Gender Differences in Judicial Decisions under Incomplete Information: Evidence from Child Support Cases*

ROBERTO ASMAT[†] LAJOS KOSSUTH[‡]

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Abstract

We compare decisions by female and male judges in child support trials where a judge decides on the father's income allocation to children. We investigate two types of cases: 1) when fathers have a formal job, their income is known to judges, and awards are set as a fraction of it, and 2) when fathers work in the informal sector, their income is unknown to judges, and awards are given as a fixed amount of money. By exploiting random assignment of cases to judges, we find that female judges set lower awards in both cases in comparison to male judges. However, the gender gap under incomplete information is around two thirds the size of that under complete information. In exploring mechanisms underlying this difference, we propose a simple framework to elicit judges' beliefs about the unknown income in such cases by using their judicial behaviour in cases where income is known. We find that female judges estimate that the unknown income is higher, but still award lower amounts of child support than male judges do. Thus, gender differences in decisions under incomplete information.

[†]Department of Economics, Warwick University (email: r.asmat-belleza@warwick.ac.uk)

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[‡]Warwick Business School, Warwick University (email: l.kossuth-cabrejos@warwick.ac.uk)

1 Introduction

The economics literature presents evidence on the factors affecting child support allocation when it is decided by a bargaining process between separated parents (Chiappori and Weiss, 2007). It is surprisingly less informative on how transfers from the non custodial parent to the child are determined when there is disagreement and they are adjudicated by a court. In this setting, the judiciary follows set legal guidelines for child support allocation with some room for discretion, leaving room for additional factors to influence the outcomes. In this paper, we explore one of these factors: the gender of judges. In particular, do male and female judges have different perspectives on a 'fair' allocation of child support?

Any attempt to map judges' preferences from observed judicial decisions faces an important empirical challenge: the judiciary is often not able to observe all relevant information to make a decision. Hence, these decisions may reflect both judges' preferences about the fair amount of child support to allocate but also their beliefs about the missing information. In particular, the vital piece of information in child support cases is the income of respondents, since it is used as a reference by judges to reach a verdict. When the respondent works in the informal economy, having complete knowledge about his income might be difficult, so judges must form beliefs about the unknown income before deciding how much child support to allocate. This issue is more salient in developing countries due to the large informal labour markets, which affects judicial decision-making (Sadka, Vera and Woodruff, 2018).

To address this, we combine judicial decisions in randomly assigned child support cases with complete and incomplete information about the income of respondents. In the former, since the respondent works in the formal economy (from now on, formal cases), the judge is able to observe his income, and decides on a child support amount that is expressed as a percentage of the respondent's income. In the latter, however, the respondent works in the informal economy (from now on, informal cases) and judges first need to form beliefs about his unknown income before deciding a child support amount, which is ultimately being awarded in absolute terms. Our sample therefore comprises judges that make decisions in both contexts, giving us a unique opportunity to inspect the degree to which incomplete information might play a role in shaping gender differences in the allocation of child support, but also in the elicitation of beliefs about the income of respondents as a potential mechanism.

We use the Peruvian judicial institutional setting for the following reasons. First, the features of the justice system allow us to identify a causal effect of gender differences in judicial decisions, since child support cases are randomly assigned to female and male judges. Second, due to the highly informal nature of the labour market, the distribution of cases across the formal and informal economies allows us to conduct the analysis described above. Third, the legal objective in child support cases is narrow and measurable: the award of a reasonable amount of money to meet the needs of the children. There are no other motives such as punishment or deterrence typically found in criminal cases. Finally, child support cases are

heavily gender-coded. In Peru, women are generally expected to take care of children and men to provide income and physical protection. Indeed, more than 98% of the cases we analysed involve a mother suing a father.

Our database includes over 3,000 published child support cases in Lima, Peru, where the petitioner is always the mother and custodial parent, and the respondent is always the father. We extract information from two stages of a typical child support case. In the first stage, the settlement hearing, the parties are encouraged to negotiate and agree on a child support amount in order to avoid the expenses of proceeding to litigation. If the parties fail to settle, the case then proceeds to litigation. Here, judges have to decide a child support amount based on the evidence presented by the parties. Depending on the job type of the respondent, the ruling is a percentage of his income (formal job) or a fixed amount of money (informal job).

Our central finding is that, relative to their male counterparts, female judges allocate smaller amounts of child support per child. Moreover, we also find that these gender differences depend on whether the income of the father is observable. The gender-based gap is -6.8% in formal cases (0.25 standard deviations) and -5.9% in informal ones (0.16 standard deviations). These results are striking for two reasons. First, female judges seem to be more harsh towards the female petitioners, although this finding is in line with some evidence found in decisions about employment (Bagues and Steve-Volart, 2010) and academic evaluations (Bagues, Sylos-Labini and Zinovyeva, 2017). Second, results show that the gender-based gap found in formal cases - when there is complete information about the income of respondents - is 56% higher than that in informal ones.

To understand how the lack of information about the income of respondents attenuates the gender-based gap, we develop a simple framework of judicial decision-making in which incomplete information operates through beliefs. We interpret the verdict reached by a judge in a formal case as their revealed child support allocation preference. We then assume the same judge should exhibit the same preference in an informal case, the difference being the degree to which they would also need to form a belief about the income of the father. To illustrate, if the award given by a judge in a formal case is 30% of the respondent's income and the same judge awards S/. 300 in an informal case with observably similar respondents, we then infer that the judge must believe the respondent earns S/. 1,000. So, we use the estimated preference in the formal case, to gether with the child support amount allocated by that same judge in the informal case, to infer how they would form a belief about the respondent's income in that same informal case.

By restricting the sample to judges who face formal and informal cases and applying the framework described, we find a gender-based gap of around -4.7% in cases where income is unknown. This gender gap is composed of a gender gap in preferences for child support allocation of -12% and a gender gap in estimates of fathers' income of 7.33%. This means female judges - relative to their male counterparts - infer higher levels of income when information

about it is incomplete or non-existent. In other words, even though female and male judges are exposed to similar sets of incomplete information (do to random allocation of cases to judges), female judges exhibit a higher reference point (estimate of the income of respondents) to decide on a 'fair' allocation of child support. Thus, gender differences in estimates act as a countervailing force and explain the attenuation of gender differences in decisions under incomplete information.

To gain a better understanding of why judges' estimates of fathers' income differ by gender, we explore the extent to which judges rely on the mother's claim (amount of money) as a signal about the unknown income of respondents. In informal cases, mothers state their claims arguing that this amount of money is a fair estimation of what the father is able to pay. It is worth noting that claims are recorded before the case is randomly assigned to a judge, and so are independent of the gender of judges. We study the relationship between beliefs and claims by using a standard Bayesian updating framework in which judges estimate the unknown income based on their priors and the signal (claim) sent by mothers. We find that female judges rely less on the claim when estimating the unknown income. This might suggest that one underlying explanation for the lack of homophily found in the reduced-form estimates is that female judges rely less on claims made by female petitioners than male judges.

Finally, we also consider how other characteristics of judges influence decision-making. Other explanations for the gender gap might be differences in age or work experience of judges. We collected data on age, work experience and self-reported wealth of judges from official sources. First, we check whether judges significantly differ across those characteristics and find that male and female judges are similar. Second, we include those characteristics as controls in our baseline regressions. We find that only for informal cases, judge's age and status have a significant negative and positive effect on the award, respectively. However, the gender gap remains statistically significant and we find no evidence of a change in the magnitude of the gap.

Our paper contributes to the large literature on the role of gender in judicial decisionmaking. Most of this research has focused on criminal cases (e.g. Gruhl, Spohn and Welch (1981); Coontz (2000); Collins and Moyer (2008)), discrimination cases (e.g. Farhang and Wawro (2004)) and a range of civil rights issues such as immigration appeals (see Gill, Kagan and Marouf (2015)) and issues affecting women¹ (e.g. Martin (1989); Peresie (2005); Boyd, Epstein and Martin (2010); Boyd (2016)), all in the context of Common Law. To the best of our knowledge, this study contributes to the unexplored branch of family law and child support cases, which has several advantages for the study of judges' gender differences in judicial decisions.

First, in many settings, judicial decisions are made by a panel of two or three judges (see

 $^{^{1}}$ The issues included in these studies are abortion, affirmative action, sex discrimination in employment and sexual harassment

Gill, Kagan and Marouf (2015) and Peresie (2005)) and the interaction between them poses the additional problem of how to disentangle the views of female and male judges. This is the main challenge to identification of judge gender effects in this literature. However, in our setting, a single judge decides child support cases so we can attribute differences to the gender of judges by exploiting random assignment. Second, the objective in child support cases is simple and narrow, as opposed to the typical issues studied in the literature (see Arnold, Dobbie and Yang (2018)). By isolating one legal objective, we can pin down preferences of judges on the single issue of income support for children. Third, as Kiser, Asher and McShane (2008) show, in most judicial instances, only 5% of cases reach litigation, so the interest should be in the settlement stage instead of the litigation stage. In child support cases, we find that 70% of cases that started the process reach litigation. Finally, in many instances there is female under-representation in courts, which poses an empirical threat when it comes to comparing decisions of male and female judges (Knepper (2018)). In stark contrast with other settings, in child support trials in Peru, 60% of judges are female.

This paper also contributes to a novel literature in attempting not only to detect outcome disparities, but also to study the reasoning and to learn about the decision-making process behind these results. For instance, Arnold, Dobbie and Yang (2018) test for racial bias in bail decisions by comparing misconduct rates of respondents for whom perceived benefits and costs of being released were equal for judges. In another recent study, Ash, Chen and Ornaghi (2020) look at gender attitudes to explain voting behaviour in gender-related cases in U.S. Circuit Courts. In the same spirit, our paper contributes to understanding gender differences in judicial decision-making by inspecting the role of incomplete information in shaping potential differences.

We structure this paper as follows. In Section 2, we describe the child support system in Peru. In Section 3, we review the data and construction of variables. In Section 4, we explain the random assignment of cases to judges, provide evidence in this regard, and then report the judge gender-based gaps. In Section 5, we show robustness checks and address sample selection concerns in our setting. In Section 6, we present a framework of judicial decision-making and discuss gender differences in estimates about the income of respondents as the main mechanism explaining results. Finally, the conclusion is in Section 7.

2 Overview of the Peruvian child support system

The goal in child support cases is for the judge to make an award (the specific monetary amount for child support the respondent will have to pay) based on the claims of both parties and all the available information. The criteria for setting an award is provided by the Peruvian Civil Procedure Law: a) the needs of the children who are trial matter; b) the respondent's income; and c) additional children the respondent must support. However, the way to balance

these variables and how to determine the award is not stated explicitly and is at the discretion of each judge. The only firm rule is that the amount, in total, should not represent more than 60% of the respondent's income.

A crucial aspect of the legislation is that it is not necessary for a judge to know the respondent's income to set an award. About 70% of the workers in Peru work in the informal sector, and often a child support case involves adjudicating two opaque income streams. Therefore, judges' awards depend on the respondent's job status. First, in cases where the respondent has a formal job and his income is known to the judges, they set an award as a percentage of income. For the sake of simplicity, we define these cases as "formal". Second, in cases where the respondent works in the informal sector, his income is unknown to the judge, who sets an award as a fixed sum. We defined such cases as "informal". In these type of cases, a reference of the respondent's income is supposed to be made by judges, although they do not often report it. In this regard, the legislation states that the reference cannot be less than the legal minimum wage.

The process that a case goes as follows. Once a child support case is filed, it will first be revised by a court and subsequently admitted for trial. If admitted, the respondent is immediately notified and has up to five days to respond to the claim. If the respondent does not respond, he is declared a "rebel" and loses his right to present evidence that supports his position. After this step, a date is set for the first stage of the process under study: the settlement hearing. The judge's goal in this stage is to get both petitioner and respondent to settle, so they can avoid incurring in the monetary and time-consuming costs of litigating. If the petitioner and the respondent fail to settle on a specific amount for child support, the case proceeds to litigation where the judge will decide the award. Finally, if any or both parties disagree with the award, they could appeal the decision and proceed to a final stage.

3 Data

This paper uses data from two Peruvian administrative sources: virtual archives of judicial records ("Consulta de Expedientes Judiciales") and the national transparency agency ("La Contraloría").

3.1 Judicial Records

We use publicly available documents from the CEJ website relating to child support cases filed in the capital city of Lima during 2017 and 2018. CEJ provides all records of each action taken by the parties and the judge assigned in each case. For a given case, we collected documents corresponding to the two stages described in section 2.1: the settlement hearing (first stage) and the litigation (second stage). The final data set was built based on 3,015 child support cases from the website. In the following subsections, we describe how we extracted variables from both documents.

Settlement hearing: This document is signed by the judge assigned to the case and records the attendance of parties and their attorneys (names and IDs), and characteristics of children who are trial matter (full names and age). As the main goal is to promote agreement between the parties, the following steps of the settlement process are conducted by the judge: i) the petitioner asks for an amount for child support, ii) the respondent either accepts or offers a different amount, iii) the judge suggests an amount, and iv) parties accept or reject the proposition. Unfortunately, most cases do not record this process and only show a no settlement/settlement result. We infer the judges' gender from their full names shown in the digital signature.

Litigation: This document is also signed by the judge assigned to the case² and contains the verdict and the judge's arguments. We extracted data from the 'case analysis' section³ that contains the judge's analysis on the three criteria established by Peruvian law to determine an award. For the first criterion, the needs of the children who are trial matter, judges typically state their age, how much the mothers spend on them, and if they have any special needs such as health conditions. For the second criterion, the economic capacity of the respondent, the judge examines all his income sources, such as salary, businesses, and properties, should there be information about them. As explained in section 2.1, it is not necessary to thoroughly investigate the income of the respondent to provide an award according to the law, and this is especially relevant for cases where the respondent works in the informal sector. Finally, for the third criterion, the judge investigates whether the respondent has other dependent children to support⁴.

Table 1 shows a summary of the data sets used in this study. Since only districts that have more than one court apply randomisation of cases to courts, we discarded cases from districts with only one court. At the settlement hearing stage, there are 2,371 cases in total. These cases were assigned among 149 judges, 59% of whom were women. 27.4% of the cases reached a agreement and did not proceed to the ligation stage. At the litigation stage, there are 1,736 cases in total. These cases were assigned among 153 cases, 61% of whom were women. In 22.7% of cases, the respondent had a formal job.

 $^{^{2}}$ We only found a judge in the litigation stage different than the one observed in the settlement hearing in a few cases. This is mostly explained by an abnormal delay between these two stages such that the judge leading the court changed.

 $^{^{3}}$ The complete analysis consists of three parts: legal framework, case analysis and verdict. In all cases, the legal framework section contains the same information about judicial principles followed and, therefore, there is no variation in this regard across cases.

⁴Descendants who are 18 years old or older, and other relatives such as parents or siblings are not considered the responsibility of the defendant although respondents often claim to have such responsibilities.

3.2 Transparency Agency

We supplement the data of judicial cases by further characteristics of judges from two publicly available sources. Given their important public responsibilities, judges are closely supervised by the Peruvian Transparency Agency to detect irregularities related to corruption. From CVs, we collected judges' ages, job position (principal judge or alternate judge) and years of experience as principal at the time of the study. The position of a judge (principal/alternate) depends on professional achievements and experience as a judge. Moreover, principal judges earn higher salaries and are held in higher esteem than alternate judges. From the second source (financial situation), we collected judges' wealth. It worth mentioning that this is self-report information, which should include savings at the financial system and valuation of their assets (mostly real estate).

4 Empirical Analysis

4.1 Identification condition

Identification is achieved by cases being randomly assigned to judges within a judicial district. According to the Peruvian Civil Law, child support cases are randomly assigned to courts within a judicial district⁵. Most judicial districts contain more than one court, and each court is led by only one judge. Thus, districts with more than one court will follow a random algorithm for assigning cases to courts. This ensures a fair distribution of caseload across courts and also prevents petitioners from targeting their cases to more favourable judges. As courts are led by one judge, court randomisation means that cases are randomly assigned to judges.

The randomisation process is conducted as follows. First, to sue for child support, the petitioner must attend a Peace Court in the judicial district corresponding to the geographical district where she lives. The forms to file a lawsuit are designed to be simple and accessible even to those who do not have the means to pay for legal services. The form is entered into the IT system in an office called 'Mesa de Partes'. The case is randomly assigned to one court office out of several within the judicial district. Finally, the court office receives the lawsuit file and the process described in 2.1 starts.

We provide a screenshot of the randomisation step in the system as is written in its user $guide^{6}$. This shows how the person in charge has to register the case into the system (see the Appendix). We highlight the fact that it is impossible for the officer to manipulate the assignment of the case to a court. This randomisation pipeline has been confirmed by two

⁵Due to different population sizes of geographical districts, the judicial system sets "judicial districts" to aggregate small population-sized districts. For instance, two small population-sized geographical districts "X" and "Y" can be merged into the judicial district called "X - Y".

⁶The user guide is available here (click to link).

separate sources in interviews conducted in Peru in 2019⁷.

To corroborate that cases are indeed randomly assigned to judges in our data set, we conduct balancing tests. Table 2 presents the balance check of cases characteristics observed at the settlement hearings. For each group of judges, it presents the means and standard errors of the variables used for the analysis. The balance check is determined by the p-values of the differences-in-means two-tailed t-tests shown in the last column. It is important to note that these calculations only contemplate judicial offices in which there is at least one male and one female judge, as randomisation of cases to judges could be conducted. A statistically significant p-value suggests that there is enough statistical evidence to reject the null hypothesis of balance. As can be observed in Table 1, there is no evidence of imbalance in any of the variables observed. Therefore, we have no reason to doubt that settlement hearings were randomised across female and male judges.

As our main analysis is based on cases that reached the litigation stage, we also check whether cases' characteristics are balanced across female and male judges at the litigation stage. Table 3 and Table 4 present balance checks for explanatory variables in the litigation stage for formal and informal cases, respectively. Analogously to Table 2 they present the means and standard errors of the relevant variables used for the analysis for male judges and female judges. The last column shows the p-values of the differences-in-means two-tailed t-tests. Again, these calculations only contemplate judicial offices in which there is at least one male and one female judge. In formal cases, Table 3 shows no imbalance except for one variable (with 90% of confidence): the number of children outside of trial that the respondent has to support. For informal cases, Table 4 shows no imbalance in all cases' characteristics.

All these pieces taken together constitute robust evidence that cases were randomised and the registration of cases followed the user guide described above.

4.2 Econometric specifications and results

Before we present the estimation of gender differences in decision-making, we provide a graphical analysis of decisions by gender of judges. Figures 1 and 2 show kernel distributions of child support allocations given by male and female judges in formal and informal cases. In both cases it can be clearly seen that the mean of the distribution for female judges is lower than that for male judges, indicating that female judges award lower amounts of child support on average. Moreover, the differences between female and male judges seem to be larger in formal cases than in informal cases. We estimate the judge gender gap in formal and informal cases by exploiting random assignment of cases to judges as follows:

(1)
$$log(\frac{\alpha_{ij}}{N_i^T}) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 N_i^{-T} + \gamma_d + \gamma_t + \epsilon_{ij}, \quad i \in F$$

 $^{^{7}}$ We interviewed the assistant of a judge who works in one of the courts in our study and a lawyer who had served as an attorney in child support cases.

(2)
$$log(\frac{A_{ij}}{N_i^T}) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 N_i^{-T} + \gamma_d + \gamma_t + \epsilon_{ij}, \quad i \in I$$

In equation (1), α_{ij} is the award (as percentage of the respondent's income) in formal case $i \in F$ assigned to judge j. $Female_{j(i)}$ is an indicator variable for whether formal case $i \in F$ was assigned to a female judge j. N_i^T and N_i^{-T} denote the number of children involved in formal case $i \in F$ and the additional number of children the respondent in formal case $i \in F$ needs to support, respectively. In equation (2), A_{ij} is the award (as a fixed amount of money) in informal case $i \in I$ assigned to judge j. $Female_{j(i)}$, N_i^T and N_i^{-T} are analogous variables for informal case $i \in I$. Finally, both equations include district γ_d and year γ_t fixed effects γ_d . All standard errors are clustered at the judge level. The main coefficient of interest is β_1 which estimates a semi-elasticity: the percentage change in the award when the case is assigned to a female judge relative to a male judge.

Table 5 contains the results of the pooled OLS regressions for the formal and informal cases. Columns (1) and (2) show that the gender-based gap is -6.8% in the formal cases, and -5.9% in the informal cases. For the formal cases, this means that female judges set an award per child that is on average 6.8% lower than that of the male judges. Looking at the other explanatory variables provides additional depth in understanding the judicial decision-making process in child support cases. Both the number of children included in the trial and the number of additional children the respondent has to support are negatively associated with the award in both formal and informal cases, since the maximum award a judge can give is 60% of the respondent's income. The coefficient associated with the number of children in trial is bigger when compared to the additional children the respondent needs to support in both formal and informal cases.

While the estimates of the gender gaps are easily interpreted (semi-elasticity), the limitation is that they cannot be comparable between formal and informal cases. Indeed, while the judge gender differences in formal cases correspond to differences in ratios (% of income awarded), in informal cases they correspond to differences in levels (amounts of money). To make them comparable we re-estimate equations (1) and (2) by standardising the awards given in formal and informal cases. Table 5 shows the results in columns (3) and (4). When a formal case is assigned to a female judge, the allocated child support amount per child is -0.25 standard deviations relative to when it is assigned to a male judge. The analogous figure for informal cases is -0.16 standard deviations. This means that the female judge effect is 56% stronger in formal cases than in formal cases. This striking result raises the question of how incomplete information has this attenuation effect in judge gender differences in child support decisions. We develop a simple framework to address the role of incomplete information in decision-making in section 6.

5 Robustness analysis

5.1 Going beyond gender

We have provided evidence of a gender-based gap when judges make child support rulings. 'Gender' might not be the only story behind these results, however. For instance, a female judge who is 60 years old at the time of trial might have views about what she considers a 'fair' allocation of child support, not because of her being female, but because she belongs to a generation with distinct social norms.

Thus, we check whether disparities are attributable to judges' characteristics other than their gender. As described in section 3.2, we collected data on their ages, job status (principal or alternate), years of experience as principal and self-reported wealth. First, we inspect whether male and female judges differ along these characteristics. Second, we include all judges' characteristics in our baseline regressions.

Table 6 presents a balance analysis for characteristics of judges by their gender. This test shows that female and male judges do not differ in other characteristics beyond gender except for their job status: 49.2% of male judges work as principal judges while for female judges it is 35.2%.

Table 7 shows the estimates of equation (4) and (5) with all judges' characteristics as control variables in addition to the variables used in Table 5. It can be seen that the gender effect prevails after including these controls. For formal cases, none of the other judge's characteristics are statistically associated with awards given by judges. For informal cases, judge's age, job status, and wealth have a significant effect on awards. However, there is no evidence that the magnitude of the gender gap changes after including them.

5.2 Sample selection bias

In this section we investigate whether the litigation stage in child support cases is suitable for detecting gender-based differences in judicial decisions. As Knepper (2018) pointed out, to detect judge gender-based differences in decisions, one must also inspect judge gender-based settlement rates. Indeed, the prior literature has focused on the trial stage and has ignored the fact that, optimistically, cases reach trial 20% of the time (Kiser, Asher and McShane, 2008). This could make the trial stage unsuitable for detecting gender-based differences if the judge's gender influences the likelihood of settlement and creates a sample selection bias in the trial stage, as Knepper (2018) finds in workplace sex discrimination cases.

Thus, we start with a hypothesis that the judge's gender has an effect on the probability of settlement. Exploiting random assignment of cases, we test this hypothesis as follows:

(3)
$$Pr(Settle_{ij} = 1) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 Formal_i + \gamma_d + \gamma_t + \epsilon_{ij}$$

Where $Settle_{ij}$ is an indicator variable for whether case *i* assigned to judge *j* settles or avoids litigation. $Female_{j(i)}$ is an indicator variable for whether case *i* was assigned to a female judge *j*. We control for N_i^T , the number of children involved in case *i* and $Formal_i$, an indicator variable for whether the respondent has a formal job. Regarding the latter, for cases that do not settle, the type of respondent's job is captured in litigation. While for cases that settle, we infer the type of job by the format that the agreed amount is expressed in⁸. Finally, γ_d and γ_t are district and year fixed effects, respectively.

Table 10 shows the marginal effects of regression (3). We find no gender effect on the likelihood of settlement. Moreover, in stark contrast with figures from discrimination cases suggested by Knepper (2018) where only 5% of cases reach litigation, in our data-set over 70% of cases failed to settle and proceeded to litigation. Interestingly, Table 10 shows that when the respondent has a formal job the likelihood of settlement decreases. Although the evidence indicates that the judge's gender does not affect the likelihood of settlement (extensive margin), this raises a concern about the potential effect of the judge's gender on the level of agreement (intensive margin) for cases that settle.

In light of that result, we also test the impact of the judge's gender on the level of agreement for cases that settle as follows:

(4)
$$Agreement_{ij} = \beta_0 + \beta_1 Female_{i(i)} + \beta_2 N_i^T + \beta_3 Formal_i + \gamma_d + \gamma_t + \epsilon_{ij}$$

Where $Agreement_{ij}$ is the level of agreement (either in fixed amount of money or in percentage terms) for case *i* assigned to judge *j* that settles in the settlement hearing. $Female_{j(i)}$ is an indicator variable for whether case *i* was assigned to a female judge *j*, N_i^T is the number of children involved in case *i* and $Formal_i$ is an indicator variable for whether the respondent has a formal job. Finally, γ_d and γ_t are district and year fixed effects, respectively.

Table 11 shows the estimates of equation (4). Again, we do not find a significant effect of the judge's gender on the level of agreement for cases that settle. This means that there is no evidence that cases would self select into litigation depending on the judge's gender. Thus, we provide strong evidence that the litigation stage in child support cases is suitable for detecting gender-based differences.

6 Understanding the effect of incomplete information

The main result from the previous section is that the gender gap in formal cases is around 56% bigger than in informal cases. We propose a simple model of how incomplete information shrinks gender differences in child support decisions, and emphasise beliefs about income as the mechanism. We elicit these beliefs based on the methodological premise that the pool of

⁸If the agreement is in percentage of income, we assume the respondent has a formal job, whereas when the agreement is a fixed amount of money, we assume he has an informal job.

judges who are making decisions in informal cases are revealing their preferences in formal cases during the period of analysis.

6.1 Conceptual Framework of Judicial Decision-making

For the sake of simplicity, let us assume a situation in which one female judge and one male judge have to make their decisions in trials where there is only one child involved, and where the respondent supports no other children. A case i is randomly assigned to a judge with gender g = m, f who sets an award to be paid by the respondent. There are two types of cases, as mentioned in the previous section: the formal case $i \in F$ and the informal case $i \in I$.

In a formal case, a judge with gender g observes y_i - the respondent's income in the formal case $i \in F$ - and awards a monthly percentage deduction from the respondent's salary $\alpha^g \in (0, 0.6]$. Note that we allow α^g to vary between gender g and that it is constant within gender g since it does not depend on any case-specific characteristic. Let us reiterate that, legally, the judge only needs three pieces of information to decide on the case: the number of children who are trial matter, the respondent's income, and any additional children the respondent has to support. Given that the judge is able to observe y_i and that, by assumption, trials only involve one child and no other children to support, α^g is the fraction that the judge considers fair to deduct from the respondent's salary to support one child who is trial matter. Thus, the fraction of income per child is our outcome of interest in formal cases and what we define as the judge's allocation preferences.

In an informal case, on the other hand, a judge with gender g does not observe y_i - the respondent's income in the informal case $i \in I$ - and this time sets an award A_i^g , $i \in I$ to be paid monthly by the respondent. To do so, the judge forms a belief about the respondent's income b_i^g , $i \in I$ and sets a percentage α^g , $i \in I$ to be deducted from it. It is worth noting that neither b_i^g nor α^g are observed in $i \in I$. We only observe the given award A_i^g . Thus, a judge with gender g will choose an award A_i^g in an informal case $i \in I$ as follows:

(5)
$$A_i^g = \alpha^g b_i^g \quad \forall i \in I$$

Again, the main outcome of interest is the award per child in an informal case. This is implicit since we assume there is only one child involved in the trial and no other children to support. Thus, under this framework, a judge with gender g grants an award that is constituted by their allocation preferences α^g and their beliefs about the respondent's income b_i^g .

This framework allows for interpreting the gender-based gaps in judicial decision making both in formal and informal cases. In the formal cases, the gap is straightforward to calculate since the award α^g only varies between gender g and does not depend on case-specific characteristics:

(6)
$$\frac{E(\alpha_i^f)}{E(\alpha_i^m)} = \frac{\alpha^f}{\alpha^m}, \quad i \in F$$

If the gap in equation (6) were less than 1, it would mean that female judges have preferences for lower shares of income to be allocated to a child than their male counterparts in formal cases. As can be seen, this gap is entirely driven by differences in allocation preferences between genders.

In the informal cases, however, the gender-based gap would take the following expression:

(7)
$$\frac{E(A_i^f)}{E(A_i^m)} = \left(\frac{\alpha^f}{\alpha^m}\right) \left(\frac{\overline{b}^f}{\overline{b}^m}\right), \quad i \in I$$

If the gap in equation (7) were less than 1, it would mean that female judges are more lenient than their male counterparts towards the respondents in informal cases. However, the gap encompasses two different gaps: the gap in allocation preferences and the gap in beliefs about the respondents' income. We use this framework to interpret the results shown in section 4. Moreover, this framework is the starting point in understanding how judges' gender-based differences in beliefs might expand or shrink the gender-based gap in allocation preferences under some assumptions, as we explain in the next section.

6.2 Methodology

Intuitively, this methodology uses the revealed allocation preferences α_{ij} in the formal cases $i \in F$ assigned to judge j to infer judge's j beliefs about the income of respondents in informal cases $i \in I$. To illustrate, if the award given by a judge in a formal case represents 30% of the respondent's income and awards S/. 300 in a similar but informal case, we can then infer that the judge believes the respondent earns S/. 1,000 by assuming that the judge should maintain, *ceteris paribus*, the same allocation preference (30%). Thus, the award in informal cases breaks down into allocation preferences and beliefs about the respondent's income and we inspect the role of each of these factors in determining the gender-based gap.

Let us remember the gender-based gap expression in informal cases under the simple framework we developed in section 6.1:

$$\frac{E(A_i^f)}{E(A_i^m)} = (\frac{\alpha^f}{\alpha^m})(\frac{\overline{b}^f}{\overline{b}^m}), \quad i \in I$$

Equation (7) computes the gender-based gap in informal cases I based on the given awards A_i^g which are observable. However, the factors of that decision, b_i^g and α_i^g , are unobserved by the researcher. If those variables were observable, we could inspect the role of uncertainty in shaping the gap in informal cases I, by taking log of equation (6):

(8)
$$log(\frac{E(A_i^f)}{E(A_i^m)}) = log(\frac{\alpha^f}{\alpha^m}) + log(\frac{\overline{b}^f}{\overline{b}^m})$$

If the gap in allocation preferences were less than 1 but the gap in beliefs more than 1, then we could conclude that incomplete information would attenuate the gap in allocation preferences. To conduct such an analysis, we propose the next methodology to calibrate α_i^g in order to estimate the parameter b_i^g .

We first calibrate the allocation preferences from the decisions made by judges in formal cases $i \in F$ as follows:

(9)
$$\frac{\alpha_{ij}}{N_i^T} = \mu_j + \beta' X_{ij} + \epsilon_{ij}, \quad i \in F$$

Where α_{ij} is the award given by judge j in formal case $i \in F$; X_{ij} is a vector that contains the main criteria for award-giving in child support cases (number of children in trial and additional children in need of support by the respondent), and μ_j is the judge fixed-effect.

Second, we infer how those same judges would have decided the award $\tilde{\alpha}_{ij}$ (as a percentage of income to be deducted) in informal cases. By using the coefficients from regression (9), we predict the allocation preferences $\tilde{\alpha}_{ij}$ in informal cases as follows:

(10)
$$\tilde{\alpha}_{ij} = (\hat{\mu}_j + \hat{\beta} X_{ij}) N_i^T, \quad i \in I$$

Where $\tilde{\alpha}_{ij}$ is the calibrated award made by judge j in informal case $i \in I$ as a percentage of the respondent's income; vector X_{ij} contains the same set of variables as in equation (9) but for informal case $i \in I$; $\hat{\beta}$ is the vector of coefficients estimated in equation (9), and $\hat{\mu}_j$ is the estimated judge fixed effect also taken from equation (9). Note that the total estimated award is the multiplication of the calibrated award per child and the number of children involved in the informal trial. Figure 3 shows the kernel densities of the calibrated awards in informal cases by judge's gender. It can be seen that awards vary from 0.1 to 0.5 in general and that distributions seem to have the same variance but not the same mean: the first moment for male judges might be higher than for female judges.

The third and last step is to estimate the judge's belief about the respondent's income b_i in informal case $i \in I$ by combining the calibrated award $\tilde{\alpha}_{ij}$ (as percentage of income) and the observed award A_{ij} (fixed amount of money) in informal case $i \in I$:

(11)
$$\hat{b}_{ij} = \frac{A_{ij}}{\tilde{\alpha}_{ij}}, \quad i \in I$$

Figure 4 shows the kernel distributions of estimates by judge's gender. As opposed to Figure 3, the mean and the variance of distribution of estimates seem to vary by judge's gender. Note that in all these estimations we are not interested in the effect that the judge's gender has on the awards: the judge's time-invariant characteristics (such as gender) are

captured by the judge fixed effect μ_j . Instead our focus is on modelling the award in formal cases to predict how judges would have awarded a percentage deduction in informal cases.

6.3 Econometric specifications and results

Given the inputs provided by the expressions (10) and (11), we decompose the awards in informal cases A_{ij} into allocation preferences $\tilde{\alpha}_{ij}$ and beliefs \hat{b}_{ij} . Then we calculate the gender-based gap in both dimensions to measure the relative contribution of both sources of variation to the total gap in awards under incomplete information.

(12)
$$log(\frac{A_{ij}}{N_i^T}) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 N_i^{-T} + \gamma_d + \gamma_t + \epsilon_{ij}, \quad i \in \mathbb{R}$$

(13)
$$log(\frac{\tilde{\alpha}_{ij}}{N_i^T}) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 N_i^{-T} + \gamma_d + \gamma_t + \epsilon_{ij}, \quad i \in I$$

(14)
$$log(\hat{b}_{ij}) = \beta_0 + \beta_1 Female_{j(i)} + \beta_2 N_i^T + \beta_3 N_i^{-T} + \gamma_d + \gamma_t + \epsilon_{ij}, \quad i \in I$$

The main coefficient of interest β_1 in equation (13) estimates the difference in the average allocation preference displayed by female versus male judges, while the main coefficient of interest β_1 in equation (14) estimates the difference in the average estimate of the respondents' income of female versus male judges for observably similar respondents. The results are in Table 8.

As can be seen in Column 1, the observed gap suggests that female judges are 4.7% more lenient towards respondents. Interestingly, however, the gap is bigger if we only take into account allocation preferences (12%, as shown in Column 2). This suggests that incomplete information about the respondent's income attenuates the gender gap in allocation preferences. Indeed, female and male judges respond differently to incomplete information: the former (compared to the latter) estimate that the income of respondents is 7.3% higher on average.

These estimates, moreover, are not driven by differences in specific case characteristics between genders. As it was shown in the balance tests (section 4.1), these are balanced between male and female judges. In particular, we look at the claim of petitioners as a possible source of variation. Figure 3 presents the kernel distributions of estimates by the judge's gender which show that the first and second moments do not differ by the judges' gender. In the next section, we develop a simple framework to investigate factors that could drive this result.

6.4 Estimates of beliefs

In this section, we propose a simple framework to estimate why male and female judges form different beliefs about the income of respondents. The starting point is based on the fact that randomisation of cases ensures that male and female judges decide on cases with the same set of (incomplete) information about cases' characteristics when respondents work in the informal sector. Therefore, it must be the case that male and female judges process the signals of the unknown income of respondents differently. In particular, we focus on the claim (the amount of money requested from the respondent by the petitioner) which is the main signal given by petitioners to judges on this regard. In fact, when setting their claims, petitioners argue that the amount asked corresponds to the level of income of respondents. Thus, we investigate to what extent male and female judges rely on this piece of information to estimate the unknown income.

This framework is based on the standard Bayesian updating model in which judges form beliefs about the respondent's unknown income Y based on a prior belief and a signal (the petitioner's claim amount C). However, we introduce one important feature to this simple model: the fact that petitioners exaggerate their claims to signal that the respondent has higher disposable income in order to increase the chances of obtaining higher awards. It is important to note that this signal, by definition, cannot depend on the gender of judges since it is set by the petitioner before the randomisation of the case. Thus, to create different income predictions based on the gender of judges, we allow the prior of judges about the unknown income to depend on their gender.

6.4.1 The model

We assume that the judge with gender g does not know the true respondent's income y = ln(Y) but has a prior y_0^g and a fixed variance $(\sigma_0^g)^2$ of the prior about y:

(15)
$$y = y_0^g + \sigma_0^g \delta \quad \delta \sim N(0, 1)$$

While the petitioner's claim amount c = ln(C) is an upward biased signal of the unknown income in the following fashion:

(16)
$$c = By + \sigma \epsilon \quad \epsilon \sim N(0,1), B > 1$$

Since the randomisation of cases occurs after the respondent makes the claim, the exaggeration rate B cannot depend on the gender of judges. Also, note that, as a simplification, the exaggeration rate B is constant and must be more than 1 to reflect the fact that the signal is an inflated version of the true income. Since the judge knows the claim has an exaggeration rate B, the judge cares about the deflated signal $\tilde{c} = \frac{c}{B}$. Thus, a more intuitive way of writing down equation (16) is:

(17)
$$\tilde{c} = y + \frac{\sigma}{B}\epsilon \quad \epsilon \sim N(0, 1), B > 1$$

Since (y, \tilde{c}) is distributed according to a bivariate Gaussian distribution, we pin down the judge's belief formation (posterior) based on the prior mean and the petitioner's deflated signal of the unknown income as follows:

(18)
$$E(y|\tilde{c}) = E(y) + \frac{Cov(y,\tilde{c})}{Var(\tilde{c})}(\tilde{c} - E(\tilde{c}))$$

Working with equations (15) and (17) to find the elements of equation (18):

(19)
$$E(y) = y_0^g, E(\tilde{c}) = y_0^g, Var(\tilde{c}) = (\sigma_0^g)^2 + \frac{\sigma^2}{B^2}, Cov(y, c) = (\sigma_0^g)^2$$

Plugging these results in equation (18):

(20)
$$E(y|\tilde{c}) = y_0^g + \frac{(\sigma_0^g)^2}{(\sigma_0^g)^2 + \frac{\sigma^2}{B^2}} (\tilde{c} - y_0^g)$$

Equation (20) shows that if the deflated signal \tilde{c} exceeds the judge's prior y_0^g , the judge's guess is adjusted upwards. Conversely, if the deflated claim \tilde{c} is lower than the judge's prior y_0^g , the judge's guess is adjusted downwards. In other words, given the judge's prior y_0^g , the updating direction depends on whether the claim c exceeds or is less than the threshold By_0^g .

Estimation and results 6.4.2

To estimate parameters of this model, we replace \tilde{c} in terms of c in equation (20) and we obtain the following:

(21)
$$E(y|c) = \theta y_0^g + \omega c$$

where $\theta = \frac{\sigma^2}{(\sigma_0^g)^2 B^2 + \sigma^2}$ and $\omega = \frac{(\sigma_0^g)^2 B}{(\sigma_0^g)^2 B^2 + \sigma^2}$. In these expressions, the weights θ and ω on y_0^g and c, respectively, can be interpreted in terms of the variance (or precision) of the judge's prior about y, relative to the variance (or precision) of the petitioner's signal about y. For instance, the more accurate or precise the petitioner's signal (i.e. the lower is σ), the greater is ω . However, it is important to note that the exaggeration rate affects these weights through σ_0^g : B expands the negative effect of σ_0^g on θ and shrinks the positive effect of σ_0^g on ω .

Since the parameter σ allows for some noise in the claim as a signal of income and cannot depend on the gender of judges, we set it equal to 1 as a simplification and focus on the comparison of y_0^g and σ_0^g across gender given a constant exaggeration rate B. Thus, we estimate equation (21) separately for male and female judges as follows:

(22)
$$\ln(b_{ij}) = \beta_1 + \beta_2 \ln(C_i) + \gamma_d + \gamma_t + \epsilon_{ij}$$

Where \hat{b}_{ij} is the belief set by judge j about the income of respondent-case i estimated from equation (11), C_i is the claim amount made by the petitioner in case i. In addition, both equations include district γ_d and year γ_t fixed effects. Thus, we interpret $\hat{\beta}_1$ and $\hat{\beta}_2$ in equation (22) as θy_0^g and ω from equation (21), respectively. By assuming that $\sigma = 1$, we recover the parameters of interest σ_0^g and y_0^g :

(23)
$$y_0^g = \frac{\hat{\beta}_1 B}{B - \hat{\beta}_2 B^2}$$

(24)
$$(\sigma_0^g)^2 = \frac{\hat{\beta}_2}{B - \hat{\beta}_2 B^2}$$

Table 9 shows the estimation of equation (22) for each gender separately. It can be seen that the estimates differ by the gender of judges. Replacing $\hat{\beta}_1$ and $\hat{\beta}_2$ for each gender in the previous expressions, it can be shown that $y_0^m > y_0^f$ and $\sigma_0^m > \sigma_0^f$ for any value of $B \in (1,3)$.⁹ These results suggest that, although female judges have a lower prior mean, the associated weight on the prior mean is higher because of the higher precision (lower σ_0^g) of the prior mean in comparison to male judges. Regarding the weight on the signal, female judges rely less on the petitioner's claim because the precision of the signal relative to the precision of prior mean, $\frac{\sigma}{\sigma_0^g}$, is lower for female judges (given the higher precision of the prior mean) which decreases the weight on the signal in comparison to male judges.

7 Conclusions

In this article, we inspect whether there are gender differences when child support is decided by a court rather than by negotiation between the parents. By exploiting random assignment of cases to judges, we find that female judges decide on a lower allocation of child support than male judges do in formal and informal cases. Moreover, we find that the effect of assigning a female judge to a formal case is 56% stronger than for an informal case.

We use a simple model of incomplete information. We assume that a judge has the same preferences for child support allocation regardless of whether a case is formal or informal. By estimating this component when the judge makes decisions in formal cases, we are able to calibrate their preferences in informal cases and infer the degree to which the amount of child support they allocate in the latter is influenced by their beliefs about the income of respondents. We find that, relative to male judges, female judges infer that the respondent has higher levels of income when they cannot observe it during trial, explaining why the

 $^{^{9}}$ An exaggeration rate B larger than 3 would generate negative values of mean and variance priors of judges.

gender gap in informal cases is smaller than in formal cases. By using a simple Bayesian updating framework in which judges form beliefs about the unknown income based on their priors and the signal (claim) sent by the petitioner, we provide a possible explanation for this fact: data shows that female judges rely less on the signal sent by the petitioner and put more weight on their priors. These findings highlight the fact that information asymmetries might play a role in influencing the outcomes of different types of judicial settings. For instance, could the lack of information explain racial disparities in the outcomes of criminal cases?

Finally, the evidence found in this paper has vital policy implications. There is evidence that parents transport less economic resources after parental separation (Bjorklund & Sundstrom 2006). For example, since the father has reduced access to the child, he has less incentives to provide resources. Further, if the mother remarries, the father has fewer incentives to support his child because part of the transfer spills over to the new husband (Chiapori 2007). Hence, child support allocation is not a trivial matter, so a discussion about the predictability of the judicial system in these type of cases is necessary, given that verdicts depend so much on variables such as the gender of the judge or the lack of information during trial. A potential solution to reduce discretion in child support cases could be for judges to rely on benchmarks based on, for instance, the type of respondent's job or the cost of living of the district where the child resides. This is an important issue for further research.

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Figures

Figure 1: Kernel distributions of awards by judge's gender in formal cases



Notes: Lines show the kernel densities of awards (as a percentage of respondent's income) set by male and female judges in formal cases.

Figure 2: Kernel distributions of awards by judge's gender in informal cases



Notes: Lines show the kernel densities of awards (as fixed amounts of money to be transferred by the respondent to the petitioner) set by male and female judges in informal cases.



Figure 3: Kernel distribution of calibrated awards in informal cases

Notes: Lines show the kernel densities of the calibrated awards (as a percentage of respondent's income) set by male and female judges in informal cases. A calibrated award is the hypothetical allocation set by judges when the respondent's income is not observable (informal job) based on the judges' revealed allocation preference when the respondent's income is observable (formal jobs). It captures weights assigned by judges to the respondent's number of children inside and outside the trial, and the judge's fixed-effect extracted from formal cases.

Figure 4: Kernel distribution of estimated judges' beliefs about the respondent's income



Notes: Lines show the kernel densities of the estimated judges' beliefs about the respondent's unknown income (in local currency) for male and female judges in informal cases. The estimated belief is the ratio of the award (given in absolute terms) divided by the calibrated award (allocation preference - share of the respondent's income to be allocated) when the respondent's income is not observable (informal job).





Notes: Lines show the kernel densities of the petitioner's claim in absolute terms (in local currency) received by male and female judges in informal cases. The claim of petitioners is the amount of money they say the father should transfer to cover the needs of children.

Tables

	All cases	Male judges	Female Judges
	(1)	(2)	(3)
Panel A. Hearings			
Settlement $(\%)$	27.4	24.5	29.7
Respondent is formal $(\%)$	20.2	20.8	19.6
Number of judges	149	61	88
Observations	$2,\!371$	1,061	1,310
Panel B. Litigations			
Respondent is formal $(\%)$	22.7	22.2	21.3
Number of judges	153	59	94
Observations	1,736	856	880

Table 1: Sample characteristics

Notes: This table describes samples corresponding to the two stages (hearing and litigation) of child support cases. Samples contain cases filed in districts with at least one court led by a male judge and one court led by a female judge.

	Male Judge		Female	Female Judge		rence
	Mean	SE	Mean	SE	Mean	p
Number of children	1.333	0.024	1.326	0.019	0.007	0.816
Petitioner attends $(\%)$	97.8	0.5	98.2	0.4	-0.4	0.591
Petitioner's attorney attends $(\%)$	67.7	2	64	1.7	3.7	0.168
Respondent attends $(\%)$	64.6	1.7	65.2	1.6	-0.6	0.785
Respondent's attorney attends $(\%)$	35.3	1.7	35.9	1.7	-0.6	0.823
Respondent is rebel $(\%)$	49.2	2.6	49.8	2.8	- 0.6	0.881
Respondent is formal $(\%)$	20.8	1.6	19.6	1.4	1.2	0.582
Observations	1,061		1,310		2,371	
Number of judges	61		88		149	

Table 2: Balance Table, Case Characteristics by Judge Gender (Hearing Settlement)

Notes: This table presents a balance table on cases' characteristics.

	Male Judge		Female	Female Judge		erence
	Mean	SE	Mean	SE	Mean	p
Number of children (in trial)	1.376	0.048	1.347	0.041	0.029	0.644
Number of children (off trial)	0.318	0.041	0.489	0.087	-0.171	0.079^{*}
Claim $(\%)$	55.5	0.6	56	0.6	-0.5	0.543
Petitioner reports resp.'s income $(\%)$	48	$5 \ 3$	51.1	4.8	-3.1	0.658
Respondent reports his income $(\%)$	43.9	4.3	46.6	4.4	-2.7	0.668
Petitioner has assets $(\%)$	0	0	1.1	1.1	-1.1	0.318
Respondent has assets $(\%)$	4	1.6	5.7	2	-1.7	0.517
Observations	173		176		349	
Number of judges	43		57		100	

Table 3: Balance Table, Case Characteristics by Judge Gender (Litigation - Formal)

Notes: This table presents a balance table on cases' characteristics for cases where the respondent has a formal job. Sample restricted to cases held at districts where there is at least one female and one male judge.

	Male Judge		Female	Female Judge		rence
	Mean	SE	Mean	SE	Mean	p
Number of children (in trial)	1.338	0.033	1.329	0.025	0.009	0.810
Number of children (off trial)	0.356	0.045	0.335	0.029	0.021	0.702
Claim $(\%)$	1425.5	97.6	1340.7	57.4	84.8	0.454
Petitioner reports resp.'s income $(\%)$	53.8	3.2	52.8	3.9	1	0.836
Respondent reports his income $(\%)$	44.3	3.1	45.0	3.1	-0.7	0.866
Petitioner has assets $(\%)$	1.0	0.4	1.2	0.5	-0.2	0.722
Respondent has assets $(\%)$	6.8	1.3	7.8	0.9	-1.0	0.536
Observations	585		642		1,227	
Number of judges	50		74		124	

Table 4: Balance Table, Case Characteristics by Judge Gender (Litigation - Informal)

Notes: This table presents a balance table on cases' characteristics for cases where the respondent has an informal job. Sample restricted to cases held at districts where there is at least one female and one male judge.

	Log(award	l per child)	Z-score(aw	ard per child)
	Formal	Informal	Formal	Informal
	(1)	(2)	(3)	(4)
Female judge	-0.068**	-0.059**	-0.25**	-0.16***
	(0.033)	(0.027)	(0.117)	(0.060)
N of children (in trial)	-0.343***	-0.291***	-0.997***	-0.357***
	(0.019)	(0.019)	(0.058)	(0.037)
N of children (off trial)	-0.169***	-0.098***	-0.490***	-0.146***
	(0.011)	(0.016)	(0.043)	(0.028)
Observations	349	1,227	349	1,227
N of judges	100	124	100	124
R2	0.616	0.383	0.540	0.239

Table 5: Judge's gender effects on child support decisions

Notes: This table presents the estimates of the judge gender-based gap in awards for formal and informal cases. Column 1 uses the log of the award per child in formal cases as a dependent variable. Column 2 uses the standardised award per child in formal cases as a dependent variable. Columns 3 and 4 use the analogue figures for informal cases. Each regression includes district and year fixed effects. Standard errors clustered at the judge level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

	Male Judge		Female	Female Judge		erence
	Mean	SE	Mean	SE	Mean	p
Age (years)	43.571	1.105	42.640	0.857	0.931	0.503
Judge is principal $(\%)$	49.2	0.066	35.2	0.051	14.0	0.093^{*}
Years as principal	6.379	1.026	5.871	0.913	0.508	0.712
Wealth (normalised)	0.061	0.118	-0.040	0.114	0.101	0.550
Observations	59		88		146	

Table 6: Balance Table, Judges' Characteristics by Judge Gender

Notes: This table shows the balance test for all characteristics of judges available. The value displayed for t-tests are p-values of the difference across groups.

	Z-score(award per child)						
	Fo	rmal	Info	ormal			
	(1)	(2)	(3)	(4)			
Female judge	-0.247^{**}	-0.261^{**}	-0.157^{***}	-0.161^{**}			
	(0.117)	(0.124)	(0.0597)	(0.0685)			
Age (years)		-0.00300		-0.0132**			
		(0.00774)		(0.00656)			
Judge is principal		0.110		0.287***			
		(0.114)		(0.106)			
Experience as principal (years)		-0.00540		0.00448			
,		(0.0169)		(0.0125)			
Wealth (standardised)		0.0353		-0.114**			
		(0.0399)		(0.0537)			
Observations	349	334	1227	1172			
N of judges	100	98	124	119			
R2	0.540	0.554	0.239	0.256			

Table 7: Pooled OLS estimates with all judges' characteristics

Notes: This table presents the estimates of the judge gender-based gap in amounts for child support when including all judges' characteristics as controls. Columns 1 and 2 use the standardised award per child as a dependent variable in formal cases without and with additional judge's characteristics as covariates, respectively. Columns 3 and 4 use the standardised award per child as a dependent variable in informal cases without and with additional judge's characteristics as covariates, respectively. Each regression controls number of children involved in the trial and other children the defendant has to support. District and year fixed effects are also included. Standard errors clustered at the judge level in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

		Likelihood of settlement in hearing session						
		All cases		Both	parties at	tended		
	(1)	(2)	(3)	(4)	(5)	(6)		
Female judge	0.0748	0.0777	0.102	0.0755	0.0800	0.100		
	(0.0826)	(0.0827)	(0.0862)	(0.116)	(0.116)	(0.120)		
N of Children		-0.0624	-0.0528		-0.0520	-0.0359		
		(0.0408)	(0.0430)		(0.0493)	(0.0507)		
Respondent is formal			-0.110*			-0.241***		
			(0.0637)			(0.0761)		
Observations	2,404	2,391	2,253	1,520	1,510	1,419		
Pseudo \mathbb{R}^2	0.023	0.024	0.027	0.045	0.045	0.052		
Number of judges	147	147	142	134	134	129		

Table 8: Marginal effects for settlement

Notes: This table shows the marginal effects of case characteristics on the likelihood of settlement. Columns 1 to 3 use the whole set of cases. Columns 4 to 6 use the restricted set of cases where both parties attended the hearing session. *Female* is an indicator variable for whether case was assigned to a female judge. *Children*^T is a variable containing the number of children involved in the trial. *Formal* is an indicator variable for whether the defendant has a formal job. Each regression controls for district and year fixed effects. Standard errors clustered at the judge level in parentheses.* p <0.10, ** p <0.05, *** p <0.01.

	Amount agreed			
	(1)	(2)		
Female judge	-24.95	-24.04		
	(27.32)	(28.19)		
Respondent is formal	-514.0***	-526.9***		
	(17.90)	(19.30)		
N of children (in trial)		115.9***		
		(19.79)		
Observations	653	651		
R^2	0.343	0.383		
Number of judges	104	104		

Table 9: Estimates for settlement agreements

Notes: This table presents the estimates of the judge gender-based gap in amounts for child support agreed in settlement hearings. Columns 1 and 2 use the log of the amount per child as a dependent variable. Each regression controls for district and year fixed effects. Standard errors clustered at the judge level in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

	Total	Preference	Belief
	(1)	(2)	(3)
Female	-0.0474**	-0.121***	0.0733^{**}
	(0.0232)	(0.0364)	(0.0364)
$Children^T$	-0.295***	-0.352***	0.0571^{***}
	(0.0127)	(0.00817)	(0.0140)
$Children^{-T}$	-0.102***	-0.183***	0.0804***
	(0.0140)	(0.00996)	(0.0113)
Observations	1382	1382	1382
N of judges	107	107	107
R2	0.444	0.820	0.195

Table 10: Gender gap decomposition - pooled OLS estimates

Notes: This table presents the estimates of the judge gender-based gap decomposition in informal cases. Columns 1 uses the log of the award per child as a dependent variable. Column 2 uses the calibrated percentage of defendant's income awarded per child as a dependent variable. Columns 3 uses the log of the belief about the defendant's income as a dependent variable. Each regression controls for district and year fixed effects. Standard errors clustered at the judge level in parentheses. * p <0.10, ** p <0.05, *** p <0.01.

	Log(belief)				
	Male judge	Female judge			
	(1)	(2)			
Log of Claim	0.370^{***}	0.253***			
	(0.0439)	(0.0341)			
Constant	4.692***	5.385***			
	(0.292)	(0.218)			
Observations	728	641			
N of judges	50	59			
R2	0.435	0.318			

Table 11: Pooled OLS estimates beliefs formation

Notes: This table presents the estimates of the belief formation framework. Both columns 1 and 2 use the log of the estimated belief as a dependent variable. Each regression controls for district and year fixed effects. Standard errors clustered at the judge level in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Appendix

Figure 6: Randomisation of cases in the Judicial System (before)

6.3.2. Registro de Información

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	Hacer clic para Guardar y genera Expediente	nr el					
DISTANCIA JUZGADO ESPECIALIZADO	ESPECIALIDAD LABORAL	SUB ESP. CONTENCIOS		*			
EXPEDIENTE MOTIVO ING DEMANDA PROCESO ABREVIADO	INSTANDA PROCEDENDA USUATIO MATERIA VULNERACO	N DE LA LIBERTAD SINDICAL	-				

Notes: This image shows the step before the system randomly assigns a case to a court within a district as shown in the user guide. As can be seen, the user, when registering the case into the system, cannot choose the court nor the ID of the case. Short translation: "To continue, select categories and characteristics of the case, then click on the save button"

Figure 7: Randomisation of cases in the Judicial System (after)

Nota: Cuando se trate del Tipo de Persona "Jurídica Privada" o "Jurídica Estatal", es indispensable ingresar el N° de RUC para el buen funcionamiento del Aplicativo. Por cada nuevo ingreso, al guardar, se asigna un número y la instancia equitativamente y aleatoriamente.

Notes: This image shows how the randomisation of cases works as shown in the user guide. As can be seen, once the user saved a case, the system randomly assigns the case to a court and assigns an ID number (increasing order). Short translation: "For each new case registered, when saved, a number is given and a court is randomly assigned"