Detection of Irregular Assignments of Cases to Judges

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October 27, 2021

Abstract

I develop tools to detect irregular 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 Ecuadorian regulations. Irregular assignments are highly localized: 7% of judges and 2% of courts account for 80% of the irregular assignments that I detect. To obtain these quantities, I derive the sharp bounds on the overall, court-specific and judge-specific probabilities that a case assignment is irregular, under two assumptions. First, I rely on *one-sided instruments*. These are variables that are excluded from one counterfactual outcome only: the assignment that would have been observed, had it been consistent with existing regulations. Second, I assume that the distribution of this counterfactual outcome is known. This assumption is stronger and yields informative lower bounds on the judge-specific probabilities that a case assignment is irregular.

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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 aim to abolish the market for judges, where judicial decisions tend to favor 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 *irregular*, meaning that they are inconsistent with existing regulations.[2]

How many case assignments are irregular? How does the rate of irregular 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. I construct a 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 irregular, or inconsistent with existing Ecuadorian regulations. Irregular assignments are highly localized: 7% of judges and 2% of courts account for 80% of the irregular assignments that I detect.

At the heart of these measurements lie the case assignment regulations. They provide an incomplete description of the way that cases should be assigned to judges. Thus, they are subject to interpretation. I use them in two different ways. First, I argue that the regulations reveal judicial case characteristics that do not influence the judge that the case should be assigned to. Examples include the plaintiff's friendly ties with government officials, the amount of money claimed in a payment dispute, or the extent of documentation that the plaintiff files along with the case. Second, I interpret them in conjunction with government officials' interviews to imply a probability distribution of the judge that each case should be assigned to. Each approach yields an identification assumption. Paired with observed assignments, each assumption is informative for the probability that a case's assignment

[1] During that century, 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).

is irregular, conditional on a court or time period. The second approach is more informative, however, since it allows me to measure another parameter of interest: the probability that a case's assignment is irregular, conditional on a given judge. This parameter gives a granular view on the structure of irregular 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 irregular 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 relating the judge that a case is assigned to with the judge that the case would have been assigned to, had its assignment been irregular, and the judge that the case would have been assigned to, had its assignment been *regular*, or in accordance with existing regulations. The counterfactual assignment that is observed will depend on whether the case's assignment is irregular or not. Unlike program evaluation models, where the treatment status is observed, we do not observe any case's irregular assignment status. Indeed, the distribution of the case's irregular assignment status is the object of interest. Thus, our model involves a discrete, two-component mixture.

I then study identification under two assumptions. First, the researcher observes a case characteristic that is statistically independent of counterfactual regular 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 irregular assignment status.[3] The second assumption

[3]They also differ from the mismeasured counterparts used in the literature on data misclassification,

involves a stronger interpretation of the regulations: the probability mass function of counterfactual regular assignments is known.

Under each assumption, I obtain analytical solutions for the sharp bounds on the probability that a case's assignment is irregular, as well as the corresponding probabilities conditional on covariates (e.g. the case's court and time of assignment) and conditional on the judge that the case is assigned to. 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 include Balke and Pearl (1997), Torgovitsky (2019) and Tebaldi, Torgovitsky, and Yang (2019), and my characterization can be seen as a special case of Lafférs (2019b), who shows that the identified set of a given discrete data-generating process under arbitrary linear restrictions can be recovered with 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 closed-form solutions for the bounds are simple. If the distribution of counterfactual regular assignments is known, the lower bound on the probability of an irregular 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. Moreover, knowledge of the distribution of counterfactual regular assignments implies that the probability that a case's assignment is irregular, conditional on a given judge, is greater than the rate 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 court, judges are selected on the basis of a lottery system that is partially specified,

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).

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. To obtain these data, I crawled the website. Then, I 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 irregular 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 irregular assignments, but not others. They detect irregular assignments made within the case's assigned court and time period of assignment. Thus, the lower bounds on irregular 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 exogeneity 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 irregular. 17 courts account for 80% of these assignments. In particular, one court accounts for a third of these assignments, with $3,200$ irregular 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 irregular. This exercise implies that 2.9% of case assignments are irregular. 70 courts account for 80% of these assignments. 111 judges out of 1568 received cases with irregular assignments.

Finally, I validate my judge-specific measures of irregular assignments. Judges that I conclude received irregular assignments are more likely to have faced corruption charges and. Anecdotally, the judge that received the largest amount of cases with irregular 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 irregular 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 regular assignments is known, the lower bound on the probability that a case's assignment is irregular 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 instruments 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 (2019b), is inspired by Tebaldi, Torgovitsky, and Yang (2019), and is related with Balke and Pearl (1997), Lafférs (2013), Demuynck (2015), Lafférs (2019a) and Torgovitsky (2019). In my setting, I do not observe a proxy variable for the cases' irregular 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 irregular 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 irregular, 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 3 then discusses the Ecuadorian context and the available data. Section 4 adapts the econometric framework to the Ecuadorian context and discusses estimation. Section 5 presents the estimation results and section 6 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 irregular 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 *irregular*, or inconsistent with the regulations. Let S_i indicate if i's assignment is irregular or not. This is a latent, binary random variable.

Irregular 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.

I consider 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 irregular. The second one is the judge that case i would have been assigned to, had its assignment been *regular*, or consistent with the regulations. We denote counterfactual irregular assignments with variable $Y_i(1)$ and counterfactual regular 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 irregular ($S_i = 1$), and equals $Y_i(0)$ otherwise.

For the sake of illustration, I implicitly condition on case i's covariates. I am interested in two parameters: the rate of case assignments that are irregular, and the rate of cases assigned to a given judge whose assignment is irregular: $\Pr(S_i = 1)$ 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 irregular 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. At this stage, no component on the right-hand side of (1) is observed. Thus, it is possible 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 $\Pr\big(Y_i = Y_i(0)\big) = 1$. 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 regular. Second, that the distribution of regular assignments is known.

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

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

Before I discuss each of these assumptions and their identification power, note that neither assumption restricts the distribution of irregular assignments, $Y_i(1)$. Assumptions IV and PMF are therefore consistent with the possibility that assignments coincide with irregular assignments: $\Pr(Y_i = Y_i(1)) = 1$. In this case, every case assignment can be irregular: $\Pr(S_i = 1) = 1$ and $\Pr(S_i = 1 \mid Y_i = y) = 1$. In other words, Assumptions IV and PMF are not strong enough to point-identify the parameters of interest. The goal of the identification analysis is to obtain informative lower bounds on these quantities.

1.2 Other 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 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 PMF.[4] 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 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.[5]

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 regular assignments. The traditional exclusion restriction, $Z_i \perp\!\!\!\perp (Y_i(0), Y_i(1))$, is unlikely to hold in this case. Indeed, Z_i is presumably correlated with counterfactual irregular assign-

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

[5]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 $S_i = 0$.

ments, $Y_i(1)$. Plaintiffs that file cases with a larger amounts 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, we can obtain a lower bound on $\Pr(S_i = 1)$ under Assumption IV with the following thought experiment. Suppose momentarily that S_i and $Y_i(0)$ were observed and that we had access to 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:

$$\tilde{y}_i = \begin{cases} y_i & \text{if } s_i = 0 \\ y_i(0) & \text{if } s_i = 1 \end{cases}$$

We construct $\tilde{y}_i$ out of y_i, by replacing y_i with $y_i(0)$ whenever $s_i = 1$. This involves one replacement for every irregular assignment. Hence, the fraction of observations whose observed assignments we replace equals the share of irregular assignments. In the population, this is $\Pr(S_i = 1)$, our parameter of interest. The key insight is that $\tilde{y}_i$ equals $y_i(0)$ for all i. Therefore, by Assumption IV, the modified assignments that we constructed will be independent of the instrument.

In reality, we may only observe realizations of (Y_i, Z_i): $\big\{(y_i, z_i) : i \in \{1, \ldots, N\}\big\}$. Now, we construct modified assignments $\tilde{y}_i$ out of y_i, by performing the minimum amount of arbitrary replacements that make the resulting assignments independent of the instrument. One possible "replacement scheme" would be the one that we implemented previously, when we also observed S_i and $Y_i(0)$. In general, there will be other ways to construct modified assignments that are independent of the instrument with a smaller amount of replacements. This is the case for the modified assignments that we construct. Therefore, the share of observations whose assignment we modify is (weakly) smaller than the share of observations whose assignment we modified when we observed S_i and $Y_i(0)$, which, in the population, equals $\Pr(S_i = 1)$.

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

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

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 equals half of their absolute (ℓ_1, taxicab, Manhattan) distance. This closed-form solution is a well-known result in optimal transport theory (see propositions 4.2 and 4.7 of Levin and Peres (2017) for a textbook treatment).

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.

Proposition 1 is a special case of the results listed in Table 2 below, which allow for multi-valued instruments and explicitly involve covariates. I prove these results in Appendix A.

Proposition 1 shows that instruments that yield informative lower 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 regular 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 irregular.

Proposition 1 also shows that Assumption IV does not yield informative bounds on $\Pr(S_i = 1 \mid Y_i = y)$. 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 irregular assignments if $\Pr(Y_i(0) = y) = \Pr(Y_i = y \mid Z_i = 1)$, or no cases with irregular assignments if $\Pr(Y_i(0) = y) = \Pr(Y_i = y \mid Z_i = 0)$, 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 PMF.

1.4 Identification Results under Assumption PMF

Assumption PMF states that the distribution of counterfactual regular 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 4.3.1.

Under Assumption PMF, the sharp lower bound on $\Pr(S_i = 1)$ takes the following form:

$$\begin{aligned}
\min_{\gamma \in \Gamma} \quad & \sum_{y, y' \in \mathcal{Y}} 1\{y \neq y'\}\, \gamma(y, y') \qquad \text{subject to:} \\
& \sum_{y' \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i = y) \quad \text{for all } y \in \mathcal{Y} \\
& \sum_{y \in \mathcal{Y}} \gamma(y, y') \;=\; \Pr(Y_i(0) = y') \quad \text{for all } y' \in \mathcal{Y}. \\
= \; & \frac{1}{2} \sum_{y \in \mathcal{Y}} \Big| \Pr(Y_i = y) \;-\; \Pr(Y_i(0) = y) \Big|.
\end{aligned} \tag{3}$$

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 regular assignments. Like (2), problem (3) has a simple analytical solution.

The primary motivation for Assumption PMF is that it produces an informative lower bound on $\Pr(S_i = 1 \,|\, Y_i = y^*)$, for any given $y^* \in \mathcal{Y}$. This lower bound is

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

$$= \max\left\{0,\; \frac{\Pr(Y_i = y^*) - \Pr(Y_i(0) = y^*)}{\Pr(Y_i = y^*)}\right\}.$$

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 at judge y^* are irregular. The following proposition summarizes.

Proposition 2. *If Assumption PMF 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. $\max\left\{0,\; \frac{\Pr(Y_i = y) - \Pr(Y_i(0) = y)}{\Pr(Y_i = y)}\right\} \;\leq\; \Pr(S_i = 1 \,|\, Y_i = y) \leq 1$, *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 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.

2 Identification Analysis

This section develops the theory of identification that underlies propositions 1 and 2, in a setting with explicit covariates.

In addition to Y_i and Z_i, the researcher observes case characteristics X_i. X_i is a random vector that takes values in finite set $\mathcal{X}$. In the empirical framework of section 4, these characteristics will be the case's court, field of law and time period of assignment. I reformulate Assumptions IV and PMF as:

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

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

Note that if X_i is degenerate, then Assumptions IVx and PMFx are identical to Assumptions IV and PMF.

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 equation (1). Second, assumptions IVx and PMFx 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 $\big(Y_i(0), Y_i(1), S_i, Z_i\big)$ conditional on X_i. f denotes a typical element of $\mathcal{F}$, and $f(y_0,\, y_1,\, s,\, z \,|\, x)$ 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.

2.1 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 PMFx.

$f \in \mathcal{F}$ satisfies observational equivalence under model (1) if:

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

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:

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

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 PMFx if:

$$\sum_{y_1, s, z} f(y_0,\, y_1,\, s,\, z \,|\, x) \;=\; \Pr(Y_i(0) = y_0 \,|\, X_i = x) \qquad \forall\, y_0, x, \tag{R$_{\text{PMF}}$}$$

where $\Pr(Y_i(0) = y_0 \,|\, X_i = x)$ is known, for all $y_0 \in \{1, \ldots, n_Y\}$ and $x \in \mathcal{X}$.

Assumptions IVx and PMFx are associated with identified sets $\mathcal{F}^\star_{\text{IV}}$ and $\mathcal{F}^\star_{\text{PMF}}$, respectively, where

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

The case where both Assumptions IVx and PMFx are imposed need not be treated separately. Under both assumptions, the distribution of $Y_i(0) \,|\, X_i, Z_i$ equals that of $Y_i(0) \,|\, X_i$, which is known. Hence, both assumptions can be cast as Assumption PMFx with covariates $\widetilde{X}_i = (X_i, Z_i)$.

2.2 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 $c = (c_1, \ldots, c_{d_\theta})$, so that

$$\theta(f;\, c) \quad \equiv \quad \begin{pmatrix} \sum\limits_{y_0, y_1, s, z, x} c_1(y_0, y_1,\, s,\, z,\, x)\; f(y_0, y_1,\, s,\, z \,|\, x) \\ \vdots \\ \sum\limits_{y_0, y_1, s, z, x} c_{d_\theta}(y_0, y_1,\, s,\, z,\, x)\; f(y_0, y_1,\, s,\, z \,|\, x) \end{pmatrix}.$$

Description	Parameter of Interest	$c(y_0, y_1, s, z, x)$
Rate of Irregular Assignments	$\Pr(S_i = 1)$	$\Pr(X_i = x) \cdot 1\{s = 1\}$
Judge y^*'s Rate of Irregular Assignments	$\Pr(S_i = 1 \mid Y_i = y^*)$	$\frac{\Pr(X_i = x)}{\Pr(Y_i = y^*)} \cdot 1\{s = 1\} \cdot 1\{y_1 = y^*\}$
Rate of Irregular Assignments, given $X_i = x_0$	$\Pr(S_i = 1 \mid X_i = x_0)$	$1\{x = x_0\} \cdot 1\{s = 1\}$
Rate of Irregular Assignments, given $X_i \in \mathcal{X}_0$	$\Pr(S_i = 1 \mid X_i \in \mathcal{X}_0 \subseteq \mathcal{X})$	$\frac{\Pr(X_i = x)}{\Pr(X_i \in \mathcal{X}_0)} \cdot 1\{x \in \mathcal{X}_0\} \cdot 1\{s = 1\}$

Table 1: Coefficients of the Linear Parameters of Interest

When θ is scalar, $\theta(f;\, c) \;\equiv\; \sum_{y_0, y_1, s, z, x} c(y_0, y_1,\, s,\, z,\, x)\, f(y_0, y_1,\, s,\, z \mid x)$.

The identified set for parameter $\theta(\cdot\,;\, c)$ is the set of parameter values that are associated with distributions that belong to the identified set for f:

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

Table 1 shows that all of our parameters of interest are linear and presents the associated vectors of coefficients.[6]

I now turn to the characterization, or computation, of identified sets. Notice first that $\mathcal{F}^{\star}_{\mathrm{IV}}$ and $\mathcal{F}^{\star}_{\mathrm{PMF}}$ are convex sets: the convex combination of any two elements of $\mathcal{F}^{\star}_{\mathrm{IV}}$ (or $\mathcal{F}^{\star}_{\mathrm{PMF}}$) is a well-defined probability mass function that also satisfies restrictions ($\mathrm{R_{OE}}$) and ($\mathrm{R_{IV}}$) (or ($\mathrm{R_{PMF}}$)). 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 ($\mathrm{R_{OE}}$) and ($\mathrm{R_{IV}}$) (or ($\mathrm{R_{PMF}}$)) is convex, which follows from the fact that these restrictions are linear equations in f.

Now, fix non-negative coefficients c and consider parameter $\theta(\cdot\,;\, c)$. Its identified

[6]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.

sets, $\Theta^\star_{\mathrm{IV}}(c)$ and $\Theta^\star_{\mathrm{PMF}}(c)$, are also convex. In particular, let $f_1, f_2 \in \mathcal{F}^\star_{\mathrm{IV}}$. For a given $\lambda \in [0,1]$, $\lambda f_1 + (1-\lambda) f_2 \in \mathcal{F}^\star_{\mathrm{IV}}$ and

$$\lambda \underbrace{\theta(f_1;\, c)}_{\in \Theta^\star_{\mathrm{IV}}(c)} + (1-\lambda) \underbrace{\theta(f_2;\, c)}_{\in \Theta^\star_{\mathrm{IV}}(c)} \quad = \quad \theta\big(\lambda f_1 + (1-\lambda) f_2;\, c\big) \;\in\; \Theta^\star_{\mathrm{IV}}(c).$$

Thus, the identified set for a scalar and linear parameter under either Assumption IVx or PMFx 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 ($\mathrm{R}_{\mathrm{PMF}}$). That is, given a vector of non-negative coefficients c, $\Theta^\star_{\mathrm{IV}}(c) = \big[\underline{\theta}_{\mathrm{IV}}(c),\, \overline{\theta}_{\mathrm{IV}}(c)\big]$, where

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

and $\underline{\theta}_{\mathrm{PMF}}(c)$ and $\overline{\theta}_{\mathrm{PMF}}(c)$ 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 PMFx equals:

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

Assumption	Parameter of Interest	$\underline{\theta}(c)$	$\overline{\theta}(c)$
IVx	$\Pr(S_i = 1 \mid X_i = x)$	$\min_{\phi \in \Phi} \sum_{z,y} \frac{1}{2} \Pr(Z_i = z \mid x) \Big\| \Pr(Y_i = y \mid x, z) \; - \; \phi(y \mid x) \Big\|$, 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
PMFx	$\Pr(S_i = 1 \mid X_i = x)$	$\frac{1}{2} \sum_{y} \Big\| \Pr(Y_i = y \mid x) \; - \; \Pr(Y_i(0) = y \mid x) \Big\|$	1
PMFx	$\Pr(S_i = 1 \mid Y_i = y^*, X_i = x)$	$\max \left\{ 0, \; \frac{\Pr(Y_i = y^* \mid x) - \Pr(Y_i(0) = y^* \mid x)}{\Pr(Y_i = y^* \mid x)} \right\}$	1

Table 2: Sharp Bounds on the Parameters of Interest, conditional on $X_i = x$.

3 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.

3.1 Context

Unlike federal states, such as Brazil, Mexico, or the United States, Ecuadorian law is homogeneous across its administrative divisions. Ecuador's judiciary 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. In the event of a power outage or any other circumstance where the computer program is not accessible, 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.[7] Ecuadorian regulations leave the precise implementation of the computer program to the Judicial Council. In a recent interview, however, the president of the Judicial 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[8] and location.[9]

Ecuador offers an ideal setting to study irregular 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.[10]

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.[11] 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,

[7] This procedure dates from 2004, when assignments were still being performed manually in some Ecuadorian provinces. Since 2013, all case assignments are computer-based by default.

[8] 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.

[9] 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.

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

[11] 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.

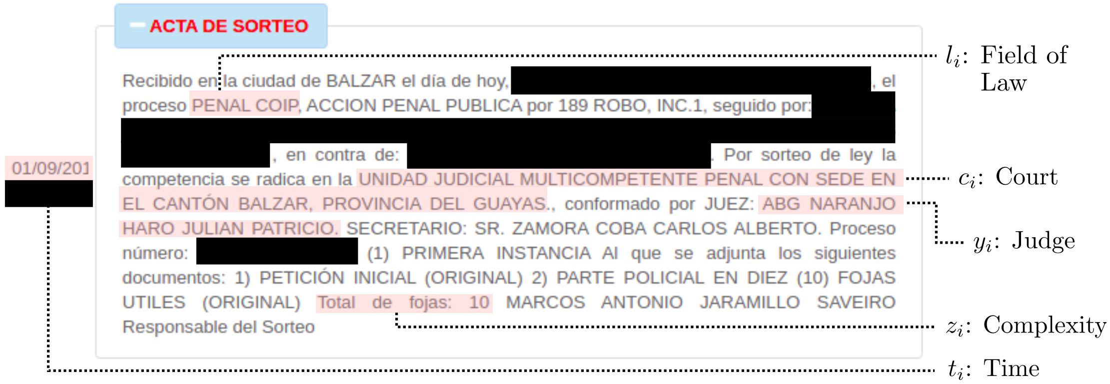

Figure 1: An annotated lottery certificate

Mexico or Peru.

The recent case assignment scandals and my conversations with Judicial Council officials reveal a variety of ways in which irregular 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 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 irregular assignment within their observed court, field of law and time of assignment from others. In particular, my measurements will only reflect this class of irregular assignments.

3.2 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.[12] 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.

[12]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.

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.

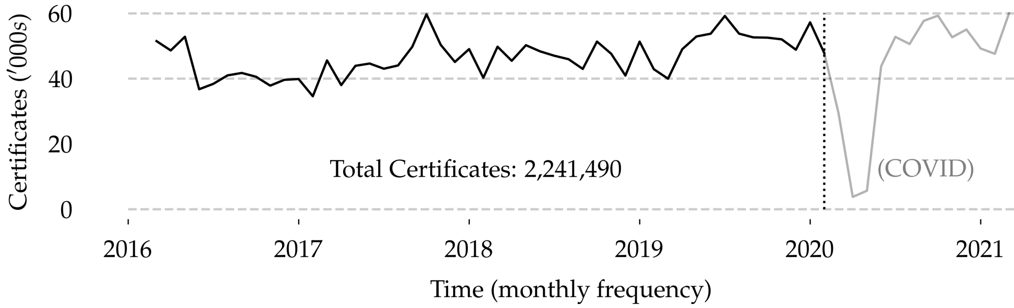

Figure 2: Lottery certificates over time

	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

Figure 1 shows a lottery certificate returned by the government's webpage.[13] 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.

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.

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

4 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.

4.1 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 $\mathcal{Y} \equiv \{1, \ldots, n_Y\}$. Moreover, I observe the page count of documentation filed by case i's plaintiff or prosecutor, Z_i. This is a random variable that takes values in finite set $\mathcal{Z}$. In the main specification, Z_i is binary and indicates if the page count exceeds 5, the median page count in the data.

I distinguish two classes of irregular assignments: those that involve manipulations of the judge that is selected *within the case's assigned court, reported field of law and time period of assignment*, and the rest. Let S_i^* indicate if case i's assignment is irregular and S_i indicate if case i's assignment is irregular within its assigned court, reported field of law and time period of assignment. It follows 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 case i's assignment is irregular due only to manipulations of the case's assigned court, field of law or time period of assignment.

S_i records several sources of irregular 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.

I focus on S_i. The parameters of interest are the rate of irregular assignments, $\Pr(S_i = 1)$, the rate of irregular assignments in court c, $\Pr(S_i = 1 \,|\, C_i = c)$, and judge y's rate of irregular assignments, $\Pr(S_i = 1 \,|\, Y_i = y)$. Notice that $S_i \leq S_i^*$ by equation (5). Hence, lower bounds for $\Pr(S_i = 1)$, $\Pr(S_i = 1 \,|\, C_i = c)$ and $\Pr(S_i = 1 \,|\, Y_i = y)$ are lower bounds for $\Pr(S_i^* = 1)$, $\Pr(S_i^* = 1 \,|\, C_i = c)$ and $\Pr(S_i^* = 1 \,|\, Y_i = y)$, respectively.

The Ecuadorian regulations imply a collection of counterfactual assignments for every judicial case. In particular, the judge that case i would have been assigned to in court c, field of law l during a given time period $\mathbf{t}$ is $\mathbf{Y}_i\big(0, (c, l, \mathbf{t})\big)$, a random variable with support in $\mathcal{Y}$.[14]

4.2 Identification with One-sided Instruments

Let $\mathcal{T}_i$ be the quarter and year when case i is assigned. The judge that case i would have been assigned to, had its assignment been consistent with the regulations within the case's court, field of law and quarter-year of assignment is $Y_i(0) \equiv \mathbf{Y}_i\big(0, (C_i, L_i, \mathcal{T}_i)\big)$. In other words, $Y_i(0)$ is case i's counterfactual assignment, had S_i been equal to zero. It is therefore related with actual assignments according to equation (1):

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

where $Y_i(1)$ is the judge that i would have been assigned to, had its assignment been irregular within the case's court, field of law and quarter-year of assignment.

According to the regulations, the page count of documentation filed by plaintiffs or prosecutors does not influence the judge that cases should be assigned to. This motivates the following assumption.

Assumption IVe. *Z_i is independent of $Y_i(0)$, conditional on $(C_i, L_i, \mathcal{T}_i)$.*

Notice that the case's court, field of law and time of assignment determine the judges that are available for case i. In a given court and field of law, the rate of cases with a large amount of plaintiff/prosecutor documentation could change over time. Therefore, under the regulations, judges who are active in times when this share is high would receive cases with more plaintiff/prosecutor documentation than others. Assumption IVe rules out this compositional variation within a quarter-year.

[14] Implicit in this counterfactual assignment are the sets of judges who should be available for assignments in court c and field of law l during period $\mathbf{t}$. I measure these sets when I impose knowledge of the distribution of $\mathbf{Y}\big(0, (c, l, \mathbf{t})\big)$ in section 4.3.

Assumption IVe is analogous to Assumption IVx with covariates $X_i = (C_i, L_i, \mathcal{T}_i)$. Thus, rows 1 and 2 of Table 2 list the sharp bounds for $\Pr\big(S_i = 1 \,|\, (C_i, L_i, \mathcal{T}_i) = (c, l, \mathbf{t})\big)$ and $\Pr\big(S_i = 1 \,|\, Y_i = y, (C_i, L_i, \mathcal{T}_i) = (c, l, \mathbf{t})\big)$ respectively, for any court c, field of law l, quarter-year $\mathbf{t}$ and judge y.

I distinguish between S_i^* and S_i because case i's court, field of law and time period of assignment can be manipulated so as to target certain courts and judges. Had these characteristics not been manipulated, one would have observed case i being assigned to judges in court C_i^*, field of law L_i^* and quarter-year $\mathcal{T}_i^*$. Case i's counterfactual assignment, had S_i^* been equal to zero is then $Y_i^*(0) \equiv \mathbf{Y}_i\big(0, (C_i^*, L_i^*, \mathcal{T}_i^*)\big)$. But Z_i is unlikely to be excluded from $Y_i^*(0)$, given $(C_i, L_i, \mathcal{T}_i)$. For example, if plaintiffs' choose $(C_i, L_i, \mathcal{T}_i)$ on the basis of $(C_i^*, L_i^*, \mathcal{T}_i^*)$, then, in general

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

As shown in row 2 of Table 2, Assumption IVe does not yield informative bounds on judge-specific rates of irregular assignments. This motivates the following alternative approach to identification.

4.3 Identification with a Known Distribution of Regular Assignments

In this approach, I assume that the counterfactual assignments implied by the regulations are uniformly distributed over the set of competent judges. A judge is competent in court c, field of law l and at point in time t if she should be available for assignments. Appointed judges need not be competent. At times, they may be on a legitimate medical leave or on vacation, for example. Competent judges need not be available: a judge that takes a medical leave so as to avoid a specific case should have been available when the case was assigned.

To state the identification assumption formally, let $\mathcal{J}_{clt}$ be the set of competent judges in court c and field of law l at time t. I discuss how I measure this set in section 4.3.1. Define $\mathcal{T}_i^J$ as the largest time interval that contains case i's time of assignment, T_i, and features the same set of competent 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 $\mathcal{T}^J(c,l,t) = \big[\underline{t},\ \bar{t}\big]$ and $\underline{t}, \bar{t}$ satisfy:[15]

i. $t \in \big[\underline{t},\ \bar{t}\big]$

ii. $\bar{t} - \underline{t} \ = \ \sup\Big\{\ \bar{\tau} - \underline{\tau}\ :\quad t \in \big[\underline{\tau},\ \bar{\tau}\big] \quad \text{and} \quad \mathcal{J}_{clt} = \mathcal{J}_{cl\tau} \text{ for all } \tau \in \big[\underline{\tau},\ \bar{\tau}\big]\Big\}.$

$\underline{t}$ and $\bar{t}$ are uniquely defined.[16] The judge that case i would have been assigned to, had its assignment been consistent with the regulations within the case's court, field of law and joint judge spell is $Y_i(0) \equiv \mathbf{Y}_i\big(0, (C_i, L_i, \mathcal{T}_i^J)\big)$. The following assumption asserts that these assignments are uniformly distributed over the set of competent judges.

Assumption PMFe. $Y_i(0)\,|\,C_i = c, L_i = l, \mathcal{T}_i^J = \mathbf{t} \ \sim\ \mathit{Unif}(\mathcal{J}_{clt})$ *where* $t \in \mathbf{t}$*, for all* c*,* l *and* $\mathbf{t}$*.*

Two features of our institutional setting, listed in Table 3, motivate Assumption PMFe. 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 competent judges, where judges' competence depends on their relative case workloads.

Assumption PMFe is analogous to Assumption PMFx with covariates $X_i = (C_i, L_i, \mathcal{T}_i^J)$. Thus, rows 3 and 4 of Table 2 list the sharp bounds for $\Pr\big(S_i = 1\,|\,(C_i, L_i, \mathcal{T}_i^J) = (c, l, \mathbf{t})\big)$ and $\Pr\big(S_i = 1\,|\,Y_i = y, (C_i, L_i, \mathcal{T}_i^J) = (c, l, \mathbf{t})\big)$ respectively, for any court c, field of law l, joint judge spell $\mathbf{t}$ and judge y.

4.3.1 Measurement of the Set of Available Judges

Assumption PMFe raises a challenge: which judges are competent in a given court c, field of law l and point in time t? I impose two conditions. First, competent

---

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

[16] Let $\underline{t}_1, \bar{t}_1$ and $\underline{t}_2, \bar{t}_2$ satisfy i. and ii. Since they satisfy i., $\big[\underline{t}_1, \bar{t}_1\big] \cap \big[\underline{t}_2, \bar{t}_2\big] \neq \varnothing$. Define $\underline{t}^* = \min\{\underline{t}_1, \underline{t}_2\}$ and $\bar{t}^* = \max\{\bar{t}_1, \bar{t}_2\}$. Because $\big[\underline{t}^*, \bar{t}^*\big] = \big[\underline{t}_1, \bar{t}_1\big] \cup \big[\underline{t}_2, \bar{t}_2\big]$,

$$\sup\Big\{\ \bar{\tau} - \underline{\tau}\ :\quad t \in \big[\underline{\tau},\ \bar{\tau}\big] \quad \text{and} \quad \mathcal{J}_{clt} = \mathcal{J}_{cl\tau} \text{ for all } \tau \in \big[\underline{\tau},\ \bar{\tau}\big]\Big\} = \bar{t}^* - \underline{t}^* \\ \geq \max\big\{\bar{t}_1 - \underline{t}_1,\ \bar{t}_2 - \underline{t}_2\big\}.$$

Thus, $\underline{t}_1 = \underline{t}_2 = \underline{t}^*$ and $\bar{t}_1 = \bar{t}_2 = \bar{t}^*$.

judges must be in an active spell: they must have been 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 $\Pr(S_i = 1)$.

4.4 Estimation

The bounds stated in Table 2 are population quantities. I now discuss how to measure them in the Ecuadorian context with data on a finite number of cases. Appendix C, **currently under construction**, provides details. I obtain consistent estimators for the lower bounds in rows 1, 3 and 4 of Table 2, denoted by $\widehat{LB}_{\text{IV}}$, $\widehat{LB}_{\text{PMF}}$ and $\widehat{LB}_y$, respectively, by replacing probabilities with relative frequencies:

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

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 more aggregate 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 is

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

I conduct statistical inference for LB_{IV} and other lower bounds obtained from Assumption IVe with permutation tests. In particular, given the following test:[17]

$$
H_0 :\; LB_{\text{IV}} = 0 \qquad \text{vs.} \qquad H_A :\; LB_{\text{IV}} > 0,
$$

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

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.

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

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

Given the test:

$$H_0 : \; LB_{\text{PMF}} = 0 \qquad \text{vs.} \qquad H_A : \; LB_{\text{PMF}} > 0,$$

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

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

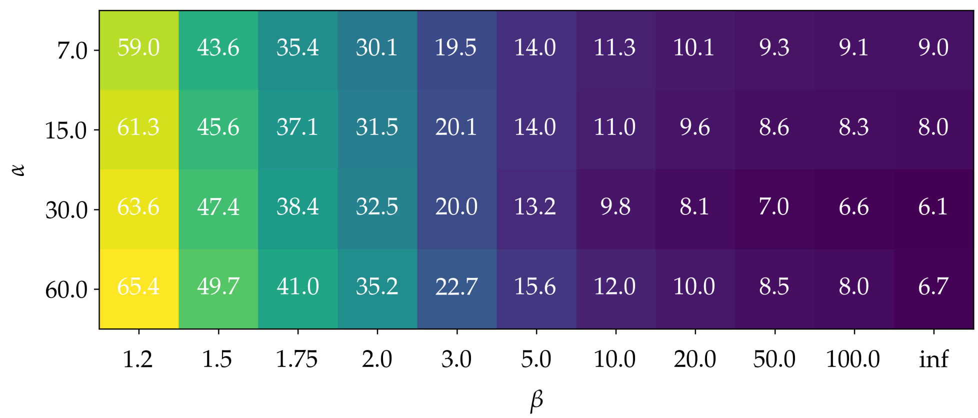

Figure 3: Lower Bounds on Overall Irregular Assignments across Tuning Parameters

Each cell shows the estimated lower bound on the rate of irregular assignments, $\Pr(S_i = 1)$, under Assumption PMFe 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.

5 Results

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

Knowledge of the distribution of regular 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 4.3.1). Figure 3 shows that I achieve a conservative lower bound on the overall rate of irregular 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 irregular assignments under Assumption PMFe.

Table 5 shows the estimated lower bounds on the overall extent of irregular assignments and the extent of irregular assignments for civil and criminal cases separately.[18] Across specifications, column (1) shows lower bounds of around six percent. These lower bounds have a substantive positive bias, however.[19] 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 irregular case assignments. The one-sided instrument, which indicates if the case's page count of documentation filed by the plaintiff or prosecutor exceeds the median page count of 5, detects irregular assignments only among criminal cases, and bounds the overall rate of irregular assignments at 0.46%. This amounts to $9,347$ irregular assignments. Thus, the instrument shows that the extent of plaintiff documentation does not influence assignments, whereas the extent of prosecutor documentation does, to a limited extent. In contrast, knowledge of the distribution of regular assignments detects irregular assignments for both criminal and civil cases, and implies $64,929$ irregular assignments overall.

Figure 4 shows the extent of irregular assignments in further detail. Each plot shows the courts and judges with significant rates of irregular assignments at the 5% level.[20] Figure 4a shows that the one-sided instrument's detections single out a handful of courts. One court accounts for a third of all irregular assignments detected. In that court, at least 16% of case assignments are irregular. When the distribution of regular assignments is known, I detect irregular assignments in more courts, and I can measure irregular assignments at the individual judge level. Four judges stand out from the rest, and irregular assignments are detected for 111 judges, out of 1568.

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

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

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

	$\widehat{LB}$	$\widehat{LB}$ percentiles under $H_0 : LB = 0$			$\widehat{LB} - p50$	$\hat{n}$ Irregular	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 PMFe							
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 Irregular 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 PMFe. 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: *** $p < 0.01$.

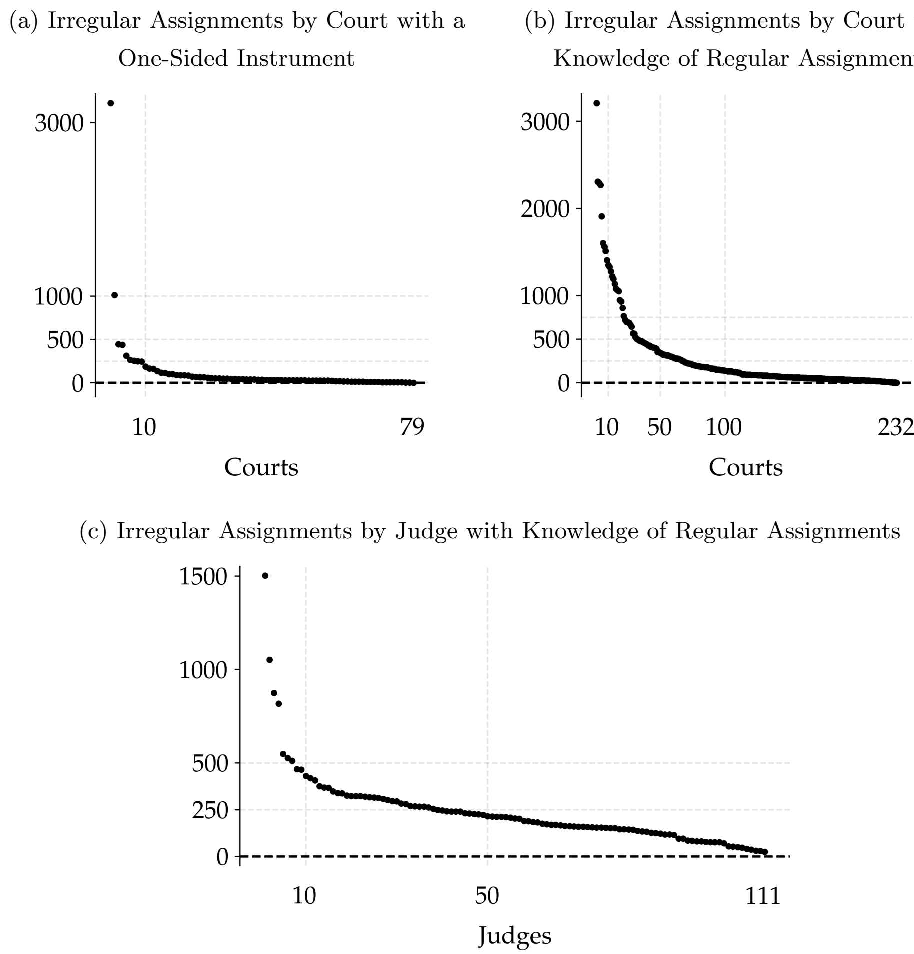

Figure 4: Disaggregate Lower Bounds on Irregular Assignments

The two top figures show the amount of irregular assignments by court, among the courts whose rate of irregular assignments is significant at the family-wise error rate of 5%, under Assumption IVe (figure 4a) and under Assumption PMFe (figure 4b). Irregular 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.

6 Conclusion

In this paper, I developed a method to evaluate a basic aspect of judicial activity: the assignment of cases to judges. The method yielded measurements on the extent to which actual assignments violated the regulations that govern them. In particular, it provided the most informative bounds on the extent of violations that can be achieved with individual case assignment data and knowledge of the existing regulations. 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 suggested an instrumental variable that detected irregular assignments in a handful of courts. A stronger interpretation of the regulations implied 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. In either case, the irregular assignments that I detected 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