-form solutions.

The resulting bounds are simple. If the distribution of counterfactual licit assignments is known, the lower bound on the probability of an illicit assignment equals the absolute (ℓ_1, taxicab, Manhattan) distance between this distribution and that of actual assignments. With a binary one-sided instrument, this lower bound equals the absolute distance between the two conditional distributions of actual assignments, weighted by the mass of the smaller group, defined in terms of the instrument values. Neither assumption yields informative upper bounds. Going further, knowledge of the distribution of counterfactual licit assignments implies that the probability of an illicit assignment conditional on a given judge is greater than the share of cases that the judge received in excess of what she should have received.

I then apply these findings in Ecuador, a country with a GDP per capita that is roughly ten times smaller than that of the U.S. (2019, World Bank), where multiple scandals involving manipulated assignments of cases to judges have surfaced in recent years. According to Ecuadorian regulations, the set of judges that a case can be assigned to depends on the case's location and field of law (i.e. whether the case pertains to criminal law, family law, administrative law, etc...). Within a

[5]They also differ from the mismeasured counterparts used in the literature on data misclassification, which satisfy the same exclusion restriction as the instrumental variables of Henry, Kitamura, and Salanié (2014) (see Bollinger 1996, Mahajan 2006, Hu 2008 and DiTraglia and García-Jimeno 2019).

court, judges are selected on the basis of a lottery system that is partially specified, but takes the judges' case workloads into consideration.

My primary data source is the public, plain text version of the government's database of judicial cases, available in a government website.[6] To obtain these data, I crawled the website in early 2021. I then structured the lottery certificates contained in these data, to obtain information on over two million case assignments, performed between March, 2016 an February, 2020 in Ecuador's 331 district courts.

The recent case assignment scandals and my conversations with government officials reveal that illicit assignments arise in many ways. The plaintiff may misreport the case's location to target certain courts or file and withdraw the case until it is assigned to a specific judge; a judge may take a medical leave precisely when a certain case will be assigned; personnel in the case assignment office may manipulate the computer program that generates assignments. The tools that I develop will detect some of these illicit assignments, but not others. They detect illicit assignments made within the case's assigned court and time period of assignment. Thus, the lower bounds on illicit assignments include those that target a specific judge within a court, but not those with manipulated locations or fields of law.

The one-sided instrument that I consider is the amount of documentation that the plaintiff or prosecutor provide when they file the case. This case characteristic is a measure of case complexity that approximates their willingness to pay for a favorable outcome. Its internal validity stems from the fact that, conditional on the case's court, field of law and time period of assignment, it does not influence the judge that should be selected according to the regulations. This instrument reveals that at least 0.8% of case assignments were illicit. 17 courts account for 80% of these assignments. In particular, one court accounts for a third of these assignments, with 3.2 thousand illicit assignments detected.

A more specific interpretation of the regulations is that, conditional on the observed court, field of law and time of assignment, a case is assigned to each of the available judges with equal probabilities. I assume that a judge is available for a given case if she is in an active spell at the time of the case's assignment, and if she has a small enough case workload, as compared with her peers. Each criterion is governed by a parameter that I select so as to obtain a conservative lower bound on the probability that a case's assignment is illicit. This exercise implies that 2.9% of case assignments are illicit. 70 courts account for 80% of these assignments. 111

[6] http://consultas.funcionjudicial.gob.ec/informacionjudicial/public/informacion.jsf

judges out of 1568 received cases with illicit assignments.

Finally, I validate my judge-specific measures of illicit assignments. Judges that I conclude received illicit assignments are more likely to have faced corruption charges and. Anecdotally, the judge that received the largest amount of cases with illicit assignments faced corruption charges shortly after the end of my sample period.

The primary contribution of this paper is to develop tools to quantify the extent of illicit assignments of cases to judges on the basis of existing regulations and observed assignments. Our setting is close to that of Daljord et al. (2021), who measure the extent of black market trade of Beijing license plates under a local government rationing policy. When the distribution of counterfactual licit assignments is known, the lower bound on the probability that a case's assignment is illicit equals their optimal transport estimator of the lower bound on the probability that a license plate is traded in the black market. I build on their analysis by introducing one-sided instrumental variables as a means to estimate the same parameter without imposing knowledge of the distribution of a counterfactual outcome. Second, I show that their optimal transport estimator equals the sharp lower bound on the parameter of interest when knowledge of the distribution of one counterfactual outcome is imposed.

My application to Ecuador's judiciary showcases the practical value of these tools to quantify behavior that is typically hard to measure. Indeed, early studies of government corruption (Reinikka and Svensson 2004, Fisman and Wei 2004, Olken 2006) rely on access to the joint distribution of actual outcomes and a potentially noisy measure of the outcomes that would have been observed, had there been no corruption.

From an econometric point of view, this paper introduces one-sided instruments to study non-parametric identification of mixture models (e.g. Hall and Zhou (2003), Henry, Kitamura, and Salanié (2014), Compiani and Kitamura (2016), Kitamura and Laage (2018)). My linear programming formulation of the identified set for the parameters of interest can be seen as an application of Lafférs (2019), is inspired by Tebaldi, Torgovitsky, and Yang (2019), and echoes the early work of Balke and Pearl (1997), who characterize the identified set for the average treatment effect in terms of linear programming problems. In my setting, I do not observe a proxy variable for the cases' illicit assignment statuses, a common feature in the data misclassification literature (e.g. Bollinger 1996, Mahajan 2006, Molinari 2008, Hu 2008 and DiTraglia and García-Jimeno 2019), I do not have access to the illicit assignment status for a subset of cases, as in Molinari (2010), nor can I credibly set an upper bound on the probability that a case's assignment is illicit, as in Horowitz and Manski (1995).

I organize the paper as follows. Section 1 introduces the econometric framework in a stylized environment, presents the identification results, and develops the identification analysis. Section 2 then discusses the Ecuadorian context and the available data. Section 3 adapts the econometric framework to the Ecuadorian context and discusses estimation. Section 4 presents the estimation results and section 5 concludes.

1 Illustrative Framework

This section illustrates my identification results in a stylized econometric framework and presents applications beyond the assignment of cases to judges. This framework forms the basis for the empirical model that I use to measure illicit assignments in Ecuador.

1.1 Setting

Consider a stylized setting where a number of judicial cases, indexed by i, are assigned to one of n_Y judges who worked in a given court during a specified time period (e.g. a quarter). Let Y_i denote the judge that case i is assigned to. Label judges from 1 to n_Y, so that Y_i is an observed random variable that takes values in $\{1, \ldots, n_Y\}$.

In this setting, there exist regulations that specify how cases should be assigned to these judges. For example, regulations could mandate simple random assignment, or simple random assignment among a subset of judges. In practice, however, case i's assignment may be inconsistent with these regulations. If this is the case, we say that i's assignment is *illicit*. We do not observe whether a given case assignment is illicit or not, but denote this latent binary status with random variable S_i.

Illicit assignments can arise for various reasons. Some reasons, such as administrative errors, do not necessarily involve illegal behavior; others, such as transactions in the black market for judges, do; and some may involve behavior whose legal status is unclear, as with judge shopping – the practice of filing and withdrawing the same case multiple times, until the case is assigned to the desired judge.

We can think of two counterfactual assignments for any given case. The first counterfactual assignment is the judge that case i would have been assigned to, had its assignment been illicit. The second one is the judge that case i would have been assigned to, had its assignment been *licit*, or consistent with the regulations. We denote counterfactual illicit assignments with variable $Y_i(1)$ and counterfactual licit assignments with variable $Y_i(0)$. They relate to actual assignments Y_i according to the potential outcomes equation:

$$Y_i \quad = \quad S_i Y_i(1) \ + \ (1 - S_i) Y_i(0). \tag{1}$$

That is, the judge that case i is assigned to equals $Y_i(1)$ if i's assignment is illicit

($S_i = 1$), and equals $Y_i(0)$ otherwise.

For the sake of illustration, I ignore case i's covariates. I am interested in two parameters: the share of case assignments that are illicit, and the share of cases assigned to a given judge whose assignment is illicit: $\Pr(S_i = 1)$ and $\Pr(S_i = 1 \mid Y_i = y)$, respectively. In this setting, these parameters offer a detailed view of the extent and structure of illicit assignments. This information is policy-relevant in at least two dimensions: it informs the allocation of regulatory enforcement resources, and it provides a basic measure of the performance of the judiciary.

To measure these quantities, however, we need assumptions.[7] I consider two alternative assumptions. First, that the researcher observes a case characteristic Z_i that does not affect the judge that the case would have been assigned to, had the case's assignment been licit. Second, that the distribution of licit assignments is known.

Assumption IV. *Z_i is statistically independent of $Y_i(0)$.*

Assumption SHP. *The probability mass function of $Y_i(0)$ is known.*

Before we discuss each of these assumptions and their identification power, note that neither assumption is strong enough to point identify the parameters of interest. Assumptions IV and SHP place no restrictions on the distribution of illicit assignments, $Y_i(1)$. Thus, one cannot discard the possibility that assignments coincide with illicit assignments, $\Pr(Y_i = Y_i(1)) = 1$. In this case, every case assignment can be illicit: $\Pr(S_i = 1) = 1$ and $\Pr(S_i = 1 \mid Y_i = y) = 1$. The goal of our identification analysis is to obtain informative lower bounds on these quantities.

1.2 Beyond Cases and Judges: Applications

The allocation of cases to judges is an instance of a broader setting where individuals are allocated to a finite number of categories. The setting in section 1.1 generalizes as follows. Redefine i to index individuals, and let Y_i denote the observed category that i is allocated to. There is a given allocation rule, and we are interested in the extent to which it generates the observed allocations. If it does so for individual i, the unobserved random variable S_i equals 0. Otherwise, it equals 1. The allocation

[7] Notice that, at this stage, we do not observe any component on the right-hand side of (1). Thus, we cannot discard the possibility that $\Pr(S_i = 1) = 1$ and $\Pr\big(Y_i = Y_i(1)\big) = 1$. Similarly, it is possible that $\Pr(S_i = 1) = 0$ and $\Pr\big(Y_i = Y_i(0)\big) = 1$.

rule may depend on individual inputs, called *messages*, so that $Y_i(0) = Y_i(0, M_i)$, where M_i is i's message, a random variable that takes values in a known, finite message space $\mathcal{M}$. The object of interest is $\Pr(S_i = 1)$: the extent to which observed allocations are not generated by the decision rule.

Notice that, if M_i is observed and $Y_i(0, m)$ is known and degenerate, for all $m \in \mathcal{M}$, then the researcher effectively observes the joint distribution of $(Y_i, Y_i(0))$. Thus, without further assumptions, S_i is known to equal one with certainty whenever $Y_i \neq Y_i(0)$. When $Y_i(0, m)$ is random, observations of individuals' messages endow the researcher with the probability mass function of $Y_i(0) \mid M_i = m$, for all $m \in \text{supp}(M_i)$, which implies Assumption SHP.[8] If the researcher does not observe individuals' messages, however, knowledge of the distribution of $Y_i(0)$ is out of reach. In this situation, Assumption IV becomes useful, because the known message space $\mathcal{M}$ and the distributions of $Y_i(0, m)$ for all m may show which individual characteristics are independent of allocations drawn by the decision rule.

1.3 Identification Results under Assumption IV

In conjunction with (1), Assumption IV views the case characteristic Z_i as a source of variation in actual assignments Y_i that operates through S_i and/or $Y_i(1)$ exclusively. I call this instrumental variable a *one-sided instrument*. It imposes satisfies less assumptions than a traditional instrument that is excluded from $(Y_i(0), Y_i(1))$ (e.g. Imbens and Angrist 1994). It differs from, and is weaker than, the traditional exclusion restriction (e.g. Imbens and Angrist 1994), whereby the instrument generates variation in assignments through S_i only (i.e. statistical independence holds with respect to $(Y_i(0), Y_i(1))$). It also differs from the exclusion restriction proposed by Henry, Kitamura, and Salanié (2014), which requires that Z_i be independent of Y_i, conditional on S_i.[9]

In my application, Z_i is a binary measure of the amount of documentation submitted by the plaintiff/prosecutor when she files the case. In support of Assumption IV, I argue that Ecuadorian regulations do not contain specific assignment procedures for cases that differ along this dimension, and that this case characteristic is independent of the case characteristics that determine licit assignments. In this

[8] The decision rule is mechanical, in the sense that $Y_i(0, m) \perp\!\!\!\perp M_i$ for all $m \in \text{supp}(M_i)$.

[9] An equivalent formulation in terms of potential outcomes is that Z_i is independent of $Y_i(1)$ within the subpopulation with $S_i = 1$ and that Z_i is independent of $Y_i(0)$ within the subpopulation with $S_i = 0$.

case, Z_i is unlikely to be excluded from counterfactual illicit assignments, $Y_i(1)$. Plaintiffs that file cases with a larger amount of documentation may value judge attributes differently from others. Plaintiffs with different preferences over judges would select different judges if they were given the chance to do so.

Informally, a lower bound on $\Pr(S_i = 1)$ implied by Assumption IV can be obtained by the following thought experiment. Suppose that we observe a large number of realizations of $(Y_i, Y_i(0), S_i, Z_i)$: $\big\{(y_i, y_i(0), s_i, z_i) : i \in \{1, \ldots, N\}\big\}$, where N is large. Consider the modified assignments:

$$\tilde{y}_i = s_i y_i + (1 - s_i) y_i(0).$$

$\tilde{y}_i$ can be constructed by replacing y_i with $y_i(0)$ whenever $s_i = 1$. The fraction of cases whose observed assignments are replaced to construct the modified assignments is precisely the share of cases with illicit assignments. Moreover, $\tilde{y}_i$ will equal $y_i(0)$ for all cases, so that modified assignments will be independent of the instrument, by assumption. Of course, in reality we may only observe realizations of (Y_i, Z_i). However, the minimum amount of modifications that one must perform on realized assignments such that the resulting modified assignments are independent of the instrument will be lower than the amount of replacements that we made previously, i.e. $\Pr(S_i = 1)$.

In the case of a binary instrument, the lower bound for $\Pr(S_i = 1)$ that we just described equals

$$p_Z \cdot \min_{\gamma \in \Gamma} \sum_{y, y' \in \mathcal{Y}} 1\{y \neq y'\}\, \gamma(y, y') \qquad \text{subject to:} \tag{2}$$
$$\sum_{y' \in \mathcal{Y}} \gamma(y, y') = \Pr(Y_i = y \,|\, Z_i = 0) \quad \text{for all } y \in \mathcal{Y}$$
$$\sum_{y \in \mathcal{Y}} \gamma(y, y') = \Pr(Y_i = y' \,|\, Z_i = 1) \quad \text{for all } y' \in \mathcal{Y},$$

where $p_Z = \min\big\{\Pr(Z_i = 0),\ \Pr(Z_i = 1)\big\}$, $\mathcal{Y} = \{1, \ldots, n_Y\}$ and Γ is the set of probability mass functions defined over $\mathcal{Y} \times \mathcal{Y}$. In words, the solution to this problem equals the minimum amount of mass that must be reallocated within the distribution of $Y_i \,|\, Z_i = 1$ (or that of $Y_i \,|\, Z_i = 0$), so that the two conditional distributions are identical, weighted by the mass of the smaller group defined in terms of the instrument realizations. Problem (2) is a discrete optimal transport, linear programming problem (see Galichon 2016). Because of its special binary cost structure, its closed-form solution equals the total variation distance between the marginal distributions ($\Pr(Y_i = \cdot \,|\, Z_i = 1)$ and $\Pr(Y_i = \cdot \,|\, Z_i = 0)$), which is simply half of their absolute (ℓ_1, taxicab, Manhattan) distance.

The following proposition asserts that this lower bound cannot be improved without further data or assumptions, and that Assumption IV is uninformative for our second parameter of interest: $\Pr(S_i = 1 \,|\, Y_i = 1)$.

Proposition 1. *Let Z_i be binary. If Assumption IV holds, then*

1. $LB \leq \Pr(S_i = 1) \leq 1$, *where*

$$LB \quad = \quad p_Z \;\cdot\; \frac{1}{2} \sum_{y \in \mathcal{Y}} \Big| \Pr(Y_i = y \,|\, Z_i = 1) \;-\; \Pr(Y_i = y \,|\, Z_i = 0) \Big|$$

   and $p_Z = \min\big\{ \Pr(Z_i = 0),\ \Pr(Z_i = 1) \big\}$.

2. *For all* $y \in \mathcal{Y}$, $0 \leq \Pr(S_i = 1 \,|\, Y_i = y) \leq 1$.

These bounds are sharp.

We prove this proposition in the more general case of multi-valued instruments in Appendix A.

Proposition 1 shows that instruments that yield substantial bounds on $\Pr(S_i = 1)$ will satisfy two conditions. First, a relevance condition: Z_i must induce variation in assignments for the absolute distance between the conditional assignment distributions to be positive. Second, Z_i must be relatively balanced. This is intuitive: if the mass of cases with $Z_i = 0$ is small, the lower bound on $\Pr(S_i = 1)$ arises when licit assignments $Y_i(0)$ are distributed according to $Y_i \,|\, Z_i = 1$, in which case only a small fraction of cases' assignments may be illicit.

Proposition 1 also shows that Assumption IV does not yield informative bounds on $\Pr(S_i = 1 \,|\, Y_i = y)$. This follows because, if judge y is assigned a substantial amount of cases with $Z_i = 0$ but no cases with $Z_i = 1$, she could either have several cases with illicit assignments if $\Pr(Y_i(0) = y) = \Pr(Y_i = y \,|\, Z_i = 1)$, or no cases with illicit assignments if $\Pr(Y_i(0) = y) = \Pr(Y_i = y \,|\, Z_i = 0)$, and Assumption IV cannot distinguish between these possibilities.

Finally, the bounds that Proposition 1 presents are sharp. This means that, for each bound, there exists a joint distribution of the latent and observed data, $(Y_i(0), Y_i(1), S_i, Z_i)$, that satisfies Assumption IV, is consistent with the observed joint distribution of (Y_i, Z_i) under equation (1), and generates the given bound. Informally, this means that more information on the parameters of interest cannot be obtained without more data or further assumptions.

The negative identification result for $\Pr(S_i = 1 \mid Y_i = y)$ motivates me to study the related, but stronger Assumption SHP. I now discuss it.

1.4 Identification Results under Assumption SHP

Assumption SHP states that the distribution of counterfactual licit assignments is known. In my application, I interpret the Ecuadorian assignment regulations to mean that, within the court that I observe case i being assigned to, i's judge is drawn from a uniform distribution defined over the set of judges that are active at the time of assignment and have a relatively low workload. I defer my discussion on the measurement of this set to section **??**.

Under Assumption SHP, the sharp lower bound on $\Pr(S_i = 1)$ takes a simpler form, given by:

$$\begin{aligned}
&\min_{\gamma \in \Gamma} \quad \sum_{y, y' \in \mathcal{Y}} 1\{y \neq y'\}\, \gamma(y, y') \qquad \text{subject to:} \\
&\sum_{y' \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i = y) \quad \text{for all } y \in \mathcal{Y} \\
&\sum_{y \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i(0) = y') \quad \text{for all } y' \in \mathcal{Y}.
\end{aligned} \tag{3}$$

In words, this problem yields the minimum amount of cases whose assignment must be modified, so that the resulting distribution of assignments equals that of the counterfactual licit assignments. Like (2), problem (3) has a simple analytical solution.

The primary motivation for Assumption SHP is that it produces an informative lower bound on $\Pr(S_i = 1 \mid Y_i = y)$. For judge y^*, this equals

$$\begin{aligned}
&\min_{\gamma \in \Gamma} \quad \sum_{y' \in \mathcal{Y}} 1\{y^* \neq y'\}\, \gamma(y^*, y') \qquad \text{subject to:} \\
&\sum_{y' \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i = y) \quad \text{for all } y \in \mathcal{Y} \\
&\sum_{y \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i(0) = y') \quad \text{for all } y' \in \mathcal{Y},
\end{aligned} \tag{4}$$

which equals $\max\{0,\ \Pr(Y_i = y^*) - \Pr(Y_i(0) = y^*)\}$.[10] The meaning of this lower bound is straightforward: if judge y^* received 10% of cases, but should have received 5% of cases, then at least half of the case assignments directed to judge y^* are illicit. The following proposition summarizes these findings.

Proposition 2. *If Assumption SHP holds, then*

1. $\frac{1}{2}\sum_{y\in\mathcal{Y}} \Big| \Pr(Y_i = y) \ - \ \Pr(Y_i(0) = y) \Big| \ \leq \ \Pr(S_i = 1) \leq 1.$
2. $\max\{0,\ \Pr(Y_i = y) - \Pr(Y_i(0) = y)\} \ \leq \ \Pr(S_i = 1 \,|\, Y_i = y) \leq 1$, *for all* $y \in \mathcal{Y}$.

These bounds are sharp. Moreover, the lower bounds belong to the joint identified set for $\big(\Pr(S_i = 1),\ \Pr(S_i = 1 \,|\, Y_i = 1),\ \ldots,\ \Pr(S_i = 1 \,|\, Y_i = n_Y)\big)$.

The fact that the sharp lower bounds in Proposition 2 belong to the joint identified set for the entire vector of parameters means that they can all be traced back to the same data-generating process and are thus coherent with each other. In other words, there exists a distribution of $\big(Y_i(0), Y_i(1), S_i, Z_i\big)$, that matches the known distribution of $Y_i(0)$, is consistent with the observed joint distribution of (Y_i, Z_i) under equation (1), and generates the lower bounds for all our parameters of interest.

Daljord et al. (2021) first proposed the solution to problem (3) as a lower bound of black market transactions of license plates in China, following the introduction of a lottery-based rationing system. In their setting, the observed outcome is the price of the car associated with license plate i, and they use the fact that license plates were supposed to be allocated by a lottery to obtain the distribution of car prices in the absence of a black market. Proposition 2 shows that this lower bound is sharp and, hence, promotes the estimand they propose.

[10] This follows from the fact that, for any feasible γ,

$$\begin{aligned}
\Pr(Y_i = y^*) \ - \ \Pr(Y_i(0) = y^*) \quad &= \quad \sum_{y'\in\mathcal{Y}} \gamma(y^*, y') \ - \ \sum_{y'\in\mathcal{Y}} \gamma(y', y^*) \\
&= \quad \sum_{y'\in\mathcal{Y}} 1\{y^* \neq y'\}\gamma(y^*, y') \ - \ \sum_{y'\in\mathcal{Y}} 1\{y^* \neq y'\}\gamma(y', y^*).
\end{aligned}$$

1.5 Identification Analysis

I now develop the theory of identification that underlies propositions 1 and 2, in a setting with covariates. In addition to Y_i and Z_i, the researcher observes case characteristics X_i, which take values in finite set $\mathcal{X}$. In the empirical model of section 3, these characteristics will be the case's court, field of law and time period of assignment. With covariates, I adapt assumptions IV and SHP as follows:

Assumption IVx. *Z_i is statistically independent of $Y_i(0)$, conditional on X_i.*

Assumption SHPx. *The probability mass function of $Y_i(0) \mid X_i = x$ is known, for all $x \in \mathcal{X}$.*

When X_i is degenerate, assumptions IVx and SHPx revert to assumptions IV and SHP.

The joint distribution of $\big(Y_i(0), Y_i(1), S_i, Z_i\big)$, conditional on covariates X_i, is the cornerstone of the identification analysis, for three reasons. First, the available data, i.e. the probability mass function of (Y_i, Z_i, X_i), constitute restrictions on this distribution, under model (1). Second, assumptions **??** and **??** can be reformulated as restrictions on this distribution. Finally, any feature of the joint distribution of the data that we do not observe, any parameter, can be seen as a function of this distribution. Let $\mathcal{F}$ denote the set of probability mass functions of $\big(Y_i(0), \ldots, Y_i(n_S - 1), S_i, Z_i\big)$ conditional on X_i. f denotes a typical element of $\mathcal{F}$, and $f(y_0 \ldots y_{n_S-1},\, s,\, z \mid x)$ denotes a typical value of f.

I proceed in two steps. First, I obtain the restrictions imposed by our data and assumptions on the primitive conditional distribution, f, to define its identified set. Then, I define the identified sets for the parameters of interest and characterize them.

1.5.1 Identified set for f

The identified set for f is the set of all distributions in $\mathcal{F}$ that are observationally equivalent under model (1), and are consistent with assumptions IVx and SHPx. $f \in \mathcal{F}$ satisfies observational equivalence under model (1) if:

$$\sum_{y_0, y_1, s} 1\big\{sy_1 + (1-s)y_0 = y\big\}\; f\big(y_0,\, y_1,\, s,\, z \mid x\big) = \Pr(Y_i = y,\, Z_i = z \mid X_i = x) \qquad \forall\, y, z, x. \tag{R$_{\text{OE}}$}$$

In other words, f is observationally equivalent whenever its implied distribution of $(Y_i, Z_i) \,|\, X_i$ under model (1) matches that which is observed. Next, any f that is observationally equivalent is consistent with Assumption IVx if:

$$\sum_{y_1,s} f(y_0,\, y_1,\, s,\, z \,|\, x) \;=\; \Pr(Z_i = z \,|\, X_i = x) \sum_{y_1,s,\tilde{z}} f(y_0, y_1, s, \tilde{z} \,|\, x). \qquad \forall\, y_0, z, x. \tag{$\mathrm{R_{IV}}$}$$

That is, f is consistent with Assumption IVx if its implied distribution of $(Y_i(0), Z_i) \,|\, X_i = x$ equals the product of the implied marginal distributions. Notice that the implied distribution of $Z_i \,|\, X_i$ equals the observed distribution by observational equivalence. Finally, $f \in \mathcal{F}$ is consistent with Assumption SHPx if:

$$\sum_{y_1,s,z} f(y_0,\, y_1,\, s,\, z \,|\, x) \;=\; \psi(y_0;\, x) \qquad \forall\, y_0, x, \tag{$\mathrm{R_{SHP}}$}$$

where $\psi(y_0;\, x)$ is the known probability of $Y_i(0) = y_0$ conditional on $X_i = x$.

Assumptions IVx and SHPx are associated with identified sets $\mathcal{F}^{\star}_{\mathrm{IV}}$ and $\mathcal{F}^{\star}_{\mathrm{SHP}}$, respectively, where

$$\begin{aligned} \mathcal{F}^{\star}_{\mathrm{IV}} \quad &\equiv \quad \big\{ f \in \mathcal{F} \,:\, f \text{ satisfies restrictions } (\mathrm{R_{OE}}) \text{ and } (\mathrm{R_{IV}}) \big\} \quad \text{and} \\ \mathcal{F}^{\star}_{\mathrm{SHP}} \quad &\equiv \quad \big\{ f \in \mathcal{F} \,:\, f \text{ satisfies restrictions } (\mathrm{R_{OE}}) \text{ and } (\mathrm{R_{SHP}}) \big\}. \end{aligned}$$

The case where both Assumptions IVx and SHPx are imposed need not be treated separately, since it corresponds to assumption SHPx with covariates $\widetilde{X}_i = (X_i, Z_i)$.

1.5.2 Identified sets for parameters of interest

I cast parameters as linear functions of distributions in $\mathcal{F}$, $\theta : \mathcal{F} \mapsto \mathbb{R}^{d_\theta}$, where d_θ is the dimensionality of parameter θ. Each parameter $\theta = (\theta_1, \ldots, \theta_{d_\theta})$ that I consider is associated with d_θ vectors of known non-negative coefficients $(c_1, \ldots, c_{d_\theta})$, arranged as rows in matrix C, so that

$$\theta(f;\, C) \;\equiv\; C \times f \;=\; \begin{pmatrix} \sum_{y_0,y_1,s,z,x} c_1(y_0, y_1,\, s,\, z,\, x)\; f(y_0, y_1,\, s,\, z \,|\, x) \\ \vdots \\ \sum_{y_0,y_1,s,z,x} c_{d_\theta}(y_0, y_1,\, s,\, z,\, x)\; f(y_0, y_1,\, s,\, z \,|\, x) \end{pmatrix},$$

where $C \times f$ refers to the matrix multiplication of C and column vector f. When θ is scalar, $\theta(f;\, C)$ is simply the dot product of vectors C and f.

The identified set for parameter $\theta(\cdot\,;\, C)$ is the set of parameter values that are

Parameter of Interest	$C(y_0, y_1, s, z, x)$
$\Pr(S_i = 1 \,\vert\, X_i = x_0)$	$1\{x = x_0\} \cdot 1\{s = 1\}$
$\Pr(S_i = 1 \,\vert\, X_i \in \mathcal{X}_0 \subseteq \mathcal{X})$	$\frac{\Pr(X_i = x)}{\Pr(X_i \in \mathcal{X}_0)} \cdot 1\{x \in \mathcal{X}_0\} \cdot 1\{s = 1\}$
$\Pr(S_i = 1)$	$\Pr(X_i = x) \cdot 1\{s = 1\}$
$\Pr(S_i = 1 \,\vert\, Y_i = y)$	$\frac{\Pr(X_i = x)}{\Pr(Y_i = y)} \cdot 1\{s = 1\} \cdot 1\{y_1 = y\}$

Table 1: Coefficients of the Linear Parameters of Interest

Note: Each parameter in this table is scalar, so that C is a vector.

associated with distributions that belong to the identified set for f:

$$\begin{aligned} \Theta^{\star}_{\text{IV}}(C) &\equiv \{\theta(f\,;\,C) : f \in \mathcal{F}^{\star}_{\text{IV}}\} \quad \text{and} \\ \Theta^{\star}_{\text{SHP}}(C) &\equiv \{\theta(f\,;\,C) : f \in \mathcal{F}^{\star}_{\text{SHP}}\}. \end{aligned}$$

Table 1 shows that all of our parameters of interest are linear and presents the associated vectors of coefficients.[11]

I now turn to the characterization, or computation, of identified sets. Notice first that $\mathcal{F}^{\star}_{\text{IV}}$ and $\mathcal{F}^{\star}_{\text{SHP}}$ are convex sets: the convex combination of any two elements of $\mathcal{F}^{\star}_{\text{IV}}$ (or $\mathcal{F}^{\star}_{\text{SHP}}$) is a well-defined probability mass function that also satisfies restrictions (R_{OE}) and (R_{IV}) (or (R_{SHP})). It is well defined because $\mathcal{F}$, the set of probability mass functions of $\big(Y_i(0), Y_i(1), S_i, Z_i\big)$ conditional on X_i, is convex. It satisfies these restrictions because the solution set to (R_{OE}) and (R_{IV}) (or (R_{SHP})) is convex, which follows from the fact that these restrictions consist of equations and inequalities that are linear in f.

Next, fix a matrix of coefficients C and consider parameter $\theta(\cdot\,;\,C)$. Its identified sets, $\Theta^{\star}_{\text{IV}}(C)$ and $\Theta^{\star}_{\text{SHP}}(C)$, are also convex. In particular, let $f_1, f_2 \in \mathcal{F}^{\star}_{\text{IV}}$. For a

[11] In fact, linear parameters are widespread. See, e.g. Mogstad, Santos, and Torgovitsky (2018). For example, the expectation of counterfactual outcome $Y_i(1)$ is the linear parameter associated with coefficients C^1, where $C^1(y_0, y_1, s, z, x) = y_1$; the "Average Treatment Effect" – the average difference between $Y_i(1)$ and $Y_i(0)$ – is the linear parameter associated with C^{ATE}, where $C^{ATE}(y_0, y_1, s, z, x) = y_1 - y_0$; the probability that $Y_i(1)$ (or $Y_i(0)$) equals a given $y \in \mathcal{Y}$ is also a linear parameter. Moreover, the versions of these parameters that condition on $X_i = x$ or $Y_i = y$ are also linear.

given $\lambda \in [0,1]$, $\lambda f_1 + (1-\lambda) f_2 \in \mathcal{F}^{\star}_{\text{IV}}$ and

$$\begin{aligned}
\lambda \underbrace{\theta(f_1;\, C)}_{\in \Theta^{\star}_{\text{IV}}(C)} + (1-\lambda) \underbrace{\theta(f_2;\, C)}_{\in \Theta^{\star}_{\text{IV}}(C)} &= \lambda(C \times f_1) \;+\; (1-\lambda)(C \times f_2) \\
&= C \times \big[\lambda f_1 + (1-\lambda) f_2\big] \\
&= \theta\big(\lambda f_1 + (1-\lambda) f_2;\; C\big) \;\in\; \Theta^{\star}_{\text{IV}}(C).
\end{aligned}$$

Thus, the identified set for a scalar parameter under either Assumption IVx or SHPx equals an interval in $\mathbb{R}^{+}$. What is left to determine are the two extreme points of this interval, also known as the *sharp bounds*. But this is straightforward: since the parameter and the restrictions are linear, the extreme points of this interval equal the solution to two linear programming problems that minimize/maximize the parameter value subject to restrictions (R_{OE}), (R_{IV}) and (R_{SHP}). That is, for a given vector of coefficients C, $\Theta^{\star}_{\text{IV}}(C) = \big[\underline{\theta}_{\text{IV}}(C),\, \overline{\theta}_{\text{IV}}(C)\big]$, where

$$\begin{aligned}
\underline{\theta}_{\text{IV}}(C) &= \min_{f \in \mathcal{F}} \quad \theta(f;\, C) \quad \text{subject to } (\text{R}_{\text{OE}}) \text{ and } (\text{R}_{\text{IV}}) \\
\overline{\theta}_{\text{IV}}(C) &= \max_{f \in \mathcal{F}} \quad \theta(f;\, C) \quad \text{subject to } (\text{R}_{\text{OE}}) \text{ and } (\text{R}_{\text{IV}}),
\end{aligned}$$

and $\underline{\theta}_{\text{SHP}}(C)$ and $\overline{\theta}_{\text{SHP}}(C)$ are defined analogously.

For our parameters of interest, listed in Table 1, these linear programs either have closed-form solutions or simpler formulations. Table 2 lists the results for parameters $\Pr(S_i = 1 \,|\, X_i = x)$ and $\Pr(S_i = 1 \,|\, Y_i = y, X_i = x)$ and Appendix A proves them. Sharp lower bounds for more aggregate parameters such as $\Pr(S_i = 1)$ or $\Pr(S_i = 1 \,|\, Y_i = y)$ can be obtained from the lower bounds listed in Table 2 through appropriate aggregation. In particular, the lower bound for $\Pr(S_i = 1)$ under Assumption SHPx equals:

$$\sum_{x \in \mathcal{X}} \Pr(X_i = x) \left(\frac{1}{2} \sum_{y \in \mathcal{Y}} \Big| \Pr(Y_i = y \,|\, X_i = x) \;-\; \Pr(Y_i(0) \,|\, X_i = x) \Big| \right).$$

Assumption	Parameter of Interest	$\underline{\theta}(C)$	$\overline{\theta}(C)$
IVx	$\Pr(S_i = 1 \mid X_i = x)$	$\min_{\phi \in \Phi} \sum_{z,y} \frac{1}{2} \Pr(Z_i = z \mid x) \Big\lvert \Pr(Y_i = y \mid x, z) \ - \ \phi(y \mid x) \Big\rvert$, where Φ is the set of p.m.f.s of $Y_i(0) \mid X_i$.	1
IVx	$\Pr(S_i = 1 \mid Y_i = y, X_i = x)$	0	1
SHPx	$\Pr(S_i = 1 \mid X_i = x)$	$\frac{1}{2} \sum_{y} \Big\lvert \Pr(Y_i = y \mid x) \ - \ \Pr(Y_i(0) \mid x) \Big\rvert$	1
SHPx	$\Pr(S_i = 1 \mid Y_i = y, X_i = x)$	$\max \big\{0, \Pr(Y_i = y \mid x) - \Pr(Y_i(0) = y \mid x)\big\}$	1

Table 2: Sharp Bounds on the Parameters of Interest

2 Context and Data

This section gives an overview of Ecuador's judicial system, discusses the existing regulations on the assignment of cases to judges, and presents the assignment data.

2.1 Context

Unlike federal states, such as Brazil, Mexico, or the United States, Ecuadorian law is homogeneous across its administrative divisions. Ecuador has a 3-tiered judiciary, composed of 331 district courts, 24 provincial courts, the National Court of Justice, and a governing body called the Judicial Council. In this paper, I focus on case assignments to judges in the country's district courts.

Table 3 presents the key institutional components that govern the assignment of cases to judges. Lottery offices deployed throughout the country perform assignments. Personnel attached to these offices use a dedicated computer program to draw assignments, provided the computer program is operational. If it is not, then the personnel draw cases that await assignment sequentially at random and assign them to available judges, who have been arranged in a pre-defined order. If it is, its usage is mandatory. Unfortunately, the regulations leave its precise implementation to the Judicial Council. In a recent interview, however, the president of the Judicial

Regulation	Original text	Source
The use of the automatic system for case lotteries is compulsory in all districts that have the technological facilities and the system installed.	En los distritos que cuentan con las facilidades tecnológicas y se encuentre instalado el sistema automático de sorteo de causas para primera y segunda instancia, su uso será obligatorio.	Article 9, Reglamento de Sorteo de Juicios (2004)
Districts that do not have the system installed will perform lotteries as follows: after numbering the cases, one ticket for each case is inserted in a container. Tickets are then randomly drawn and determine the judge that the case must be assigned to.	En los distritos o lugares carentes del sistema informático para el sorteo éste tendrá el procedimiento siguiente: Numeradas las demandas o expedientes con arreglo en un recipiente apropiado se colocarán tantas fichas cuantas sean aquellos. Estas fichas se sacarán por la suerte y determinarán a los jueces que deben conocer de las causas.	Article 11, Reglamento de Sorteo de Juicios (2004)
The algorithm of the system assigns cases to judges randomly, according to the judges' case workloads. That is, if we have five judges and each judge has a case workload of ten, then (the system) assigns randomly. But if one of them has a case workload of one hundred, then the system skips that judge, because she has too high a workload	El algoritmo del sistema asigna de manera aleatoria las causas segun la carga procesal que tenga un juzgador. Es decir, si tenemos cinco juzgadores, los cinco tienen carga procesal de diez, entonces va asignando aleatoriamente. Pero si a uno de ellos se le pone una carga procesal de cien causas en trámite, entonces el sistema se salta ese juzgador porque tiene muchas causas en trámite	Minutes 5:48 – 6:30 of an interview with the President of the Judicial Council, available here.

Table 3: Ecuadorian Case Assignment Regulations

Note: English translations are my own.

Council briefly explains the implementation: the computer program assigns cases at random among available judges who have a relatively low case workload at the time of assignment. Finally, judges who are available for a given case must work in courts that have competence over the case's field of law[12] and location.[13]

Ecuador offers an ideal setting to study illicit assignments of cases to judges, for two reasons. First, this topic is salient and raises concerns among public officials in the Judicial Council, and among the general public. In recent months, several case assignment scandals have surfaced which involve judges in courts across the country as well as high profile individuals, such as the mayor of Quito, the country's capital, who was recently removed from office.[14]

Second, large scale access to case-level assignment information across the country's courts is possible for non-confidential cases, and this information is regularly updated by the Judicial Council.[15] In Latin America, this is exceptional: case-level assignment data is scattered across different judiciaries in federal states such as Mexico or Brazil, and large scale access to case assignment information is effectively denied to the general public in countries such as Argentina, Chile, Colombia, Mexico or Peru.

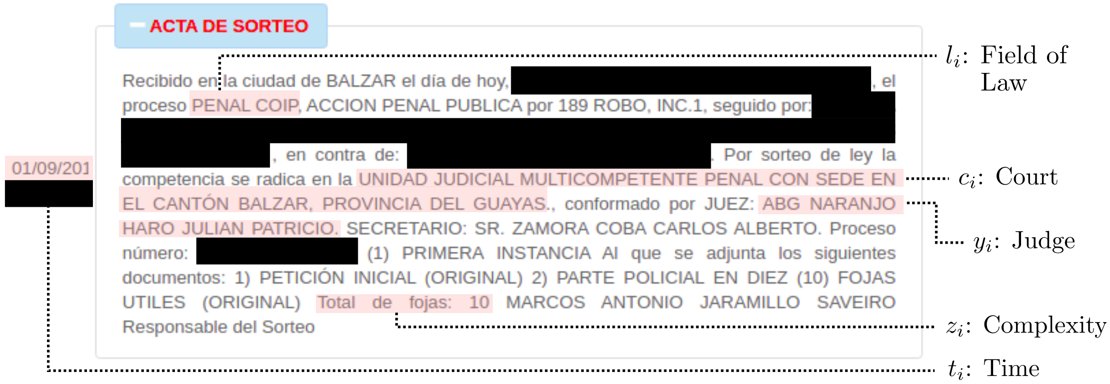
The recent case assignment scandals and my conversations with Judicial Council officials reveal a variety of ways in which illicit assignments may arise. The plaintiff may misreport the case's location to target certain courts or file and withdraw the case until it is assigned to a specific judge; a judge may take a medical leave

[12]Each district court has competence over cases that belong to a subset of the following fields of law: criminal law (e.g. a homicide), civil law (e.g. a payment dispute that involves a bank and a credit card debtor), administrative law (e.g. a dispute related with a government contract), tax law (e.g. a tax payment dispute), juvenile law (e.g. a robbery conducted by someone under 18 years of age), transit law (e.g. drunk driving), family violence law (e.g. a case of household violence), family law (e.g. a divorce), labor law (e.g. wrongful termination of an employee) and landlord-tenant law.

[13]The Judicial Council specifies the territory associated with each court. In general, the location of criminal cases is the location where the alleged crime was committed and the location of other cases is the address of the defendant. See article 404 of Código Orgánico Integral Penal 2014, which contains further rules to obtain the jurisdiction if the location of the crime is unknown, and articles 9-15 of Código Orgánico General de Procesos 2015.

[14]See the media coverage here, here, here, and here.

[15]Confidential cases are those that involve sexual crimes, family violence, and crimes against the state. See article 562 of Código Orgánico Integral Penal (2014). Crimes against the state are listed in arts. 336-365. They include rebellion, insubordination of military and police personnel, sabotage, treason, espionage, non-authorized possession of firearms and arms dealing.


ACTA DE SORTEO

01/09/201 [redacted]

Recibido en la ciudad de BALZAR el día de hoy, [redacted], el proceso PENAL COIP, ACCION PENAL PUBLICA por 189 ROBO, INC.1, seguido por: [redacted], en contra de: [redacted]. Por sorteo de ley la competencia se radica en la UNIDAD JUDICIAL MULTICOMPETENTE PENAL CON SEDE EN EL CANTÓN BALZAR, PROVINCIA DEL GUAYAS., conformado por JUEZ: ABG NARANJO HARO JULIAN PATRICIO. SECRETARIO: SR. ZAMORA COBA CARLOS ALBERTO. Proceso número: [redacted] (1) PRIMERA INSTANCIA Al que se adjunta los siguientes documentos: 1) PETICIÓN INICIAL (ORIGINAL) 2) PARTE POLICIAL EN DIEZ (10) FOJAS UTILES (ORIGINAL) Total de fojas: 10 MARCOS ANTONIO JARAMILLO SAVEIRO Responsable del Sorteo

Figure 1: An annotated lottery certificate

precisely when a certain case will be assigned; personnel in the case assignment office may manipulate the computer program that generates assignments. In the empirical model, I will distinguish those cases that had an illicit assignment within their observed court, field of law and time of assignment from others. In particular, my measurements will only reflect this class of illicit assignments.

2.2 Data

My data is a collection of lottery certificates that record individual case assignments to judges. I obtain each lottery certificate from the public, plain text version of Ecuador's unique database of judicial cases, called *Sistema Automático de Trámite Judicial Ecuatoriano*. The Judicial Council maintains this database and makes it publicly accesible for individual case searches in this government webpage.[16] To obtain the entire collection of publicly-available lottery certificates, I crawled this webpage in early 2021. Details of this data collection exercise are in Appendix B.

Figure 1 shows a lottery certificate returned by the government's webpage.[17] Each certificate contains the date when the assignment is produced, the case's reported field of law, as well as the court and judge that the case is assigned to. It also includes the page count of documentation that the plaintiff or prosecutor submits when the case is filed.

[16] See Machasilla, Mejía, and Torres Feraud (2020) for a description of the internal version of this database, and articles 118 − 119 in Código Orgánico General de Procesos (2015) and 578 − 579 in Código Orgánico Integral Penal (2014) for the legal content requirements of this database.

[17] The black regions conceal the case's identifiable information.

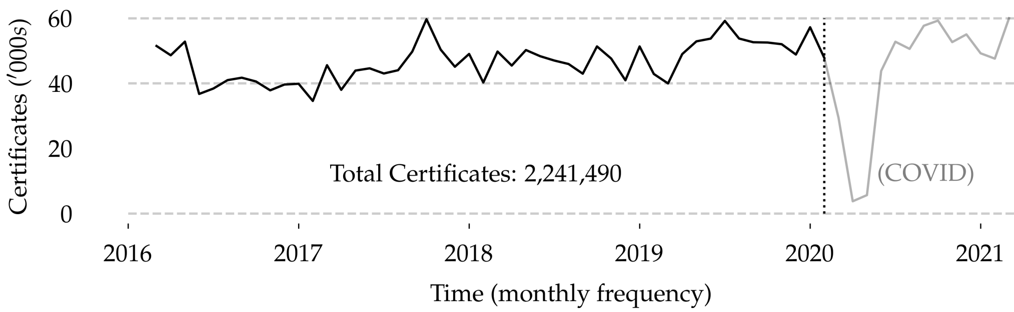


Figure 2: Lottery certificates over time

	Percentiles							
	5	10	25	50	75	90	95	observations
Certificates per Judge	10	72	582	1213	1886	2937	3827	1568
Certificates per Court	17	152	1408	3118	6025	16348	31815	331
Plaintiff Documentation (number of pages)	0	0	1	5	12	26	44	$2,023,010$

Table 4: Summary Statistics

My data collection exercise returns 2 million lottery certificates that record assignments made in district courts between March, 2016 and February, 2020. I chose the beginning of my sample period for practical reasons: before this time, lottery certificates come in a vast array of formats, which makes the construction of accurate text processing programs a daunting task. I chose to end my sample period before the onset of the SARS-CoV-2 pandemic, which had a sizeable impact on the judiciary's activities, as Figure 2 shows.

3 Empirical Framework

This section presents the model that I take to the Ecuadorian setting, adapts the identification results from section 1 and discusses statistical inference.

3.1 Setting

Section 1.1 presented an econometric model of case assignments within a given court, field of law and time period. Now, the model's scope includes every Ecuadorian district court and field of law, between March, 2016 and February, 2020. In section 1.1, data units were judicial cases. Now, they are lottery certificates, although I will loosely refer to them as cases. For each case, the data reveal the court where it is assigned – C_i – its reported field of law – L_i – and the date and time of assignment – T_i. $n_Y \equiv 1568$ judges worked in Ecuadorian district courts during this time period. Label judges from 1 to n_Y, so that the judge that case i is assigned to – Y_i – is a categorical random variable that takes values in $\mathcal{Y} \equiv \{1, \ldots, n_Y\}$. I coarsen the cases's date and time of assignment to obtain its time period of assignment – $\mathcal{T}_i$ – where $\Pr(T_i \in \mathcal{T}_i) = 1$.

The Ecuadorian regulations presented in section 2.1 are in the background and induce counterfactual licit and illicit assignments, as in section 1.1. As we discussed in section 2.1, illicit assignments arise in many ways. Some of them involve manipulation of the case's assigned court through misrepresentation of the case's location, for example; others involve manipulation of the case's field of law or time of assignment; and others target judges by other means, e.g. through manipulation of the computer program that draws assignments. My empirical analysis accounts for the latter category of illicit assignments only. Concretely, let S_i^* indicate whether the case's assignment is illicit or not, and let S_i indicate whether the case's assignment is illicit *within i's assigned court, reported field of law and time period of assignment*, so that

$$S_i^* \quad = \quad 1\big\{S_i = 1 \quad \text{or} \quad \widetilde{S}_i = 1\big\}, \tag{5}$$

where $\widetilde{S}_i$ indicates if the case's assignment is illicit through manipulations of the case's assigned court, field of law or time period of assignment.

S_i records several sources of illicit assignments. It indicates if i's judge is somehow hand-picked among judges who worked in i's court and specialized in i's field of law during i's time period of assignment. It need not reflect illegal behavior, since it also indicates if i's judge was selected by mistake among this set of judges. The longer the case's defined time period of assignment, the more illicit assignments detected by S_i.

The counterfactual assignments that I consider are associated with this illicit status. $Y_i(1)$ is the judge that case i would have been assigned to, had its assignment been illicit within i's assigned court, reported field of law and time period, and $Y_i(0)$ is the corresponding counterfactual licit assignment. Actual and counterfactual assignments are related according to:

$$Y_i \quad = \quad S_i Y_i(1) \ + \ (1 - S_i) Y_i(0).$$

The share of illicit assignments across district courts and time, $\Pr(S_i = 1)$, conditional on certain courts or time periods, $\Pr(S_i = 1 \,|\, C_i \in \mathcal{C}, \mathcal{T}_i \in \mathcal{T})$, and conditional on a specific judge, $\Pr(S_i = 1 \,|\, Y_i = y)$, are the parameters of interest. Every illicit assignment detected by S_i is detected by S_i^*, as evidenced by equation (5). Therefore, the parameters of interest are lower bounds on those obtained with S_i^*.

3.2 Identification with One-sided Instruments

Let Z_i be the binary random variable that indicates if the page count of documentation submitted by i's plaintiff/prosecutor exceeds 5, the median page count in our data. Consider the following assumption.

Assumption IVe. *For every* $(y, c, l, \mathbf{t})$,

$$\begin{aligned} & \Pr\big(Y_i(0) = y \,|\, Z_i = 0, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}\big) \\ = \quad & \Pr\big(Y_i(0) = y \,|\, Z_i = 1, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}\big). \end{aligned}$$

Assumption IVe states that Z_i is statistically independent of counterfactual licit assignments, conditional on the case's court, field of law and time period of assignment. My main specification defines $\mathcal{T}_i$ as the year and quarter when case i is assigned. The primary motivation for Assumption IVe is that Ecuadorian regulations do not specify that cases with different amounts of documentation filed by the case's plaintiff or prosecutor be assigned to judges differently. This does not imply that Z_i be independent of counterfactual licit assignments, however. The case's field of law, court and time of assignment determine which judges are available for case i, and the composition of cases may differ across courts, fields of law and over time. Therefore, under the regulations, certain judges may receive cases with more associated documentation than others. Assumption IVe rules out this compositional variation within court, field of law and quarter.

The following proposition establishes the empirical content of Assumption IVe under our binary instrument.

Proposition 3. *If Assumption IVe holds, then*

1. *For all* c, l *and* $\mathbf{t}$, $\quad LB_{IV}(c, l, \mathbf{t}) \;\leq\; \Pr(S_i = 1 \,|\, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}) \;\leq\; 1$, *where*

$$LB_{IV}(c, l, \mathbf{t}) \;=\; p_Z \;\cdot\; \frac{1}{2} \sum_{y \in \mathcal{Y}} \Big| \Pr(Y_i = y \,|\, Z_i = 1, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}) - \Pr(Y_i = y \,|\, Z_i = 0, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}) \Big|$$

and

$$p_Z \;=\; \min \big\{ \Pr(Z_i = 0 \,|\, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}),\; \Pr(Z_i = 1 \,|\, C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}) \big\}.$$

2. *For all* y, $\quad 0 \;\leq\; \Pr(S_i = 1 \,|\, Y_i = y) \;\leq\; 1$.

These bounds are sharp.

Proposition 3, proved in Appendix A, adapts Proposition 1 to the Ecuadorian setting. Its takeaways are those of Proposition 1: one-sided instruments are informative for the extent of illicit assignments, even conditional on case characteristics, but are uninformative for the extent of illicit assignments for individual judges.

3.3 Identification with a Known Distribution of Licit Assignments

One-sided instruments are silent regarding $\Pr(S_i = 1 \,|\, Y_i = y)$, for any $y \in \mathcal{Y}$. This motivates the following stronger assumption.

Assumption SHPe. $Y_i(0) \,|\, C_i = c, L_i = l, T_i = t \;\sim\; Unif(\mathcal{J}_{clt})$*, where* $\mathcal{J}_{clt}$ *is known for all* c*,* l *and* t*.*

$\mathcal{J}_{clt}$ is the set of judges that are active and have a relatively low case workload in court c and field of law l at time t. I discuss the measurement of this set, and its relationship with the set of judges who *should* be available for case i in court c and field of law l at time t – $\mathcal{J}^{\star}_{clt}$ – in the next section.

Two features of our institutional setting, listed in Table 3, motivate Assumption SHPe. First, the case assignment procedure specified by the regulations when the

Judicial Council's computer system is out of order implies that cases be assigned to available judges with equal probabilities. Second, the President of the Judicial Council asserts that the computer system assigns cases randomly, among available judges who have a relatively low case workload at the time of assignment.

I discretize the cases' time of assignment before adapting Proposition 2 to our setting. Let $\mathcal{T}_i^J$ be the largest time interval that contains T_i and features the same set of available judges in court C_i and field of law L_i, i.e. the joint judge spell when case i was assigned. Formally, $\mathcal{T}_i^J = \mathcal{T}^J(C_i, L_i, T_i)$, where $\mathcal{T}^J(c,l,t) = \left[\underline{t},\ \bar{t}\right]$ and[18]

$$\underline{t},\ \bar{t} \ = \ \arg\max_{\underline{t},\bar{t}} \left\{ \bar{t} - \underline{t} \ : \quad t \in \left[\underline{t},\ \bar{t}\right] \quad \text{and} \quad \mathcal{J}_{clt} = \mathcal{J}_{clt'} \text{ for all } t' \in \left[\underline{t},\ \bar{t}\right] \right\}.$$

It follows that $Y_i(0) \,|\, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t} \ \sim \ \text{Unif}\left(\mathcal{J}_{cl\mathbf{t}}\right)$, where $\mathcal{J}_{cl\mathbf{t}} = \mathcal{J}_{clt'}$ for some $t' \in \mathbf{t}$. Proposition 4 establishes the empirical content of Assumption SHPe.

Proposition 4. *If Assumption SHPe holds, then*

1. *For all c, l and $\mathbf{t}$,* $\quad LB_{SHP}\left(c,l,\mathbf{t}\right) \ \leq \ \Pr(S_i = 1 \,|\, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t}) \ \leq \ 1,$ *where*

$$LB_{SHP}\left(c,l,\mathbf{t}\right) \ = \ \frac{1}{2} \sum_{y \in \mathcal{Y}} \left| \Pr(Y_i = y \,|\, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t}) \ - \ \frac{1}{\#\mathcal{J}_{cl\mathbf{t}}} \right|$$

2. *For all y,* $\quad LB_y(c,l,\mathbf{t}) \ \leq \ \Pr(S_i = 1 \,|\, Y_i = y, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t}) \ \leq \ 1,$ *where*

$$LB_y\left(c,l,\mathbf{t}\right) \ = \ \max\Big\{0, \quad \Pr(Y_i = y \,|\, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t}) - \Pr(Y_i(0) = y \,|\, C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t})\Big\}$$

These bounds are sharp.

3.3.1 Measurement of the Set of Available Judges

Assumption SHPe raises a challenge: which judges should be available in a given court c, field of law l and point in time t? I impose two conditions. First, available judges must be in an active spell: they be assigned cases in court c during the α days that lead up to time t. Second, available judges must have a case workload that is less than β times that of their peer with the lowest case workload, within court c, field of law l and at time t. α and β are tuning parameters that I select so as to obtain conservative bounds on $\Pr(S_i = 1)$.

[18]Notice that $\underline{t} = \underline{t}(c,l,t)$ and $\bar{t} = \bar{t}(c,l,t)$. I omit these arguments for conciseness.

3.4 Estimation

LB_{IV}, LB_{SHP} and LB_y are population quantities. I now discuss how to measure them with data on a finite number of cases. Appendix C, currently under construction, provides details. I obtain consistent estimators $\widehat{LB}_{\text{IV}}$, $\widehat{LB}_{\text{SHP}}$ and $\widehat{LB}_y$ by replacing probabilities with relative frequencies:

$$\begin{aligned}
\widehat{LB}_{\text{IV}}(c,l,\mathbf{t}) \;&=\; \widehat{p}_Z \;\cdot\; \frac{1}{2}\sum_{y\in\mathcal{Y}}\Big|\widehat{\Pr}(Y_i=y\,|\,Z_i=1,C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t}) \\
&\qquad\qquad -\; \widehat{\Pr}(Y_i=y\,|\,Z_i=0,C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t})\Big| \\
\widehat{LB}_{\text{SHP}}(c,l,\mathbf{t}) \;&=\; \frac{1}{2}\sum_{y\in\mathcal{Y}}\left|\,\widehat{\Pr}(Y_i=y\,|\,C_i=c,L_i=l,\mathcal{T}_i^J=\mathbf{t}) \;-\; \frac{1}{\#\mathcal{J}_{cl\mathbf{t}}}\right| \\
\widehat{LB}_y\,(c,l,\mathbf{t}) \;&=\; \max\left\{0,\quad \widehat{\Pr}(Y_i=y\,|\,C_i=c,L_i=l,\mathcal{T}_i^J=\mathbf{t}) \;-\; \frac{1}{\#\mathcal{J}_{cl\mathbf{t}}}\right\}
\end{aligned}$$

where

$$\widehat{p}_Z \;=\; \min\Big\{\widehat{\Pr}(Z_i=0\,|\,C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t}),\; \widehat{\Pr}(Z_i=1\,|\,C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t})\Big\}.$$

I combine these estimators to measure the lower bounds on broader parameters, such as $\Pr(S_i=1)$, $\Pr(S_i=1\,|\,C_i=c)$ or $\Pr(S_i=1\,|\,Y_i=y)$. For example, a consistent estimator for the lower bound on $\Pr(S_i=1)$ under Assumption IVe, given by

$$LB_{\text{IV}} \;\equiv\; \sum_{c,l,\mathbf{t}}\Pr(C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t})LB_{\text{IV}}(c,l,\mathbf{t}).$$

is the following:

$$\widehat{LB}_{\text{IV}} \;=\; \sum_{c,l,\mathbf{t}}\widehat{\Pr}(C_i=c,L_i=l,\mathcal{T}_i=\mathbf{t})\widehat{LB}_{\text{IV}}(c,l,\mathbf{t}).$$

I conduct statistical inference for LB_{IV} and other lower bounds obtained from Assumption IVe with permutation tests. In particular, given the following test:[19]

$$H:\; LB_{\text{IV}}=0 \qquad \text{vs.} \qquad H':\; LB_{\text{IV}}>0,$$

I reject the null hypothesis at the 5% level if $\widehat{LB}_{\text{IV}}$ exceeds the 95-th percentile of the distribution of estimates of LB_{IV} obtained from repeated permutations of the realizations of Z_i, within each court, field of law and quarter.

[19]Notice that $LB_{\text{IV}} \geq 0$.

I conduct statistical inference for the lower bounds obtained from Assumption SHPe by directly simulating the distribution of the estimator under the null hypothesis. For illustration, consider the implied lower bound on $\Pr(S_i = 1)$:

$$LB_{\text{SHP}} \equiv \sum_{c,l,\mathbf{t}} \Pr(C_i = c, L_i = l, \mathcal{T}_i = \mathbf{t}) LB_{\text{SHP}}(c, l, \mathbf{t}).$$

Given the test:

$$H: \ LB_{\text{SHP}} = 0 \qquad \text{vs.} \qquad H': \ LB_{\text{SHP}} > 0,$$

I reject the null hypothesis at the 5% level if $\widehat{LB}_{\text{SHP}}$ exceeds the 95-th percentile of the distribution of estimates of LB_{SHP} obtained from repeated simulated judge assignments drawn according to the distribution of $Y_i(0) \mid C_i, L_i, \mathcal{T}_i^J$ within each court, field of law and quarter.

Finally, a comparison between the lower bounds on illicit assignments by court, by time period, or by judge requires testing multiple hypotheses. Consider a judge-level analysis of illicit assignments. The lower bound on illicit assignments made to judge y, $\Pr(S_i = 1 \mid Y_i = y)$, is:

$$LB_y \equiv \sum_{c,l,\mathbf{t}} \Pr(C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t}) LB_y(c, l, \mathbf{t}),$$

and for each $y \in \{1, \ldots, 1568\}$, I test:

$$H_y: \ LB_y = 0 \qquad \text{vs.} \qquad H'_y: \ LB_y > 0.$$

I adopt the procedure from Romano and Wolf (2016) to obtain the $p-$values associated with each of these tests that account for multiple hypothesis testing.

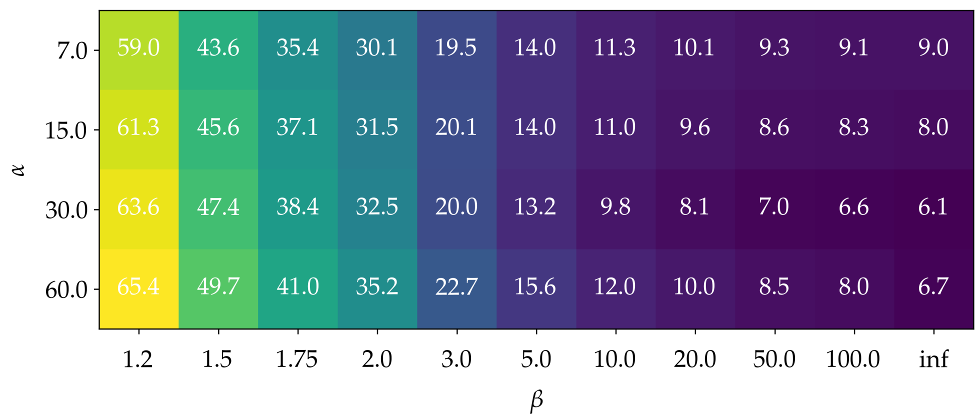


Figure 3: Lower Bounds on Overall Illicit Assignments across Tuning Parameters

Each cell shows the estimated lower bound on the share of illicit assignments, $\Pr(S_i = 1)$, under Assumption SHPe for a given value of α and β. α is measured in days and equals the minimum frequency of cases assignments made to a judge for her to be in an active spell. β is the maximum case workload of a judge (relative to the peer with the lowest workload) for her to be available for case assignments. When $\beta = \infty$, judges' workloads do not determine if they are available for case assignments or not.

4 Results

This section describes my estimates of illicit assignments in Ecuador. The one-sided instrument detects a small number of illicit assignments, but most of them occur in a handful of courts. When I impose knowledge of the distribution of licit assignments (Assumption SHPe), I detect more illicit assignments, in more courts and among 7% of judges.

Knowledge of the distribution of licit assignments requires measurement of the set of judges available for each case. I parameterize the sets of available judges in terms of two tuning parameters that govern the definition of judges' active spells, α, and that of excessive case workloads of judges, β (see section 3.3.1). Figure 3 shows that I achieve a conservative lower bound on the overall share of illicit assignments when I ignore judges' case workloads ($\beta = \infty$), and when judges must receive cases at a frequency of at least $\alpha = 30$ days to be considered active. I use these parameter values in my analysis of illicit assignments under Assumption SHPe.

Table 5 shows the estimated lower bounds on the overall extent of illicit assignments and the extent of illicit assignments for civil and criminal cases separately.[20] Across specifications, the column (1) shows lower bounds of around six percent.

[20] That is, the lower bounds on $\Pr(S_i = 1)$, $\Pr(S_i = 1 \mid L_i = \text{civil})$ and $\Pr(S_i = 1 \mid L_i = \text{criminal})$.

These lower bounds have a substantive positive bias, however.[21] Its magnitude can be seen in columns (2), (3) and (4), which give the fifth, median and ninety-fifth quantiles of the distributions of the estimators under the null hypothesis of an uninformative lower bound. Notice that the estimated lower bounds are significant at the 5% level if they exceed the ninety-fifth quantile. The fifth column shows what is left of the estimated lower bound after differencing the median, and the next column shows the resulting magnitude, in terms of the number of illicit case assignments. My one-sided instrument detects illicit assignments only among criminal cases, and bounds the overall share of illicit assignments at 0.46%. This amounts to $9,347$ illicit assignments. In contrast, knowledge of the distribution of licit assignments detects illicit assignments for both criminal and civil cases, and implies $64,929$ illicit assignments overall.

Figure 4 shows the implied amounts of illicit assignments by court and by judge. Each plot shows the courts and judges with significant shares of illicit assignments at the 5% level.[22] Figure 4a shows that the one-sided instrument's detections single out a handful of courts. One court accounts for a third of all illicit assignments detected. In that court, at least 16% of case assignments are illicit. When the distribution of licit assignments is known, illicit assignments are detected in more courts, and I can measure illicit assignments at the individual judge level. Four judges stand out from the rest, and illicit assignments are detected for 111 judges, out of 1568.

[21] This is because the lower bounds involve absolute distances, so that any discrepancy between two probability distributions increases the distance.

[22] I use the procedure from Romano and Wolf (2016) to adjust the $p-$values for multiple hypothesis testing.

	$\widehat{LB}$	$\widehat{LB}$ percentiles under $H_0: LB = 0$			$\widehat{LB} - p50$	$\hat{n}$ Illicit	Observations
		$p5$	$p50$	$p95$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Estimates Based on Assumption IVe							
Overall	6.05^{***}	5.57	5.59	5.62	0.46	9,347	2,023,010
By Field of Law:							
Civil	6.19	6.14	6.18	6.22	0.00	39	937,765
Criminal	5.94^{***}	5.05	5.08	5.13	0.86	9,303	1,085,245
Panel B: Estimates Based on Assumption SHPe							
Overall	6.13^{***}	3.20	3.23	3.26	2.90	64,929	2,241,490
By Field of Law:							
Civil	6.00^{***}	3.51	3.56	3.60	2.44	26,776	1,096,693
Criminal	6.25^{***}	2.87	2.92	2.96	3.33	38,144	1,144,797

Table 5: Aggregate Lower Bounds on Illicit Assignments

The three rows in Panel A show the estimation results for the lower bounds on $\Pr(S_i = 1)$, $\Pr(S_i = 1 \mid L_i = \text{civil})$ and $\Pr(S_i = 1 \mid L_i = \text{criminal})$ in percentage points, respectively, under Assumption IVe. The three rows in Panel B show the results under Assumption SHPe. Column (1) shows the estimated lower bounds. Columns (2) – (4) show percentiles 5, 50 and 95 of the distribution of the estimator under the null hypothesis of an uninformative lower bound. In Panel A, this distribution is obtained from repeated permutations of the instrument realizations. Column (5) substracts the median of these distributions from the estimated lower bound. Column (6) scales column (5) with the total number of assignments, given in column (7). Significance levels: *** $p < 0.01$.

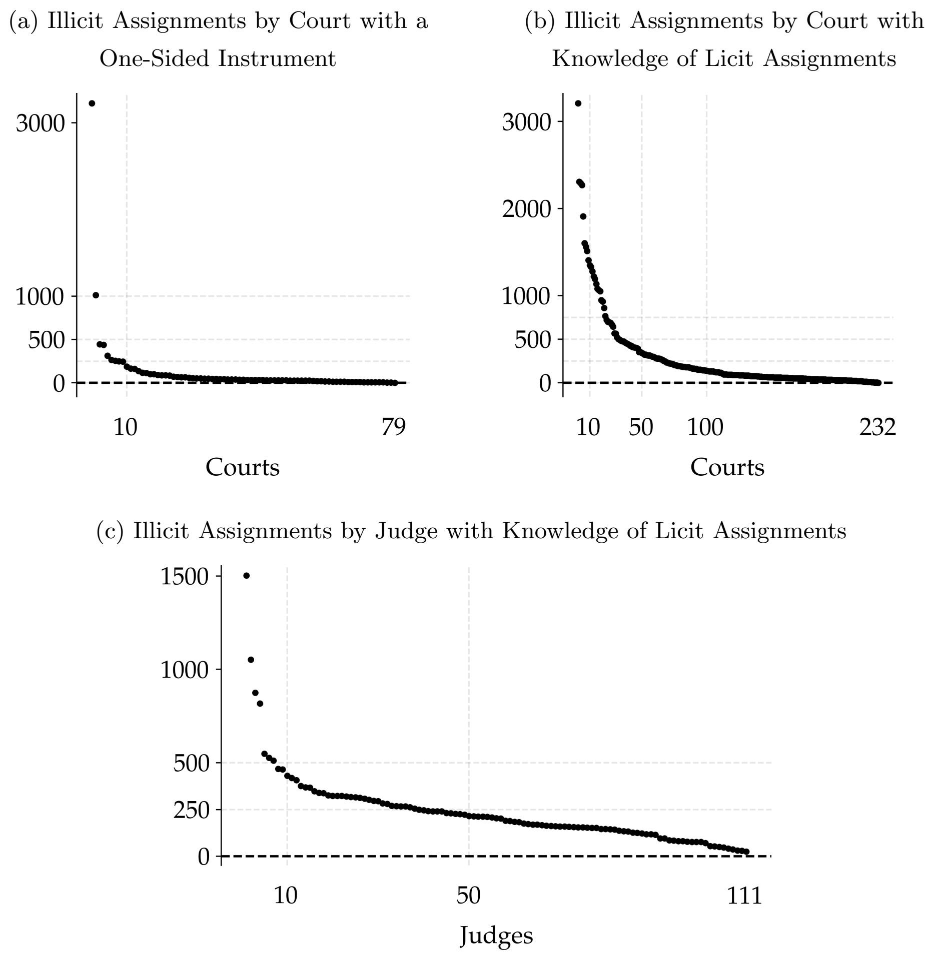


Figure 4: Disaggregate Lower Bounds on Illicit Assignments

The two top figures show the amount of illicit assignments by court, among the courts whose share of illicit assignments is significant at the family-wise error rate of 5%, under Assumption IVe (figure 4a) and under Assumption SHPe (figure 4b). Illicit assignment amounts are computed as in Table 5: they equal the estimated lower bounds net of the median of the distribution of the estimator under the null hypothesis of an uninformative lower bound, multiplied by the number of assignments made in the given court or to the given judge.

5 Conclusion

This paper develops a method to evaluate a basic aspect of judicial activity: the assignment of cases to judges. The method yields measurements on the extent to which actual assignments violate the regulations that govern them. In particular, it provides the most informative bounds on the extent of violations that can be achieved with individual case assignment data and knowledge of the regulations that govern case assignments. Such data is available to the public in Ecuador, but is routinely collected by judiciaries around the world.

In Ecuador, a weak interpretation of the regulations suggests an instrumental variable that detects assignments that violate the regulations in a handful of courts. A stronger interpretation of the regulations implies that 7% of judges who worked in district courts between March, 2016 and February, 2020 were involved in such assignments, and that 2.9% of case assignments violated the regulations. Under either interpretation, the illicit assignments that I detect are highly localized. These findings suggest that the method is a useful tool to direct regulatory enforcement resources.

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A Proofs

B Data Collection

C Statistical Inference