Conditional Cash Transfers and Gender Norms: The Role of Policy Design*

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Abstract

This paper examines how policies affect gender norms by analyzing the impact of Peru's conditional cash transfer program, *Juntos*, on children's gender attitudes. Using the Young Lives Survey and a fuzzy regression discontinuity design, I find that *Juntos* reinforces traditional norms and generates gender-differentiated cognitive outcomes. Boys devote more time to studying, while girls spend more time on housework and are less likely to pursue higher education. Leveraging the program's design that channels payments to mothers, I show that *Juntos* reduces maternal labor force participation and increases time devoted to childcare and program compliance, shaping children's gendered behaviors and beliefs.

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Keywords: Cash Transfer, Gender Attitudes, Intergenerational Transmission, Regression Discontinuity, Maternal Labor Supply, Time Use

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1 Introduction

Gender norms - informal societal rules that define appropriate roles for men and women - pose significant challenges to achieve gender equality (Bursztyn et al., 2023).[1] Harmful norms restrict women's access to education, health, and labor markets (Fortin, 2005; Bertrand et al., 2015; Field et al., 2021), and weaken their protection against violence (Herrero et al., 2017). These norms are deeply rooted and resistant to change (Fernández and Fogli, 2009; Alesina et al., 2013; Hansen et al., 2015); therefore, it is essential to understand their determinants. Recent research suggests that certain policies can shift gender norms, yet much remains unknown about the pathways responsible for these changes.

This paper provides new evidence on *how* policies can affect gender norms by studying conditional cash transfer (CCT) programs in Latin America. I hypothesize that these programs can affect how children internalize gender roles and expectations. CCTs are designed to reduce poverty and its intergenerational transmission by providing financial support to poor households conditional on investments in children. In most programs, mothers are designated as recipients and must fulfill requirements such as ensuring children's school attendance and health check-ups. In so doing, CCTs may affect incentives and generate changes in women's economic and caregiving roles. These potential shifts can shape children's gender attitudes through the process of intergenerational transmission of preferences (Bisin and Verdier, 2001).[2] I test this hypothesis using *Juntos*, Peru's largest CCT program, which has been in operation since 2005.

For the main analysis of children's outcomes, I use data from the Young Lives Study (YLS), which follows a nearly nationally representative cohort of 2,000 Peruvian children who were between 6 and 18 months old in 2002. The YLS provides rich information not only on children's developmental trajectories from early childhood to adolescence but also on their household characteristics, expectations, investments, and family members. Importantly, it includes data on attitudes toward gender roles—an area where information is often scarce in children's surveys and unavailable in administrative data.

To identify the *causal* effect of Juntos on children's gender attitudes, I exploit its eligibility rules: households qualify if they (i) live in an eligible district, (ii) include pregnant women or children under 19, and (iii) exceed a poverty threshold. This framework allows for a comparison between children in *barely eligible* and *barely ineligible* households in eligible districts, as all YLS children were under 19 during the study period. Using the rich household-level data from the YLS, I compute the household poverty score following the official formulas. I further show that any

[1]For an extended discussion of the concept of gender norms, see Akerlof and Kranton (2000) and Pearse and Connell (2016).

[2]Empirical evidence supports the intergenerational transmission of gender role expectations, such as: Fernández et al. (2004) and Bertrand (2019).

potential measurement error arising from differences between the YLS data and the administrative data used to assign eligibility does not pose a concern. Following Battistin et al. (2009), I employ a fuzzy regression discontinuity (RD) design, using eligibility status to address both measurement error and endogeneity in program participation.

My results fall into four categories. The first set of results focuses on Juntos' impact on children's gender norms at age 15, measured by a composite index, which I call "gender attitudes". Gender attitudes refer to individuals' beliefs about the appropriate roles, behaviors, and characteristics of men and women, shaped by societal norms and cultural expectations. This index is obtained from a set of questions regarding gendered behaviors, intellectual and educational beliefs, family and career roles, where 0 indicates a non-traditional attitude and 1 reflects an extremely traditional attitude. I find that Juntos children exhibit a 13.3 percentage point increase in agreement with traditional attitudes, representing 41.4% over the mean of the control group. The gender attitude index is further analyzed by breaking it down into three subindices: power, equality, and behavior dimensions. The results suggest that the effects are most pronounced in the power and equality dimensions, reflecting gender power dynamics and aspirations for greater equality.

The second set of results examines the impact of Juntos on children's performance in the Peabody Picture Vocabulary Test (PPVT), as well as in reading and mathematics assessments. The findings reveal a gender-differentiated pattern: beneficiary girls score lower across all three tests, whereas beneficiary boys exhibit a statistically significant improvement in reading scores. Their PPVT and mathematics scores also increase, though the changes are not statistically significant. These results are consistent with the observed gender attitudes, particularly in the power dimension.

The third set of results examines whether self-reported gender attitudes translate into actual behaviors, using data on daily time use in three survey rounds and higher education enrollment at age 19. The findings show that beneficiary boys devote more time to studying after school, offset by a reduction in leisure time. In contrast, beneficiary girls spend more time on domestic tasks, less time studying after school, and more time on leisure activities. Importantly, by age 19, beneficiary girls are less likely to enroll in higher education, suggesting that gender attitudes observed at age 15 may influence their later educational choices.

Finally, I show that the main results are stable for a broad set of robustness checks. These checks include different selections of local polynomial degree, kernel, and bandwidths in the non-parametric method, estimations from a parametric model, different approaches to measure the main outcome variable, and inference based on the wild cluster bootstrap procedure.

To shed light on the underlying mechanisms, I focus on the program's impact on mothers. I begin by analyzing household data from the YLS' fourth round, focusing on the three primary activities reported by mothers in terms of time spent during the last 12 months before the survey. I find that beneficiary mothers are more likely to prioritize home production, less likely to engage in self-employment, and less likely to report unstable jobs as their priority activity. Building on these findings, I further examine the association between exposure to Juntos and maternal time allocation using data from the 2010 National Time Use Survey (NTUS). The results indicate that Juntos increases time spent on childcare during both weekdays (by 24 minutes per day) and weekends (by 30 minutes per day), as well as time devoted to household organization on weekdays (by 11 minutes per day). The latter includes activities such as budgeting, paying bills, collecting subsidies, and transporting household members to fulfill program requirements. To further illustrate the time costs mothers face when collecting cash transfers, I use data from the 2014 Provincial Survey of Rural Households (EPHR) and find that over 92% of collectors from beneficiary households are mothers. On average, they spend 152 minutes traveling one way from their homes to national banks or bank agencies.

I then use data from the Peru Continuous Demographic and Health Survey (DHS) for the period 2004–2016 to investigate the impact of Juntos on maternal labor force participation. Leveraging the dynamic difference-in-differences estimator of Sun and Abraham (2021), I find that Juntos reduces mothers' labor force participation by 3.9 percentage points (about 5% of the sample mean) but has no significant effect on occupation types. Although alternative explanations remain possible, the reallocation of mothers' time toward domestic duties and reduced labor market engagement offers a plausible mechanism for reinforcing traditional gender attitudes among children.

This paper contributes to several strands of literature. First, it advances the emerging field of research on public policy and culture, which shows that policies can change cultural attitudes and practices (Beaman et al., 2009; Dahl et al., 2014; Algan et al., 2016; Rao, 2019; Bau, 2021; Ghosh et al., 2023; Okunogbe, 2024). Within the realm of gender norms, only a few studies link policy to gender attitudes, and most focus on high income countries. For instance, differences in politico-economic regimes shape gender role attitudes, with East Germans holding more progressive views than West Germans (Campa and Serafinelli, 2019), the U.S. Earned Income Tax Credit boosts support for working women (Bastian, 2020), and paternal leave in Estonia and Spain reduces sexist attitudes (Tavits et al., 2024; Farré et al., 2023). In contrast, I study a child-focused program in Peru, where mothers are key implementers. I provide the first causal evidence from a developing country that this type of program can reinforce, rather than shift, traditional gender attitudes. Importantly, I further show that changes in self-reported attitudes translate into changes in behaviors and educational choices later in life. These findings highlight that policies can change culture (Fernández, 2025). However, the direction of that change, whether progressive or regressive, depends on policy design, context, and the target population.

Second, this paper contributes to the literature on adult labor supply responses to CCT programs, which has produced mixed evidence. On the one hand, several studies find no significant effects on male or female labor supply (Rubio-Codina, 2010; Banerjee et al., 2017; Bosch and Schady,

2019) or increased self-employment in the short term (Gertler et al., 2012; Bianchi and Bobba, 2013). On the other hand, some studies document reductions in female labor supply (De Brauw et al., 2015; El-Enbaby et al., 2019). This paper complements this literature by showing that Juntos reduces women's labor force participation. The analysis relies on rich data from Peru's Continuous DHS spanning 12 years and employs a modern difference-in-differences estimator to identify the impact. In addition, it documents shifts in women's time priority—from labor market activities toward household chores—coinciding with the reduction in labor force participation.

Third, this paper contributes to the growing literature on the participation burden faced by women in development programs, which has largely relied on qualitative evidence. Such programs often require significant time and resource commitments from women (Nagels, 2016; Cookson, 2018; Margolies et al., 2023). Also, they may reinforce traditional gender roles by presuming untapped potential rather than recognizing existing constraints (Mayoux, 1995). This study adds to the literature by providing suggestive quantitative evidence that Juntos increases women's time demands, particularly for childcare and household organization, including time devoted to fulfilling program requirements.

Finally, this paper adds to the limited evidence on parental, particularly maternal, influences on children's gender attitudes. Most existing studies focus on maternal behaviors and beliefs in developed countries (Serbin et al., 1993; Cunningham, 2001; Cano and Hofmeister, 2023), with only two studies examining the inter-generational transmission of gender norms in developing contexts (Dhar et al., 2019; Leight, 2021). This paper closes this gap by showing that when mothers prioritize domestic responsibilities over labor force participation, their children adopt more traditional gender attitudes in a Latin American setting.

The paper unfolds as follows. In the next section, I introduce the institutional context in Peru. Section 3 presents the data sources and measurement of the main outcome variable. Section 4 describes the empirical approach. Section 5 provides the results, followed by the mechanisms in Section 6. Finally, Section 7 concludes the paper.

2 Institutional Context

In April 2005, the Peruvian government launched the National Direct Support Program for the Poorest - *Juntos*, which targets poor households with children or pregnant women. Juntos is the largest social program in Peru, with a budget of US$308 million in 2016 - equivalent to 26.1% of the total budget of the Ministry of Development and Social Inclusion (MIDIS) and 0.16% of the country's gross domestic product (GDP).[3] Starting with only 70 districts, the program now supports

[3]Inter American Development Bank Data 2016. https://www.iadb.org/en/toolkit/conditional-cash-transfer-programs/peru-juntos

over 700,000 families, and has 96% of recipients as mothers (as of 2023). Beneficiary households receive a fixed monthly transfer of 100 soles (approximately US$30), representing about 10% of their total monthly consumption and over 50% of their per capita household expenditure.[4]

Juntos determines eligibility through a two-stage selection process. In the first stage, districts are selected based on various criteria related to poverty, malnutrition, and basic needs. Although these criteria have evolved over the years, Juntos continues to focus on poor districts. In the second stage, eligible households are identified within the selected districts. A household must have resided in the district for more than six months before the enrollment date in the program. Household eligibility is determined by a poverty score based on household-level census data collected in each district. Before 2012, the government implemented a universal threshold value in all regions. Starting in 2012, the government introduced a new poverty score—*Índice de Focalización de Hogares (IFH)*—and established 15 region-specific thresholds. Households in eligible districts that include pregnant women or children under 19 qualify for the program if their poverty score exceeds the corresponding cutoff. A final verification step involves a commission of community members and government representatives.[5]

The program enrolls all eligible members of a household selected as beneficiaries, and a representative, typically the mother, signs an agreement form with the program. Upon enrollment, the mother becomes responsible for fulfilling the program conditions for her children. To receive transfers, households must meet several conditions: children up to 59 months old must receive comprehensive health and nutrition care; pregnant women must attend regular prenatal check-ups; school-age children from 6 up to 19 or until they finish school must maintain at least 85% school attendance; and all children must possess a national identification number.

Whether or not the households meet conditions of the program relative to health and education services are monitored by local managers and Juntos fieldworkers, who have access to information from schools and health centers. In particular, health visits are verified by attendance (pre-birth checkup) and check-up records (growth and development controls), while the educational condition is verified by school attendance records. Disaffiliation from the program occurs when a household cannot meet conditions frequently or when all household members no longer belong to the targeted population or when the household loses eligibility according to their poverty score. Note that disaffiliation could also be voluntary.[6]

[4]The transfer amount is converted to US dollars using the 2005 exchange rate.

[5]Appendix B provides the algorithms and variables used to calculate the poverty score in both periods.

[6]For detailed explanation, see Huerta and Stampini (2018).

3 Data and Measures

3.1 Data

I use several data sources for this analysis, including a longitudinal child panel survey, multiple household surveys, and administrative data on the Juntos rollout.

Young Lives Study (YLS). The main dataset is the YLS, a longitudinal research initiative led by the University of Oxford. It includes household- and child-level surveys collected over five rounds (2002, 2006, 2009, 2013, and 2016), as well as a COVID-19 phone survey conducted in 2020–2021. The household surveys cover topics such as participation in Juntos, household composition, housing quality and assets, access to basic services, and the employment and education of household members. The child surveys provide rich information on demographics, health, cognitive abilities, and attitudes toward gender roles.

This paper focuses on the younger cohort of the Peruvian sample, which consists of approximately 2,000 children aged 6 to 18 months in 2002.[7] Although the sample is pro-poor by design, it remains broadly comparable to nationally representative datasets. Escobal and Flores (2008) support this by comparing the YLS sample with the 2001 Living Standards Measurement Survey (ENAHO 2001) and the 2000 Demographic and Health Survey (DHS 2000), concluding that it reflects the diversity of Peruvian children. Moreover, YLS stands out for its exceptionally low annual attrition rate of just 0.6%, significantly lower than that of similar longitudinal surveys in low- and middle-income countries (Sánchez and Escobal, 2020).

Demographic and Health Survey (DHS). To investigate the potential effects of Juntos on labor participation of beneficiary mothers, I supplement the analysis with data from the DHS. This is a nationally representative survey providing detailed information on education, health, employment, and sociodemographic characteristics of women of reproductive age (15–49 years). Since 2004, the National Institute of Statistics and Informatics (INEI) has conducted the DHS annually, yielding a substantially larger sample size than the YLS dataset. This broader coverage supports more robust statistical analysis and enhances the generalizability of findings.

National Time Use Survey (NTUS). To examine effects of Juntos on maternal time use, I employ data from the NTUS, conducted by INEI in November and December 2010 - the first time-use survey implemented in Peru. It includes a nationally representative sample of 4,350 households across

[7] The sampling procedure in Peru followed a multi-stage, cluster-stratified, random sampling approach. Based on the 2000 poverty map by FONCODES, the richest 5% of districts were excluded. Sentinel sites were selected from the remaining pool and then households within each selected district were randomly sampled.

both urban and rural areas, with the time-use module completed by all household members aged 12 and older.

Provincial Survey of Rural Households (EPHR). To examine challenges related to participation in the Juntos program, I use data from the 2014 EPHR. This provincially representative survey was designed to inform the prioritization of public investment projects and their integration into the 2015 national budget. Although the survey focuses on rural areas, it is relevant because, during the study period, eligible districts were predominantly poor and rural. Importantly, the EPHR includes a dedicated module on the Juntos program, covering over 27,000 beneficiary households.

Other Data. Finally, I rely on administrative records detailing the rollout of the Juntos program. These data include the timing and geographic scope of implementation, allowing me to link program exposure with household-level outcomes across surveys. Additionally, I incorporate data from the 2009 Poverty Map prepared by INEI to capture relevant district, provincial, and departmental characteristics.[8]

3.2 Measurement of Gender Attitudes

The main variable of interest is the attitudes toward gender roles and expectations, measured when the children were approximately 15 years old in the YLS. To capture these attitudes, I construct a composite index based on 12 questions exclusively in the fifth round. These questions ask respondents whether they agree with statements regarding the attributes, expectations, roles, and rights deemed appropriate for each gender. The elements are adapted from the Attitudes Toward Women Scale for Adolescents (AWSA), a widely used instrument in psychology to assess gender attitudes among adolescents.[9]

Following Dhar et al. (2019), I transform the original four-point Likert scale into binary indicators. An indicator is coded as 1 if the respondent agrees or strongly agrees with a statement endorsing traditional gender roles, or disagrees or strongly disagrees with a statement opposing them. The gender attitude index is then calculated as the unweighted average of the twelve binary indicators. The index ranges from 0 to 1, where a score of 0 signifies extremely nontraditional attitudes, while 1 denotes extremely traditional attitudes.[10] To assess whether children's responses reflect broader gender attitude patterns, Appendix Figure A2 compares YLS results with similar

[8]The 2009 Poverty Map is the earliest version available on INEI's official website; no data prior to 2009 is available.

[9]The AWSA is derived from the short form of the Spence-Helmreich Attitudes Toward Women Scale (Galambos et al., 1985). It has been widely applied in the psychology literature to measure gender beliefs; see, for example, Caso et al. (2020), Puzio and Best (2020), and Coyne et al. (2022).

[10]Appendix Figure A1 presents the distribution of the gender attitude index. The full wording of the statements used to construct the index is provided in Appendix C.

statements from the World Values Survey (WVS) on whether men are better political leaders across Peru, other Latin American countries, and Western countries. Despite differences in respondents' ages, the mean responses of the YLS and the Peruvian WVS are highly similar. Moreover, Peru shows a more progressive stance than neighboring countries, comparable to the United States but less progressive than some European countries, such as Germany, Sweden, and the Netherlands.

Building on Jaruseviciene et al. (2014), I further decompose gender attitudes into three dimensions: (i) *power dimension*: measures the level of power held by girls and women in comparison to boys and men, (ii) *equality dimension*: captures the desire for greater gender equality, such as expectations around sharing housework or the same freedoms for boys and girls, and (iii) *behavior dimension*: measures social expectations for the behaviors of boys and girls.[11] The three sub-indices are obtained using the same procedure as the gender attitude index. Table 1 summarizes children's attitudes toward gender roles, reporting descriptive statistics for twelve statements, three sub-indices, and the overall index. Overall, children exhibit regressive views in the behavior and power dimensions, while traditional norms are less supported in the equality dimension.

Table 1. Descriptive Statistics of Attitudes towards Gender Roles (YLS Round 5, Age 15)

Agree/Strongly Agree with...	Mean	SD	Min	Max
Behavior dimension	**0.51**	**0.28**	**0.00**	**1.00**
Women should not swear	0.58	0.49	0.00	1.00
Men pay for date expenses	0.54	0.50	0.00	1.00
Women cannot ask men out	0.42	0.49	0.00	1.00
Equality dimension	**0.14**	**0.20**	**0.00**	**1.00**
Women are not smart as men	0.18	0.39	0.00	1.00
Women should not play rough sports	0.11	0.32	0.00	1.00
Husband should not share housework duties with wives	0.16	0.37	0.00	1.00
Women should not have the same freedom as men	0.13	0.33	0.00	1.00
Power dimension	**0.34**	**0.30**	**0.00**	**1.00**
Incentivize college attendance more for sons than daughters	0.26	0.44	0.00	1.00
Fathers should have greater authority than mothers in family decisions	0.35	0.48	0.00	1.00
Men's academic success is more significant than women's	0.57	0.50	0.00	1.00
Men are better leaders than women	0.23	0.42	0.00	1.00
Women's priority should be good homemakers and mothers	0.27	0.44	0.00	1.00
Gender attitude index	**0.32**	**0.16**	**0.00**	**0.83**
Observations	1099			

Note: Data is from the YLS Round 5. All variables, except Gender attitude index and three sub-indices related to behavior, equality and power dimensions, are indicators taking value 1 if children answer "Agree" or "Strongly agree" ("Disagree" or "Strongly disagree") when the statement is in favour of (opposed to) traditional views. Gender attitude index and three sub-indices (unweighted indices) are as the averages of their respective component indicators.

[11] Jaruseviciene et al. (2014) conduct a factorial analysis of the AWSA with the same 12 statements as in this paper. Using a sample of 3,518 adolescents in Bolivia and 2,401 adolescents in Ecuador, the authors provide three distinct dimensions of gender attitudes, including the power dimension, the equality dimension, and the behavior dimension.

3.3 Analysis Sample

The main analysis focuses on children from households located in 12 eligible districts in the YLS. Since gender attitudes are measured only in the fifth round, I construct a cross-sectional dataset based on this round, supplemented with relevant data from earlier rounds. The analysis sample includes 1,119 children: 596 from beneficiary households and 523 from non-beneficiary households. *Beneficiary children* are defined as those who lived in households that ever received Juntos transfers at any point between 2005 and 2016.

Table 2 presents summary statistics for key variables in the sample. Over the 15-year study period, 596 children (53%) received support from the Juntos program at some point. The sample is balanced by child gender, with the majority of children identified as Mestizo (94%) and raised in Catholic households (81%). At baseline, mothers were, on average, 27 years old, and 63% had not completed secondary education. In 2002, the average household size was approximately six members. Moreover, most of the families resided in mountainous areas (75%).

Table 2. Summary Statistics for Analysis Sample

	Mean	SD	Min	Max	Count
Juntos (Yes=1)	0.53	0.50	0.00	1.00	1,119
Female (Yes=1)	0.50	0.50	0.00	1.00	1,119
Mountainous area in 2002 (Yes=1)	0.75	0.43	0.00	1.00	1,119
Weight-for-age z-score	-0.47	1.13	-5.54	5.33	1,112
Height-for-age z-score	-1.64	1.29	-9.50	4.79	1,112
Polio vaccination (Yes=1)	0.97	0.16	0.00	1.00	1,113
BCG Vaccination (Yes=1)	0.96	0.19	0.00	1.00	1,113
Age of child (months, 2002)	11.68	3.56	5.00	22.00	1,119
Health long term issues (Yes=1, 2002)	0.22	0.41	0.00	1.00	1,119
Catholic (Yes =1)	0.81	0.39	0.00	1.00	1,119
Mestizo (Yes = 1)	0.94	0.24	0.00	1.00	1,119
Mother education (<secondary school = 1)	0.63	0.48	0.00	1.00	1,119
Age of mom (years, 2002)	27.13	6.91	15.00	49.00	1,108
Household size (members, in 2002)	5.81	2.33	2.00	18.00	1,119
Caregiver's gender preference (Girl=1)	0.38	0.49	0.00	1.00	1,110
Caregiver's gender preference (Boy=1)	0.40	0.49	0.00	1.00	1,110
Attending School in 2016 (Yes=1)	0.96	0.20	0.00	1.00	1,110
Centered Poverty Score	-0.08	0.22	-0.73	0.52	1,119
Gender attitude index	0.32	0.16	0.00	0.83	1,099
Observations	1119				

Note: Data is from the YLS Panel. Descriptive statistics is computed from the analysis sample to examine the effect of Juntos on gender attitudes. The variables, including *Juntos, Female, Polio vaccination, BCG vaccination, Health long term issues, Catholic, Mestizo, Mother education, Attending school in 2016, Caregiver's gender preference (boys, girls), Mountainous area in 2002* are indicators. The z-scores for Weight-for-age and Height-for age calculated based on the World Health Organization (WHO) reference tables and software (Briones, 2018). The formula proposed by WHO is *z-score = (X-m)/SD*, where X is the observed value of the child (height, weight), m and SD are the mean and standard deviation value of the distribution corresponding the reference population.

4 Empirical Strategy

4.1 Household Poverty Score

To exploit the program's assignment rule, whereby households with poverty scores at or above a specified threshold are eligible, I compute these scores using rich data from five rounds of household surveys from the YLS, following the official formulas. The calculation method depends on the year the household's district became eligible for the Juntos program, between 2005 and 2016. As detailed in Section 2, Juntos revised its scoring methodology in 2012. Accordingly, for districts that became eligible between 2005 and 2011, I use the earlier method, which applies a universal threshold. For districts that joined the program between 2012 and 2016, I employ the updated method, which uses the IFH index and region-specific thresholds.

In principle, the poverty scores are calculated using data from the previous round corresponding to the eligibility time of districts for non-beneficiary households. For Juntos beneficiary households, poverty scores are determined based on data from their previous round corresponding to the time of enrollment, indicating the initial program entry. Since the former method's poverty scores range from 0-1 (higher = poorer) while the current method uses 0-100 (higher = wealthier), I rescale the current scores by dividing by 100 and reversing their direction to align with the former method. The poverty scores are centered around their corresponding eligibility cutoff values, such that the *eligibility threshold* is set to zero. A non-negative centered poverty score therefore indicates that a household is *eligible* for the program.

One concern in the identification strategy is potential inconsistency between the YLS data and administrative data used to assign eligibility. My calculations show that 25.83% of households have centered poverty scores below zero yet reported receiving benefits. Conversely, 13.5% have centered scores above zero but did not participate in the program—likely because participation is not mandatory. This evidence is also consistent with the presence of measurement error in the reporting of participation status. However, such inaccuracy is unlikely, as households were asked about their beneficiary status in Juntos from the third to the fifth survey round, and their responses remained consistent over time. Therefore, I assume that participation status is not misreported. Any inconsistencies between the poverty score and observed participation status are thus attributed to measurement error in the poverty score.

Measurement error would pose an issue if it had smoothed out any discontinuity in the share of participating households at the threshold (Davezies and Le Barbanchon, 2017). However, as shown in Appendix Figure A3, this is not the case. When I plot the share of participating households, the figure shows a clear jump at the threshold. Therefore, I can infer that the measurement error in the eligibility variable arises due to *contaminated data*, where the observed distribution of centered poverty scores includes both accurate values and those with some degree of error (Battistin et al., 2009).[12]

4.2 Identification Strategy

Following Battistin et al. (2009), I employ the fuzzy regression discontinuity design, using eligibility status to address measurement error and endogeneity in participation to recover consistent causal estimates. In the RD design framework, it is assumed that households near the eligibility cutoff on either side share similar characteristics, except for their program eligibility status. The specific estimating equations are as follows:

$$Juntos_{ij} = \alpha + \beta \mathbb{1}_{[X_{ij} \geq 0]} + h(X_{ij}) + \lambda_j + \epsilon_{ij} \tag{1}$$

$$Y_{ij} = \mu + \gamma \mathbb{1}_{[X_{ij} \geq 0]} + h(X_{ij}) + \kappa_j + \upsilon_{ij} \tag{2}$$

where $Juntos_{ij}$ is a binary variable that takes the value of one if the household of child *i* in district *j* participated in Juntos at any point between 2005 and 2016. The variable Y_{ij} represents my measure of gender attitudes for child *i* in district *j*. X_{ij} is the centered poverty score of the household of child *i* in district *j*. $\mathbb{1}_{[X_{ij} \geq 0]}$ is an indicator variable that equals 1 if the centered poverty score is greater than or equal to 0. $h(X_{ij})$ captures the relationship between the outcome variable and running variable X_{ij}. λ_j and κ_j are district fixed effects, which account for time-invariant factors specific to each district.[13] Intuitively, I compare the gender attitudes of children within the same district. ϵ_{ij} and υ_{ij} are error terms. Following Abadie et al. (2022), standard errors are clustered at the district level.

The relevant parameters include $\hat{\beta}$ in equation 1, the intention-to-treat (ITT) estimate $\hat{\gamma}$ from equation 2, and the ratio $\tau_{FRD} = \hat{\gamma}/\hat{\beta}$, which represents the local average treatment effect (LATE) given some additional assumptions.[14] I employ a non-parametric RD design, which does not impose functional form assumptions on the relationship between the outcome and the running

[12] Appendix Table A1 shows a positive correlation between the poverty scores computed from YLS and those from ENAHO. Using the former method, the correlation between averages in 14 departments (YLS 2002 and ENAHO 2004) is 0.639. Using the current IFH method, the correlation between averages in 13 clusters (YLS 2009 and ENAHO 2009) is 0.591. These correlations and similar average values in several departments and clusters support the claim that the household poverty score is partially observed with errors.

[13] I control for district fixed effects in the first stage due to differences in how household poverty scores are calculated across districts. Moreover, as described in Appendix B, household poverty scores are influenced by some district-specific factors, such as household access to water, electricity, and drainage systems.

[14] According to Hahn et al. (2001), there are three additional assumptions for identification, which allows τ_{FRD} to be interpreted as LATE. The first assumption is monotonicity, that is having a non-negative centered poverty score does not decrease the probability of receiving cash transfer for any household (which seems plausible). The second assumption is the existence of the first stage. The third assumption - local independence - indicates that in a neighborhood around the threshold, treatment status and potential outcomes are jointly independent of the centered poverty score.

variable. Moreover, as highlighted by Calonico et al. (2014), the traditional bandwidth selection procedure of the non-parametric method often leads to bias in the distributional approximation of the estimator. To overcome this challenge, I adopt the local polynomial non-parametric RD design with data-driven bandwidth selectors and bias-correction techniques proposed by Calonico et al. (2014) and Calonico et al. (2019).

I mainly use the mean square error (MSE) optimal bandwidth ($\hat{h}_{MSE}$), which optimizes point estimates by minimizing the asymptotic mean square error (Calonico et al., 2020). In my baseline regression specification, I use triangular weights and linear local polynomial. In all RD specifications, I report the conventional point estimators and the corresponding robust p-values.

4.3 Threats to Identification and Assessment of Validity

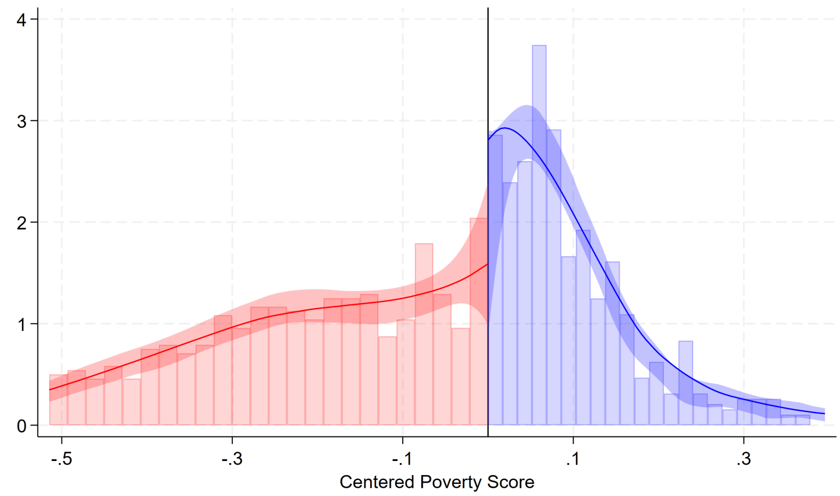
4.3.1 Testing Discontinuities in the Running Variable Density

In the Juntos program, manipulation of household poverty scores might occur at different levels, including the household level and district level. Manipulation behaviors often require knowledge of the formulas to calculate poverty scores before applying to the program. At the household level, it is hard to believe that households could precisely manipulate their poverty scores. First, the targeted population of the program is poor households, who are less likely to know the formulas. Second, those formulas are quite complicated with several different variables and their corresponding coefficients. Most of variables are long term and not easy to adjust in response to expectations regarding the program's commencement. Moreover, it is very unlikely that the households know the cutoff value. The households only know the result of the eligibility evaluation, but not the value of their poverty scores.

Another concern related to manipulation is that districts might attempt to "adjust" the poverty scores of their households to maximize the program's benefits. However, the likelihood of such an event is pretty low, given that Juntos has implemented a checked stage with a commission consisting of both local and national representatives to verify the list of eligible households.

Taking a statistical perspective, we can assess the potential manipulation by examining the density of the running variable around the eligibility threshold. To do this, I use a manipulation test that involves a local-polynomial density estimator based on the observed sample's cumulative distribution function. This allows me to estimate the probability density function of the centered poverty score, following the approach by Cattaneo et al. (2018). The null hypothesis posits that the density of the centered poverty score variable is continuous at the cutoff. In Figure 1, the results of the manipulation test indicate that we cannot reject the null hypothesis as the test yields a robust p-value of 0.7475. This suggests that there is no statistical evidence of manipulation around the cutoff.

Figure 1. Manipulation Testing Plot (robust p-value = 0.7475)



Note: This graph presents the manipulation test based on density discontinuity following Cattaneo et al. (2018). The observations situated to the right of the vertical line are considered eligible for Juntos.

4.3.2 Testing Discontinuities in Covariate Distributions Around the Threshold

To provide additional evidence regarding the exogeneity of the running variable, I examine characteristics of children and their households close to the threshold. The RD design is valid when other factors are smooth through the cutoff value. I run the estimating equations 1 and 2 with the dependent variable replaced by the characteristics of interest. I focus on two categories of characteristics, including child characteristics (such as: gender, vaccination, health issues in 2002) and household characteristics (such as: baseline household size, age of moms, mother's education).

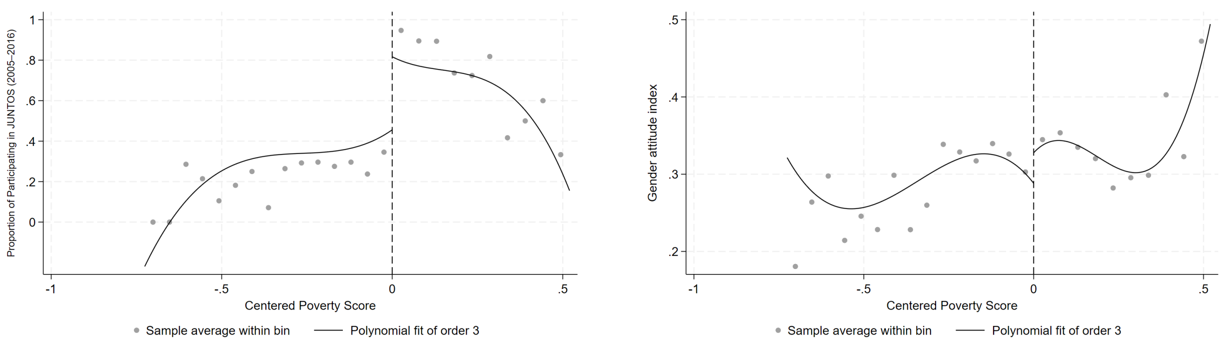
Appendix Table A2 reports the estimates of τ_{FRD} when characteristics of interest are outcome variables. The results suggest that there is no significant discontinuity in observable characteristics at the cutoff when all robust p-values are larger than 0.1. Note that in all regressions conducted on equation 1, the estimates of β are strongly significant with an approximate magnitude of 0.36.

5 Results

5.1 Effects on Gender Attitudes

I first present the RD graphical evidence to intuitively illustrate the discontinuous changes at the threshold. Figure 2 shows the discontinuities in both the proportion of Juntos participating households and the gender attitude index. Panel A plots the proportion of Juntos participation against the running variable, controlling for district fixed effects that capture differences in poverty score calculations and district-specific factors affecting household poverty scores. The circles present the sample average within bin over disjoint bins of the running variable. The solid lines represent separate third-order global polynomial fits on each side of the threshold. The figure reveals a clear jump in the proportion of participating in the Juntos program at the threshold level. Panel B plots the gender attitude index as a function of the running variable. The figure shows a clear jump at the threshold level, in which the gender attitude index of beneficiary children is roughly 0.05 points higher than non-beneficiary children.

Figure 2. First Stage and Intention-to-Treat



(a) Panel A: First Stage **(b) Panel B: Intention-to-Treat**

Note: Data is from the YLS Panel. Each graph plots the outcome as a function of the running variable (centered poverty score). In both graphs, the support of centered poverty score is divided into disjoint bins. The circles illustrate the outcome's local mean at the midpoint of individual bins. The solid lines depict distinct third-order global polynomial fits on either side of the threshold. The observations situated to the right of the vertical dashed line are considered eligible for Juntos.

Next, I present the main regression results using the local polynomial approach. Table 3 reports estimates of β and τ_{FRD} from equations 1 and 2. The first-stage results in row (1) confirm the visual evidence from Figure 2, with all β estimates statistically significant at the 1% level. Regarding the estimates of τ_{FRD}, column (2) shows that children in beneficiary households exhibit a 13.3 percentage point increase in agreement with traditional attitudes (robust p-value = 0.01). This effect is sizable, corresponding to a 41.4% increase relative to the control group's mean within the optimal bandwidth.

Table 3. Effects on Gender Role Attitudes

	Gender Attitude Index		Dimension					
			Power		Equality		Behavior	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: First Stage								
First stage (β)	0.371	0.369	0.371	0.369	0.371	0.369	0.371	0.369
	(0.059)	(0.058)	(0.059)	(0.058)	(0.059)	(0.058)	(0.059)	(0.058)
Robust p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: LATE Estimates								
LATE (τ_{FRD})	0.142	0.133	0.163	0.152	0.175	0.164	0.054	0.048
	(0.050)	(0.041)	(0.086)	(0.069)	(0.071)	(0.064)	(0.112)	(0.106)
Robust p-value	0.020	0.010	0.112	0.079	0.036	0.033	0.816	0.824
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Control Group Mean	*0.321*	*0.321*	*0.323*	*0.323*	*0.155*	*0.155*	*0.537*	*0.537*
Observations	586	579	586	579	586	579	586	579

Note: Data is from the YLS Panel. This table reports the effect of Juntos on gender attitudes and three subindices in the analysis sample. For specification details, see Equations 1 and 2. Panel A presents estimates of the first stage, where the dependent variable is participation in the Juntos program. Panel B reports the LATE estimate of participation in Juntos on gender attitudes, computed as the ratio of the ITT estimate to the first-stage coefficient. The bandwidth for the local linear estimator (h) is 0.144, while the bandwidth for estimating a second local quadratic model (b) is 0.274. Several control variables are included in the analysis, such as the age of mothers (years) in 2002, dummy variables for gender of the child, mother education, child's religion, child's ethnicity and child's long term health problem. The robust p-values are constructed using robust bias correction. Standard errors clustered at the district level are shown in parentheses.

Building upon the main results, I further investigate which dimensions of gender attitudes are most affected, as outlined in Section 3.2. I present the results from estimating equations 1 and 2 when the dependent variables are three sub-indices in columns (3) to (8) of Table 3. The findings suggest that Juntos has a significant impact on the power dimension, which reflects the extent of power women hold in comparison to men, and the equality dimension, which captures the desire for greater equality in housework and freedom. However, no significant effects are observed in the domain of behavior.[15]

In brief, the results indicate that Juntos leads to more traditional gender attitudes among beneficiary children. This finding contrasts with most existing studies, which report shifts toward more progressive attitudes (Bastian, 2020; Farré et al., 2023; Tavits et al., 2024). However, it is important to note that these studies primarily examine policies implemented in high-income

[15] In Appendix Figures A4 and A5, I present the RD graphical evidence of the first stage, along with the intention-to-treat estimates, using the optimal bandwidth for the gender attitude index and three sub-indices, including: power dimension, equality dimension and behavior dimension.

countries and usually target adult household members, such as mothers or fathers. By contrast, this paper examines a CCT program in a developing country context, which targets children's human capital development and designates mothers as the key implementers. These differences in context, target population and policy design may help explain the divergence in findings.

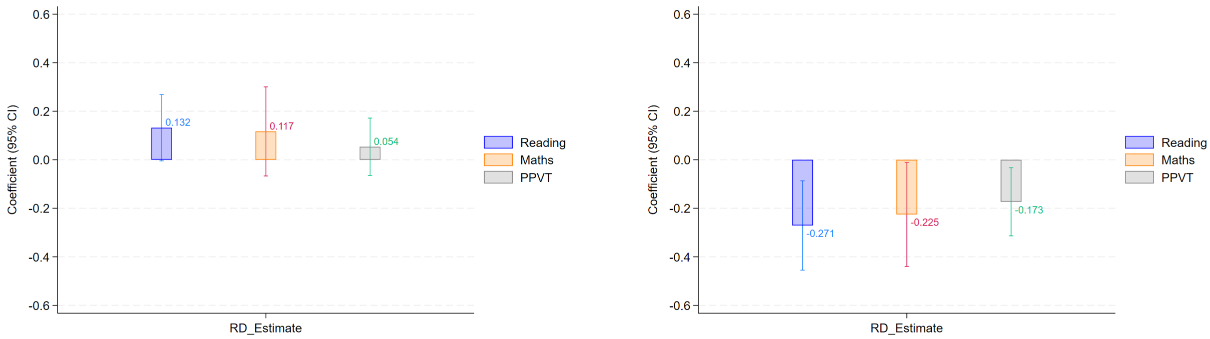
5.2 Effects on Cognitive Tests

In this subsection, I examine the impact of Juntos on children's performance in the Peabody Picture Vocabulary Test (PPVT), as well as in reading and mathematics assessments. All cognitive tests were first introduced in the second survey round and were developed by the YLS team to measure academic proficiency. The PPVT is a receptive vocabulary test that assesses children's understanding of spoken words. For each item, the child is presented with four simple illustrations and asked to select the one that best represents the meaning of a word spoken aloud by the examiner. The mathematics test draws on items from both international and national evaluations, while the reading comprehension test evaluates literacy skills and the understanding of informational and narrative texts encountered in daily life. Beginning in Round 4, the tests were refined to better reflect contextual realities, and the formats in the last two rounds are more consistent. Therefore, I restrict the analysis to cognitive test data from Rounds 4 and 5.

Figure 3 presents the estimated effects of Juntos on test performance, highlighting important gender differences. Beneficiary girls score lower across all three tests compared to non-beneficiary girls. In contrast, beneficiary boys experience a statistically significant improvement in reading scores, with an increase of 13.2%. Although boys also show higher scores in mathematics and the PPVT, these effects are not statistically significant.[16] The improvement in boys' reading scores aligns with findings from Nicaragua's CCT program, Red de Protección Social (RPS), which also reports cognitive gains among boys (Barham et al., 2013). Conversely, the decline in girls' performance contrasts with much of the existing literature, which generally finds no significant effects on learning outcomes (e.g., Behrman et al., 2008; Barham et al., 2024). One possible explanation may lie in the sociocultural context. As discussed in Subsection 5.1, gender attitudes among beneficiary children appear to become more regressive, particularly regarding the power dimension—including increased agreement with beliefs about male academic superiority. These reinforced attitudes may influence educational aspirations and behaviors, contributing to the observed disparities in test performance.

[16]Detailed regression results are provided in Appendix Table A4.

Figure 3. Effects on Test Scores



(a) Panel A: Boys **(b) Panel B: Girls**

Note: Data is from the YLS Panel. This graph shows the effects of Juntos on children's test scores. The point estimates are obtained from Equations 1 and 2 with year fixed effects, using PPTV scores, reading test scores, and math test scores as the dependent variables. Panel A shows the results for boys, while Panel B reports the estimates for girls, using the same three outcome variables. Test scores are measured as accuracy rates, in percent.

5.3 Effects on Time Use and Higher Education Enrollment

A challenge in this study is the potential for social desirability bias in responses to gender attitude questions, as children may adjust their answers to align with perceived social norms (Yan, 2021). To assess whether their self-reported attitudes are in line with their actual behaviors, I use time-use data to analyze the effect of Juntos on children's involvement in caregiving, household chores, school (including traveling time to school), studying (after school) and leisure in Rounds 3, 4 and 5. I also draw on data from the 2020–2021 Phone Survey to evaluate Juntos' impact on higher education enrollment, which includes both university and non-university programs under the Ministry of Education, at age 19.

Table 4 presents the results for male and female sub-samples. In Panel A, the results suggest that boys spend less time on caring and school activities and slightly more time on household chores, although none of these effects is statistically significant. Interestingly, in columns (4) and (5), boys spend approximately one additional hour on studying at home or attending extra tuition (robust p-value < 0.01), which appears to be offset by a corresponding reduction in leisure time. Moreover, column (6) indicates that boys are more likely to enroll in higher education, although this effect is not statistically significant.

Panel B reports the pattern of girls' time allocation. Girls spend more time on household chores, less time on studying after school (robust p-value < 0.01), and more time on leisure (robust p-value = 0.084). They also spend more time on caring for others and less time at school, but these effects are not distinguishable from zero. The negative coefficients for school time for both boys and girls may seem counterintuitive, since attending school is a condition of Juntos. However, school

Table 4. Effects on Time Allocation and Higher Education Enrollment

	Time Allocation (hours)					Higher Education
	Caring	**Household Chores**	**School**	**Study (after school)**	**Leisure**	**Enrollment**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Boys						
LATE (τ_{FRD})	-0.306	0.154	-0.400	1.071	-1.015	0.192
	(0.334)	(0.203)	(0.388)	(0.237)	(0.456)	(0.241)
Robust p-value	0.374	0.468	0.557	0.000	0.038	0.269
Control mean	*0.537*	*0.960*	*6.228*	*1.636*	*4.062*	*0.247*
Observations	664	664	664	664	664	248
Panel B: Girls						
LATE (τ_{FRD})	0.381	0.694	-0.553	-0.780	0.718	-0.397
	(0.309)	(0.173)	(0.418)	(0.247)	(0.370)	(0.176)
Robust p-value	0.153	0.000	0.155	0.001	0.084	0.028
Control mean	*0.642*	*1.011*	*6.234*	*1.962*	*3.785*	*0.312*
Observations	683	683	683	683	683	244
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data are from the YLS Panel. This table reports the effect of Juntos on children's time allocation and higher education enrollment. *Caring* includes caregiving activities for younger siblings, or ill household members. *Household chores* consist of fetching water, firewood, cleaning, cooking, washing, shopping, etc. *School* includes time at school and traveling time to school. *Study* contains studying outside of school time (at home, extra tuition). *Leisure* includes time spent eating, drinking and bathing. Panel A presents estimates for boys, and Panel B for girls. Control variables include mother's age (in 2002), child's gender, mother's education, child's religion, ethnicity, and long-term health condition. Robust p-values are constructed using robust bias correction. Standard errors, shown in parentheses, are clustered at the child level for columns 1–5 and at the district level for column 6.

time includes both time spent at school and travel time to school, and therefore may not accurately reflect actual instructional time. Furthermore, previous studies document no significant attendance gains from Juntos participation (Perova and Vakis, 2009), potentially due to the availability of free public schools in Peru. The last column reveals an interesting finding: beneficiary girls are 39.7% less likely to enroll in any higher education program (robust p-value = 0.028), aligning with their gender attitudes at age 15.

The increase in time spent on studying at home or attending extra tuition among boys, along with the rise in time devoted to household chores and the lower likelihood of higher education enrollment among girls, aligns with traditional gender norms, particularly in the dimensions of power and equality. However, the magnitude of reported hours should be interpreted with caution, as they are rounded to the nearest integer.[17] These findings are consistent with the evidence in Subsection 5.2, in that boys spend more time studying outside of schools and have better test scores, while girls devote more time to home production and less to studying, which may lead to lower test scores across all cognitive tests. Overall, these patterns suggest that children's traditional gender attitudes are reflected not only in their gendered behaviors but also in their educational choices as they grow older.

5.4 Robustness Checks and Falsification Analysis

I conduct a number of checks to verify the robustness of my main findings.

Different Selections of Local Polynomial Degree, Kernel, or Bandwidth. Table A5 confirms the robustness of my main results across various polynomial orders, kernels, and bandwidth choices. Following Gelman and Imbens (2019), column (1) uses a quadratic polynomial with the MSE-optimal bandwidth ($\hat{h}_{MSE}$). Columns (2)–(3) apply uniform and epanechnikov kernels, while column (4) uses the CER-optimal bandwidth ($\hat{h}_{CER}$), which improves confidence interval coverage.[18] Column (5) follows standard RD practice by using $\hat{h}_{MSE}$ for the ITT only. Columns (6)–(7) allow for asymmetric bandwidths around the cutoff. Overall, the estimates remain statistically significant and are consistent in both sign and magnitude with the baseline results.

Bootstrap Inference for Few Clusters. One concern is the small number of eligible districts in the YLS (12), which may result in unreliable asymptotic approximations for standard errors clustered at the district level. To the best of my knowledge, only He and Bartalotti (2020) develops

[17]Time use is recorded such that durations of less than 30 minutes are coded as 0, while durations of 30 minutes or more are rounded up to 1 hour. To account for this recording method, I winsorize the total home-hours data at the top 5% to limit the influence of outliers.

[18]Calonico et al. (2020) show that $\hat{h}_{MSE}$ is optimal for point estimates, whereas $\hat{h}_{CER}$ minimizes coverage error for inference.

a wild bootstrap procedure that provides robust, bias-corrected, and valid confidence intervals for the fuzzy RD design, building on Calonico et al. (2014). However, their procedure does not allow for covariates. To address this concern, I apply the wild bootstrap method with clustering and covariates in the sharp RD design, following Bartalotti et al. (2017) and Bluhm and Pinkovskiy (2021). Appendix Table A6 reports the wild bootstrap estimator, its standard deviation, and the 95% confidence interval. The coefficients are consistently positive, supporting the robustness of the main findings. In particular, the confidence intervals for the estimated coefficients of Juntos and the gender attitude index lie entirely in the positive range, reinforcing the credibility of the results.

Different Approaches to Measure the Outcome Variable. In Appendix Table A7, I further show that the estimates are robust when using different approaches to construct the outcome variable. Columns (1)–(2) use a weighted gender attitude index following Anderson (2008), while columns (3)–(4) apply a polychoric principal component analysis (PCA) of twelve Likert-scale variables following Kolenikov and Angeles (2009). Across all specifications, the RD estimates consistently align with the baseline findings in terms of direction and significance level. This finding suggests that Juntos leads to more traditional gender attitudes among beneficiary children.

Parametric Model. Appendix Table A8 presents the parametric fuzzy RD results estimated using the two-stage least squares (2SLS) technique. In all columns, the optimal bandwidths are selected based on the methodology proposed by Imbens and Kalyanaraman (2011). I also report the wild bootstrap cluster 95% confidence intervals (WCR 95% CI) that take into account the small number of clusters. The results show positive and statistically significant effects, consistent with those from the nonparametric fuzzy RD approach using a linear local polynomial. Although the second-order local polynomial yields similar positive effects, they are not statistically significant.

Placebo Cutoffs. One useful falsification exercise to validate the fuzzy RD design is to examine the treatment effect at the placebo cutoffs. In this test, the true threshold value is replaced with alternative values at which the treatment status remains unchanged. I present the results of this falsification test in Appendix Table A9, using six artificial cutoffs (-0.2, -0.1, -0.05, 0.05, 0.1, and 0.2). Following Cattaneo et al. (2020), I use only treated observations for artificial cutoffs exceeding the true cutoff, while only control observations are employed for artificial cutoffs falling below the true cutoff. Overall, the results reveal no evidence of significant treatment effects at the placebo thresholds.

6 Mechanisms

This section investigates the mechanisms through which Juntos reinforces children's gender attitudes, focusing on how the program influences mothers' labor supply and time allocation. CCTs typically designate mothers as cash recipients and require them to fulfill program conditions. Economic models of the family suggest that directing resources to women can enhance their bargaining power and increase their participation in decision-making processes (Blundell et al., 2005). While several empirical studies support these predictions by showing that CCTs can promote more equitable intra-household dynamics (Attanasio and Lechene, 2002; De Brauw et al., 2014; Bergolo and Galván, 2018), other evidence highlights potential unintended constraints on women's roles (Chant, 2008; Nagels, 2016). Moreover, several studies report declines in maternal labor supply, including reduced working hours (Fernández and Saldarriaga, 2014) and lower employment rates (De Brauw et al., 2015; El-Enbaby et al., 2019), attributed to both income effects (e.g., Becker, 1965) and increased time burdens.

In the context of Juntos, Díaz and Saldarriaga (2022) find that the program does not significantly affect women's involvement in household decision-making or financial autonomy, although it does reduce the prevalence of domestic violence. Because children's gender attitudes often reflect the gendered behaviors they observe at home, shifts in mothers' labor supply and time allocation may serve as channels through which Juntos reinforces traditional gender norms. Building on these findings, I examine these mechanisms using data from Peru's Continuous DHS (2004–2016), the 2010 NTUS, the 2014 EPHR, and Round 4 of the YLS household survey.

6.1 Effects on Mothers' Time Allocation

I begin by using data from Round 4 of the YLS's household survey that identifies mothers' most important occupation based on the time spent in the past 12 months. I classify reported jobs into four categories: household chores/housewife, self-employment, wage employment, and other jobs.[19] Based on this classification, I construct four binary indicators. I then re-estimate equations 1 and 2, replacing the dependent variable in the intention-to-treat stage with each of these indicators.

Table 5 provides key insights into mothers' time allocation. Column (1) shows that beneficiary mothers are 41.7% more likely to report household chores or homemaking as their priority activity in terms of time spent (robust p-value < 0.05), consistent with Nagels (2016), who finds that Juntos reinforces maternalistic behaviors. Column (2) indicates a 32.7% decrease in the likelihood of prioritizing self-employment (robust p-value < 0.1). Column (3) shows no significant effect

[19] Other jobs include income-generating activities characterized by non-salaried, irregular, or unstable income, such as: part-time agricultural laborer or housemaid. Note that I exclude the residual category "non-remunerated household member/other unwaged," which was chosen by only a small share of mothers and thus represents a negligible portion of the sample (less than 10%).

Table 5. Effects on Maternal Time Priority

	Household chores	Self-employment	Wage employment	Other jobs
	(1)	(2)	(3)	(4)
LATE (τ_{FRD})	0.417	-0.327	0.016	-0.320
	(0.192)	(0.192)	(0.119)	(0.113)
Robust p-value	0.024	0.089	0.839	0.003
District FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Control Group Mean	*0.392*	*0.066*	*0.223*	*0.223*
Observations	511	511	511	511

Note: Data is from Round 4 of the household survey from the YLS. This table reports the effect of Juntos on maternal time priority. The LATE estimates are computed as the ratio of the ITT estimates to the first-stage coefficient. For specification details, see Equations 1 and 2, where the dependent variable in the ITT stage is replaced by maternal activities. *Household chores/Housewife* equals 1 if the mother selects household chores or being a housewife as the most time-priority activity, and 0 otherwise. *Self-employment* equals 1 if the mother selects self-employment in agriculture, animal husbandry, fishing, forestry, manufacturing, or services, and 0 otherwise. *Wage employment* equals 1 if the mother selects regular salaried or wage work, and 0 otherwise. *Other jobs* equals 1 if the mother selects part-time, irregular, or non-salaried jobs—such as part-time agricultural labor, forestry, crafts, independent trading, or housekeeping—as the main time priority, and 0 otherwise. Controls include the mother's age, an education dummy (equals 1 if education is below secondary), marital status, and presence of long-term health conditions. Robust p-values are calculated using bias correction, and standard errors clustered at the district level are reported in parentheses.

on wage employment, while column (4) reveals a 32% reduction in unstable income-generating activities.[20] These findings suggest that Juntos shifts mothers' time priorities toward homemaking and away from labor market activities.

To obtain a more detailed picture of time allocation and increase statistical power, I next examine the association between exposure to the Juntos program and maternal time use, using data from the 2010 NTUS linked to administrative records on the program's rollout. Since the NTUS does not include information on household-level participation, I define exposure based on whether a woman resides in a district eligible for Juntos as of 2010. I then compare time use between women in eligible and ineligible districts. Following Rutstein (2015), I construct a household wealth index and restrict the analysis to the bottom 60 percent of the wealth distribution. The sample

[20]Appendix Figure A6 presents a discontinuity test for each job category around the threshold in Round 2 (2006). To ensure robustness, households reporting transfer receipt before Round 2 were excluded. The results show no pre-intervention differences near the threshold.

is further limited to ever-married women aged 15–59 with children. The final sample comprises 1,756 women, of whom 18 percent reside in eligible districts.

To capture the relationship between mothers' time allocation across different activities and their exposure to the *Juntos* program, I estimate the following specification:

$$\text{Time use}_{ijpq} = \alpha + \beta\,\text{Juntos}_{ijp} + X_i + \text{Wealth index}_i + \text{Total poverty}_j + \gamma_p + \varepsilon_{ijpq} \quad (3)$$

where Time use$_{ijpq}$ denotes the total number of minutes that woman i, residing in district j and province p, spends on activity q during weekdays or weekends. Juntos$_{ijp}$ equals one if woman i lives in a district eligible for the *Juntos* program. X_i includes individual characteristics such as age and education. Wealth index$_i$ is the household wealth index, Total poverty$_j$ is the district-level poverty rate, γ_p represents province fixed effects, and ε_{ijpq} is the error term. Standard errors are clustered at the district level.

Figure 4 presents the correlation between Juntos and women's time allocation across various activities. Consistent with the results reported in Table 5, Juntos increases time spent on child care—by 119 minutes over five weekdays (19.5% of the sample mean) and by 60 minutes over the weekend (25.7% of the sample mean). On weekdays, women in eligible districts also devote more time to household organization (56 minutes, roughly 40.7% of the sample mean), including budgeting, paying bills, collecting subsidies, and transporting household members to comply with program requirements. Meanwhile, there is no significant effect on time spent on domestic tasks or personal care.[21] These patterns provide suggestive evidence of the additional time burden associated with program participation.[22]

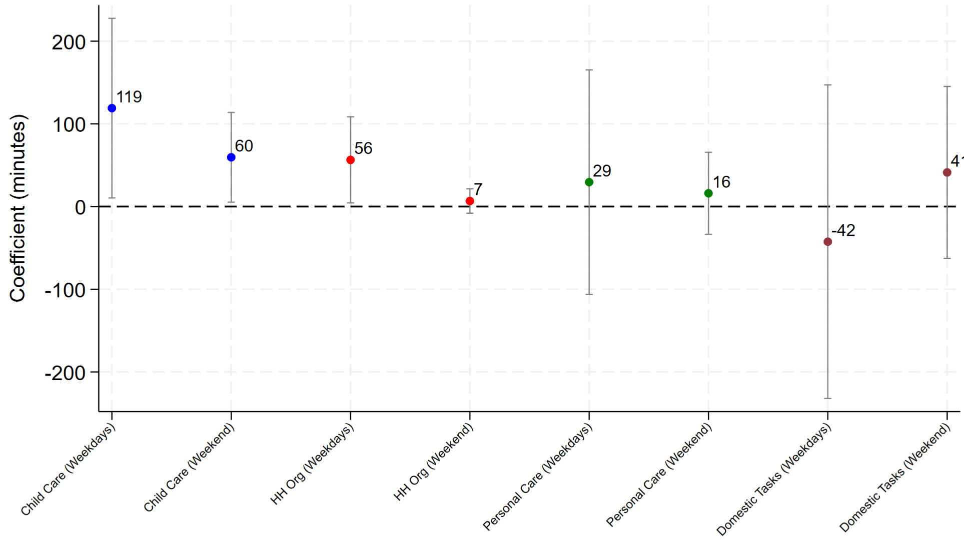
To investigate this further, I draw on the 2014 EPHR, which covers 27,189 Juntos beneficiary households. Figure 5 presents suggestive evidence of the time burden mothers face when collecting the cash transfer. Panel A shows that 92.38% of collectors are mothers, 3.7% are other female household members, and approximately 4% are male household members.[23] Among these mothers, 79.11% rely on a single mode of transportation, 19.93% use two combined modes, and 0.96% use three modes. Panel B documents the average travel time by transportation mode for those using only one mode, with most women traveling by foot or by bus/minivan. On average, mothers spend 152 minutes to travel from their homes to national banks or bank agencies. Although collection occurs once a month or every two months, the average one-way travel time of two and a half

[21]Note that the results of maternal time in domestic tasks refer to all mothers, not only those with daughters. Thus, the absence of change in mothers' domestic tasks is not inconsistent with the increase in household chores observed among beneficiary girls. Differences in activity definitions and potential intra-household substitution further help reconcile the findings.

[22]To mitigate the influence of outliers, all time use categories are winsorized at the 1st and 99th percentiles.

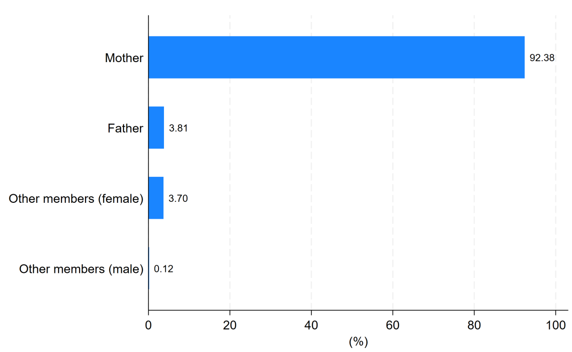
[23]Using the third, fourth, and fifth rounds of the YLS's household survey, I identify Juntos recipients within beneficiary households, revealing that approximately 93% of the recipients are mothers.

Figure 4. Association Between Juntos and Women's Time Use (NTUS 2010, 1,756 women)

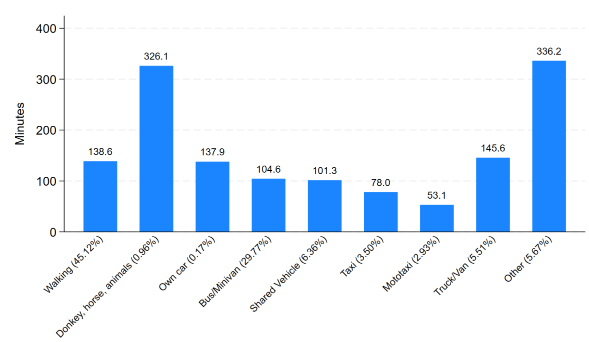


Note: Data is from the 2010 NTUS. *Child care* includes caring for babies, children, and adolescents, such as breastfeeding, helping with school tasks, and attending meetings, celebrations, or other activities required by social programs. *Household organization* comprises tasks such as budgeting, paying bills, collecting social program subsidies, and transporting household members to fulfill program conditions. *Personal care* includes sleeping, eating meals, hygiene, personal grooming, and resting in bed. *Domestic tasks* involve cooking, house cleaning, clothing care, and shopping for the household. All time use is measured in minutes. Weekday time use reflects the total time spent over five weekdays, while weekend time use reflects the total time spent on Saturday and Sunday.

Figure 5. Average Travel Time to Collect Cash Transfers, by Transportation Mode (EPHR data)



(a) Panel A: Who Collected Juntos Cash Transfer in Past Year?



(b) Panel B: Average Travel Time to Collect Cash Transfers (Only One Mode of Transport)

Note: Data is from the 2014 EPHR. In the sample, there are 27,189 Juntos beneficiary households that started receiving the cash transfer from 2005 to 2014.

hours suggests that mothers spend most of a day on this task, adding to their unpaid workload. These findings are in line with Cookson (2016) and Cookson (2018), who report that compliance with program requirements substantially increases women's workloads by requiring attendance at services, seeking care, and collecting payments.

6.2 Effects on Mothers' Workforce Participation

To gain further insight into mothers' labor behaviors, I use data from the Peru Continuous DHS (2004–2016), linked to district-level administrative data on the geographic rollout of Juntos. Following Laszlo et al. (2024), I restrict the sample to women who have ever been in a union (marriage or cohabiting), live in rural districts, have children under age 19, and belong to households in the bottom 40% of the wealth distribution. I examine the impact of Juntos on four outcomes: (i) mothers' labor force participation, (ii) self-employment in agriculture, (iii) white-collar employment, and (iv) service or manual employment. To estimate these effects, I employ an event study framework based on the following semi-dynamic specification:

$$Y_{idt} = \gamma_t + \delta_d + \sum_{\tau=0}^{6} \mu_{d\tau} \mathbf{1}\{\tau = t - E_d\} + \tau_{7+} \mathbf{1}\{\tau = t - E_d \geq 7\} + \nu X_{idt} + \varepsilon_{idt} \tag{4}$$

Where Y_{idt} is the outcome of interest for woman *i* living in district *d* at time *t*. E_d refers to the first year Juntos was implemented in district *d* where woman *i* resides. γ_t and δ_d represent year fixed effects and district fixed effects, respectively. Treatment lags beyond $\tau = 6$ are binned together to ensure sufficient observations in each bin. The coefficient μ_τ captures the dynamic treatment effects of Juntos. This approach identifies intent-to-treat effects at the district level, and I apply the estimator developed by Sun and Abraham (2021) to account for heterogeneity in treatment effects between cohorts.

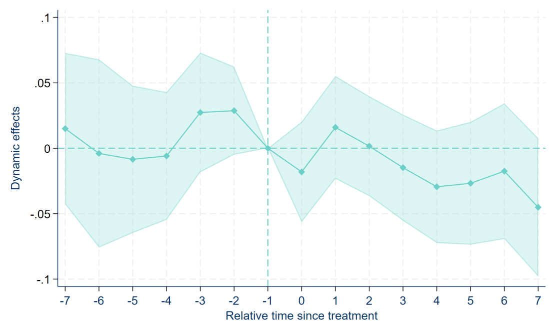
The identification strategy relies on the assumption that, in the absence of Juntos, the evolution of outcomes of women in treated districts is similar to that of women in non-treated districts. I test this assumption by examining the differential evolution of women in treated and non-treated districts prior to Juntos implementation using the fully dynamic specification. Specifically, I estimate the following equation:

$$Y_{idt} = \gamma_t + \delta_d + \sum_{\substack{\tau \geq -6 \\ \tau \neq -1}}^{6} \mu_{d\tau} \mathbf{1}\{\tau = t - E_d\} + \tau_{7-} \mathbf{1}\{\tau = t - E_d \leq -7\} + \tau_{7+} \mathbf{1}\{\tau = t - E_d \geq 7\} + \nu X_{idt} + \varepsilon_{idt} \tag{5}$$

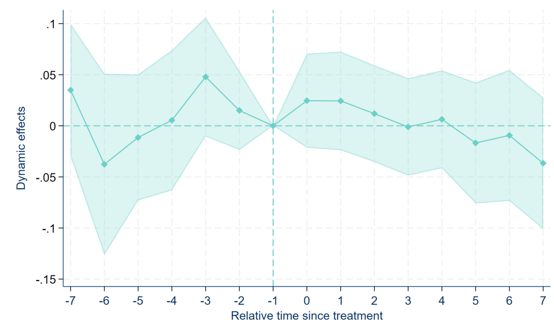
where μ_t for $\tau < 0$ denote the pre-trend coefficients, while μ_t for $\tau > 0$ capture the estimated dynamic treatment effects. Following standard practice in the literature, I normalize $\tau = -1$

and aggregate all distant leads (i.e., time points with $\tau < -6$) into a single bin to increase the sample size. Figure 6 confirms the plausibility of the parallel trends assumption both visually and through significance tests for all outcomes: labor force participation, self-employment, white-collar employment, and service or manual employment.

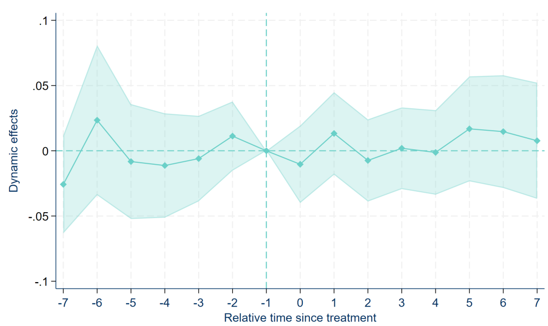
Figure 6. Testing the Plausibility of the Parallel Trend Assumption (DHS 2004-2016)



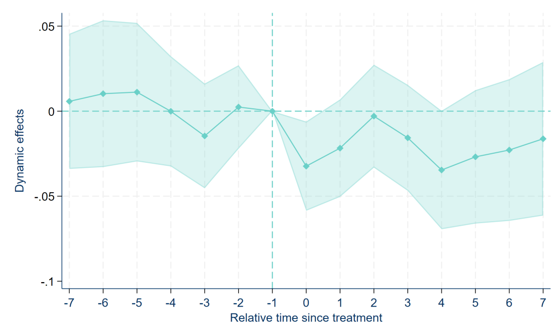
(a) Fully Dynamic Event Study: Workforce participation. Leads joint significance F-test p-value: 0.525. Pre-Juntos average effect p-value: 0.614



(b) Fully Dynamic Event Study: Self-employment. Leads joint significance F-test p-value: 0.277. Pre-Juntos average effect p-value: 0.678



(c) Fully Dynamic Event Study: White-collar jobs. Leads joint significance F-test p-value: 0.356. Pre-Juntos average effect p-value: 0.853



(d) Fully Dynamic Event Study: Services & manual jobs. Leads joint significance F-test p-value: 0.816. Pre-Juntos average effect p-value: 0.850

Table 6 reports the estimated effects of Juntos on four labor market outcomes for women. Column (1) shows a statistically significant decline in labor force participation, with the effect becoming more persistent three years after program implementation in treated districts. The average treatment effect is -0.039, corresponding to a 3.9-percentage-point reduction (5% of the sample mean). This contrasts with Fernández and Saldarriaga (2014), who find no significant effect, likely due to their smaller sample—limited to the 2009 ENAHO round—and shorter four-year follow-up. However, the direction of their coefficient aligns with my results, reinforcing the potential negative impact of Juntos on women's labor participation. Column (2) examines agricultural self-employment, showing an average effect of -0.015, which is not statistically significant. Despite this, the negative sign is consistent with the evidence in Table 5, based on YLS household data, indicating that beneficiary women are less likely to prioritize self-employment in their time allocation. Similarly, Columns (3) and (4) show no significant effects of Juntos on white-collar or service and manual employment.

Table 6. Effects on Mothers' Workforce Participation

	Workforce Part. (Y=1)	Agr. self-employment (Y=1)	White-collar (Y=1)	Services & Manual (Y=1)
	(1)	(2)	(3)	(4)
Year Juntos implemented	-0.042**	0.024	-0.026*	-0.039***
	(0.021)	(0.023)	(0.015)	(0.013)
1 year later	0.010	0.028	0.004	-0.022*
	(0.022)	(0.026)	(0.016)	(0.013)
2 years later	-0.025	-0.011	-0.013	-0.000
	(0.021)	(0.025)	(0.013)	(0.014)
3 years later	-0.038*	-0.018	-0.011	-0.009
	(0.020)	(0.023)	(0.014)	(0.014)
4 years later	-0.047**	0.000	-0.016	-0.031**
	(0.021)	(0.023)	(0.014)	(0.015)
5 years later	-0.052*	-0.029	-0.004	-0.019
	(0.027)	(0.034)	(0.019)	(0.017)
6 years later	-0.046	-0.031	-0.000	-0.014
	(0.028)	(0.036)	(0.021)	(0.019)
7 or more years later	-0.076***	-0.042	-0.019	-0.015
	(0.026)	(0.033)	(0.019)	(0.019)
Average Effect	-0.039**	-0.015	-0.009	-0.016
	(0.019)	(0.023)	(0.013)	(0.013)
Individual Characteristics	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Mean Dep Var	0.783	0.564	0.134	0.086
Observations	66,795	66,795	66,795	66,795

Note: Data is from the Peru Continuous DHS from 2004 to 2016. This table reports the impact of Juntos on mothers' participation in the labor force and three categories of occupations: agricultural self-employment, white-collar, and service and manual work. The coefficients represent intent-to-treat effects at the district level. *Workforce Participation* equals 1 if a mother has worked in the past 12 months, and 0 otherwise. *Agricultural self-employment* equals 1 if a mother is self-employed in agriculture, and 0 otherwise. *White-collar* equals 1 if a mother works in professional, technical, managerial, clerical, or sales occupations, and 0 otherwise. *Service & Manual* equals 1 if a mother works in household and domestic, services or in skilled or unskilled manual labor, and 0 otherwise. Individual characteristics include the mother's age, age squared, household size, an indicator for residence in a rural area, and dummy variables for educational attainment and wealth index. All regressions include DHS sampling weights. Standard errors are clustered at the district level. Asterisks denote significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

In Appendix Table A10, using DHS data, I examine the effect of Juntos on fathers' labor market outcomes, focusing on labor force participation and three types of occupation. The results indicate no significant effect on fathers' overall working status, with the estimated coefficient close to zero. Interestingly, however, there is evidence of changes in the composition of occupations. Fathers in treated districts are significantly more likely to be self-employed in agriculture, with an average effect of 0.054, representing 7.6% of the sample mean. Conversely, they are 4.7 percentage points less likely to work in services or manual occupations, corresponding to 21.46% of the sample mean. These patterns are consistent with findings from similar cash transfer programs in Honduras (Galiani and McEwan, 2013) and Zambia (Ervin et al., 2017).

To sum up, Juntos appears to reinforce traditional gender roles by shifting mothers' time away from labor market activities toward domestic responsibilities, thereby reducing their overall labor force participation. These changes provide a plausible explanation for the traditional gender attitudes observed among children, given mothers' central role in shaping their gender expectations.

Alternative Explanation. In Appendix Table A11, I explore an additional channel using Round 3 of the YLS household survey and a parametric fuzzy RD model. Specifically, I examine the effects of Juntos on household expenditure per capita by child gender composition. The suggestive evidence points to asymmetric effects: boys with sisters receive higher expenditures, whereas girls with brothers receive lower expenditures, particularly in non-food spending. These patterns may reflect underlying gender norms in intra-household resource allocation, which could in turn shape children's gender attitudes. However, distinguishing between role modeling effects (children observing mothers) and resource allocation effects (children experiencing differential investment) requires additional data beyond the scope of this paper.

7 Conclusion

CCT programs have become a key policy tool to reduce poverty and break its intergenerational transmission in many developing countries. While substantial evidence emphasizes their effectiveness in enhancing human capital formation, less is known about their broader social impacts, particularly regarding gender norms. This study investigates the impact of CCT programs on the gender attitudes of children in beneficiary households, focusing on the Juntos program in Peru.

The findings reveal that Juntos reinforces traditional gender attitudes among children. These attitudinal patterns are consistent with observed behaviors: boys spend more time studying after school, while girls devote more time to domestic work and less time to studying. Moreover, beneficiary girls are less likely to enroll in higher education as they grow older. Analysis of cognitive outcomes further shows that beneficiary girls have lower accuracy rates in PPVT, math, and reading tests, whereas beneficiary boys perform better in reading.

To investigate potential mechanisms, I analyze changes in mothers' time allocation and labor market engagement. Evidence from the YLS and the 2010 NTUS indicates that Juntos increases mothers' time devoted to homemaking and childcare, while reducing their participation in self-employment and irregular work. Data from Peru's Continuous DHS further show that Juntos leads to a decline in mothers' labor force participation in treated districts. While I cannot completely rule out other mechanisms, the strengthening of maternal roles in the household strongly underlies the effects of CCTs on children's gender attitudes.

These results raise important questions about the gendered design and unintended consequences of CCT programs. While targeting transfers to mothers may improve certain child outcomes, it can also reinforce traditional gender roles and place additional burdens on women. This underscores the need to integrate women's experiences and constraints into the design of social protection programs. Moreover, the findings highlight the importance of further research to better understand and address these complex dynamics.

Finally, these findings may extend to other CCT programs in Latin America that share key design features—such as designating mothers as recipients, imposing time-intensive conditionalities, and operating in contexts with persistent gender gaps. Peru exemplifies such settings: women spend 24 more hours per week on unpaid work than men, a disparity comparable to Chile (23), Colombia (22), and Costa Rica (23) (OECD, 2022). Violence against women is also widespread, with 29.5% reporting physical violence—close to the Latin American average of 28% (UNDP, 2017). Nonetheless, the effects may vary depending on baseline gender norms, women's labor market opportunities, and program implementation. Future research should explore whether similar patterns emerge in other contexts.

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Conditional Cash Transfers and Gender Norms: The Role of Policy Design

Online Appendix

Ha Luong[†]

A Appendix Tables and Figures

Appendix Table A1. Comparing Poverty Scores and IFH Index: YLS vs. ENAHO

Panel A: Former method (YLS 2002 & ENAHO 2004)			**Panel B: Current method (YLS 2009 & ENAHO 2009)**		
Department	*YLS (Poverty)*	*ENAHO (Poverty)*	**Cluster**	*YLS (IFH)*	*ENAHO (IFH)*
Tumbes	0.146	0.363	2	48.843	38.151
Piura	0.535	0.535	3	43.580	42.803
Amazonas	0.688	0.661	4	37.100	40.701
San Martin	0.389	0.563	5	47.224	41.522
Cajamarca	0.192	0.695	6	63.971	55.567
La Libertad	0.148	0.452	7	48.173	45.923
Ancash	0.448	0.624	8	51.190	58.236
Huanco	0.752	0.687	9	62.292	55.274
Lima	0.076	0.206	10	61.840	52.017
Junin	0.495	0.468	11	50.328	48.149
Ayacucho	0.707	0.636	12	33.466	49.854
Apurimac	0.708	0.711	13	48.030	44.363
Arequipa	0.238	0.237	15	56.667	60.798
Puno	0.119	0.595	–	–	–
Correlation		*0.639*	**Correlation**		*0.591*

Note: This table compares the poverty score (Panel A) and IFH index (Panel B) between YLS and ENAHO data. The methods used to calculate each metric are described in Appendix B. The poverty score ranges from 0 to 1, while the IFH index ranges from 0 to 100.

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Appendix Table A2. Covariate Discontinuity Test Around the Threshold

Variable	MSE-Optimal Bandwidth	RD Estimator	Robust Inference p-value	Robust Inference Conf. Int.	Eff.Number Observations
Child characteristics					
Female	0.124	-0.029	0.744	[-0.390, 0.278]	538
Weight-for-age z-score	0.132	-0.373	0.399	[-1.621, 0.645]	560
Height-for-age z-score	0.143	0.394	0.516	[-0.778, 1.549]	601
Age of child (months, 2002)	0.138	-2.074	0.392	[-5.452, 2.136]	577
Polio vaccination (Yes=1)	0.132	0.053	0.384	[-0.096, 0.250]	557
BCG Vaccination	0.124	0.037	0.530	[-0.134, 0.260]	537
Health long term issues (Yes=1, 2002)	0.151	0.167	0.295	[-0.158, 0.521]	623
Mestizo (Yes = 1)	0.150	-0.038	0.803	[-0.243, 0.188]	620
Catholic (Yes =1)	0.120	0.038	0.397	[-0.131, 0.330]	529
Household characteristics					
Age of mom (years, 2002)	0.147	-2.745	0.397	[-9.757, 3.869]	604
Age of dad (years, 2002)	0.123	-2.413	0.549	[-9.963, 5.297]	463
Household size (members, in 2002)	0.130	-0.820	0.401	[-3.810, 1.524]	552
Mother education (<secondary school = 1)	0.127	-0.105	0.496	[-0.694, 0.336]	545
Caregiver's gender preference (Girl = 1)	0.148	0.057	0.709	[-0.371, 0.546]	609
Caregiver's gender preference (Boy = 1)	0.126	0.266	0.223	[-0.199, 0.854]	538

Note: Data is from the YLS. This table presents the LATE estimates when I replace the dependent variable in equation 2 by the characteristics of interest. The estimates are obtained by utilizing the MSE optimal bandwidth, triangular weights and linear local polynomial. The p-values and 95% confidence intervals reported are constructed using robust bias correction.

Appendix Table A3. Heterogeneous Effects by Child Gender and Region

	Child Gender		**Region in 2016**	
	Female	Male	Mountain	Jungle & Coast
	(1)	(2)	(3)	(4)
Panel A. First stage (β)	0.284	0.396	0.379	0.463
	(0.081)	(0.073)	(0.079)	(0.143)
Robust p-value	0.002	0.000	0.000	0.001
Panel B. LATE (τ_{FRD})	0.211	0.090	0.151	0.204
	(0.099)	(0.104)	(0.073)	(0.078)
Robust p-value	0.108	0.480	0.094	0.010
District FEs	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Control Group Mean	*0.298*	*0.342*	*0.266*	*0.384*
Observations	285	294	454	125

Note: Data is from the YLS. Panel A presents estimates of equation 1, where the dependent variable is participation in the Juntos program. Panel B report the LATE estimate of participation in Juntos on gender role attitudes, computed as the ratio of the ITT estimate to the first-stage coefficient. Several control variables are included in the analysis, such as the age of mothers (years) in 2002, dummy variables for mother education, child's religion, child's ethnicity and child's long term health problem. The robust p-values are constructed using robust bias correction. Standard errors clustered at the district level are shown in parentheses.

Appendix Table A4. Effects on Test Scores

	Boys			Girls		
	Reading	Maths	PPVT	Reading	Maths	PPVT
	(1)	(2)	(3)	(4)	(5)	(6)
LATE (τ_{FRD})	0.132	0.117	0.054	-0.271	-0.225	-0.173
	(0.070)	(0.094)	(0.060)	(0.094)	(0.110)	(0.072)
Control mean	*0.584*	*0.446*	*0.715*	*0.628*	*0.451*	*0.722*
Robust p-value	0.049	0.158	0.297	0.012	0.052	0.044
Observations	522	536	530	541	552	547
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data is from the YLS. All specifications replicate the specification in Table 3's Column (2) with year fixed effects by replacing the dependent variable with PPVT scores, reading test scores, and maths test scores. Several control variables are included in the analysis, such as the age of mothers (years) in 2002, dummy variables for mother education, child's religion, child's ethnicity, and child's long-term health problem. The robust p-values are constructed using robust bias correction. Standard errors clustered at child level are shown in parentheses.

Appendix Table A5. Effects on Gender Role Attitudes, Robustness

	Local Polynomial Degree	Kernel		Alternative bandwidths			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender Attitude Index							
LATE (τ_{FRD})	0.120	0.156	0.135	0.129	0.129	0.128	0.131
	(0.058)	(0.049)	(0.044)	(0.041)	(0.041)	(0.041)	(0.041)
Robust p-value	0.064	0.022	0.019	0.010	0.033	0.012	0.008
Observations	599	377	590	536	538	590	523
Power Dimension							
LATE (τ_{FRD})	0.209	0.194	0.148	0.164	0.157	0.136	0.140
	(0.111)	(0.098)	(0.073)	(0.078)	(0.069)	(0.068)	(0.065)
Robust p-value	0.074	0.083	0.116	0.065	0.052	0.088	0.060
Observations	580	380	596	479	538	520	462
Equality Dimension							
LATE (τ_{FRD})	0.271	0.208	0.150	0.186	0.157	0.191	0.221
	(0.117)	(0.109)	(0.074)	(0.073)	(0.065)	(0.069)	(0.074)
Robust p-value	0.036	0.115	0.068	0.023	0.033	0.014	0.007
Observations	488	254	479	470	538	496	448
Behavior Dimension							
LATE (τ_{FRD})	-0.139	0.078	0.014	-0.027	0.036	-0.028	-0.041
	(0.163)	(0.120)	(0.098)	(0.092)	(0.102)	(0.101)	(0.097)
Robust p-value	0.328	0.749	0.689	0.469	0.317	0.626	0.570
Observations	489	461	486	460	538	477	413
Bandwidth selection	$\hat{h}_{MSE}$	$\hat{h}_{MSE}$	$\hat{h}_{MSE}$	$\hat{h}_{CER}$	ITT $\hat{h}_{MSE}$	$\hat{h}_{MSE2}$	$\hat{h}_{CER2}$
Local Polynomial Degree	2	1	1	1	1	1	1
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Data is from the YLS. The dependent variables are gender attitude index, power dimension, equality dimension , and behavior dimension indices as defined in Table 3. In each column, the specific local polynomial degree and the algorithm for optimal bandwidth selection are indicated. The $\hat{h}_{MSE}$ bandwidth selection algorithm is optimal for point estimation; the $\hat{h}_{CER}$ selection algorithm is optimal for inference of confidence intervals. The use of subscript 2 in the description of the bandwidth selection algorithm indicates that different bandwidth lengths have been chosen on each side of the threshold. Several control variables are included in the analysis, such as the age of mothers (years) in 2002, dummy variables for gender of the child, mother education, child's religion, child's ethnicity and child's long term health problem. The p-values reported are constructed using robust bias correction. Standard errors clustered at district level are shown in parentheses.

Appendix Table A6. Effects on Gender Role Attitudes (Wild Cluster Boostrap), Robustness

	First stage	Gender Attitude Index	Power dimension	Equality dimension	Behavior dimension
	(1)	(2)	(3)	(4)	(5)
Panel A: Without controls					
Wild Est.	0.358	0.050	0.049	0.061	0.033
Std. Dev.	0.076	0.026	0.041	0.040	0.061
Wild 95% CI	[0.212, 0.500]	[0.000, 0.099]	[-0.029, 0.127]	[-0.015, 0.138]	[-0.087, 0.143]
Panel B: With controls					
Wild Est.	0.358	0.050	0.045	0.062	0.036
Std. Dev.	0.078	0.025	0.041	0.037	0.055
Wild 95% CI	[0.209, 0.504]	[0.003, 0.099]	[-0.033, 0.123]	[-0.012, 0.133]	[-0.065, 0.140]
District FEs	Yes	Yes	Yes	Yes	Yes

Note: Data is from the YLS Panel. This table reports the estimates for Equation 1 and Equation 2 separately. The Wild 95% confidence intervals use a cluster variant of the iterative bootstrap following Bartalotti et al. (2017) and Bluhm and Pinkovskiy (2021) with 1,000 replications for both estimators and for obtaining the empirical distribution of the bias-corrected estimator. Standard errors are clustered at the district level.

Appendix Table A7. Effects on Gender Role Attitudes (different measures), Robustness

	Weighted Gender Attitude Index		**Polychoric PCA Gender Attitude index**	
	(1)	(2)	(3)	(4)
Panel A. First stage (β)	0.368	0.367	0.385	0.378
	(0.055)	(0.056)	(0.052)	(0.046)
Robust p-value	0.000	0.000	0.000	0.000
Panel B. LATE (τ_{FRD})	0.815	0.755	0.704	0.596
	(0.320)	(0.285)	(0.296)	(0.226)
Robust p-value	0.052	0.039	0.039	0.046
District FEs	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	644	610	592	654

Note: Data is from the YLS. The dependent variable in columns (1) and (2) is the weighted gender attitude index constructed using dummy variables as in Anderson (2008). In columns (3) and (4), following the method of Kolenikov and Angeles (2009), I conduct the polychoric principal component analysis (PCA) using the twelve Likert rating scale variables and use the resulting first component as an index for gender role attitudes. These gender attitude indices are normalized to be mean-zero with a standard deviation of one for the control group. The estimates are obtained using MSE-optimal bandwidths and a linear local polynomial. The robust p-values are constructed using robust bias correction. Standard errors clustered at the district level are shown in parentheses.

Appendix Table A8. Effects on Gender Role Attitudes (Parametric Method), Robustness

	Gender attitude index			
2SLS	**(1)**	**(2)**	**(3)**	**(4)**
LATE (τ_{FRD})	0.116**	0.123**	0.141	0.137
	(0.0557)	(0.0554)	(0.111)	(0.109)
Controls	No	Yes	No	Yes
WCR 95% CI	[0.002, 0.241]	[0.006, 0.255]	[-0.078, 0.485]	[-0.080, 0.481]
First stage				
Z	0.367***	0.351***	0.340***	0.347***
	(0.0907)	(0.0872)	(0.103)	(0.103)
X	0.637	0.676	1.161	0.855
	(0.545)	(0.514)	(1.905)	(1.740)
Z × X	-1.175	-1.111	-1.307	-1.307
	(0.726)	(0.655)	(1.719)	(1.617)
X^2			2.782	0.954
			(9.355)	(8.199)
Z × X^2			-5.049	-0.863
			(14.46)	(12.87)
District FEs	Yes	Yes	Yes	Yes
Regression type	Linear	Linear	Quadratic	Quadratic
F-test	16.328	16.240	10.847	11.297
Observations	703	694	703	694

Note: Data is from the YLS. The dependent variable is the gender attitude index as defined in Table 3's columns (1) and (2). Z is the binary variable indicating eligibility for Juntos. X is the centered poverty score. In all columns, the optimal bandwidths are selected following the methodology of Imbens and Kalyanaraman (2011) (0.191). The wild cluster bootstrap confidence intervals (WCR 95% CI) are computed using 99,999 bootstrap replications under the null of no difference in discontinuities following Cameron et al. (2008). Standard errors, shown in parentheses, are clustered at the district level. Asterisks denote significance: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Appendix Table A9. Placebo Cutoffs

Alternative cutoffs	RD Estimates	*p*-value	Confidence Interval 95%	Optimal bandwidth	Obs Left	Obs Right
-0.2	0.062	0.900	[-0.561, 0.493]	0.061	81	85
-0.10	-0.088	0.917	[-0.862, 0.776]	0.038	40	66
-0.05	-0.737	0.979	[-4.083, 4.192]	0.069	98	81
0	0.142	0.020	[0.021, 0.250]	0.144	213	375
0.05	-1.499	0.588	[-7.932, 4.496]	0.014	43	52
0.10	-1.524	0.408	[-4.285, 1.741]	0.022	50	45
0.2	1.586	0.345	[-2.623, 7.498]	0.027	18	9

Note: Data is from the YLS. The dependent variable is the gender attitude index as defined in Table 3's columns (1) and (2). The LATE estimates are calculated at the zero threshold and across different placebo thresholds. Following Cattaneo et al. (2020), I use only treated observations for artificial cutoffs exceeding the true cutoff, while only control observations are employed for artificial cutoffs falling below the true cutoff. Estimates are obtained through the utilization of a triangular kernel, a local linear polynomial, and a $\hat{h}_{MSE}$ optimal bandwidth. The robust p-values are constructed using robust bias correction. Standard errors are clustered at district level.

Appendix Table A10. Effects on Fathers' Workforce Participation

	Workforce Part. (Y=1)	**Agr. self-employment (Y=1)**	**White-collar (Y=1)**	**Services & Manual (Y=1)**
	(1)	(2)	(3)	(4)
Year Juntos implemented	-0.001	0.062***	-0.013	-0.049**
	(0.002)	(0.023)	(0.011)	(0.022)
1 year later	-0.004**	0.034	-0.009	-0.030
	(0.002)	(0.022)	(0.011)	(0.020)
2 years later	0.001	0.034*	-0.007	-0.026
	(0.002)	(0.019)	(0.010)	(0.020)
3 years later	-0.002	0.051***	-0.016	-0.037**
	(0.002)	(0.020)	(0.010)	(0.018)
4 years later	-0.001	0.062***	-0.005	-0.058***
	(0.002)	(0.020)	(0.010)	(0.018)
5 years later	-0.001	0.064*	-0.005	-0.060**
	(0.002)	(0.034)	(0.017)	(0.029)
6 years later	-0.001	0.044	-0.004	-0.040
	(0.002)	(0.032)	(0.017)	(0.030)
7 or more years later	0.001	0.088***	-0.012	-0.076***
	(0.002)	(0.029)	(0.014)	(0.027)
Average Effect	-0.001	0.054***	-0.008	-0.047***
	(0.001)	(0.019)	(0.010)	(0.017)
Individual Characteristics	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Mean Dep Var	0.998	0.709	0.069	0.219
Observations	55,254	55,254	55,254	55,254

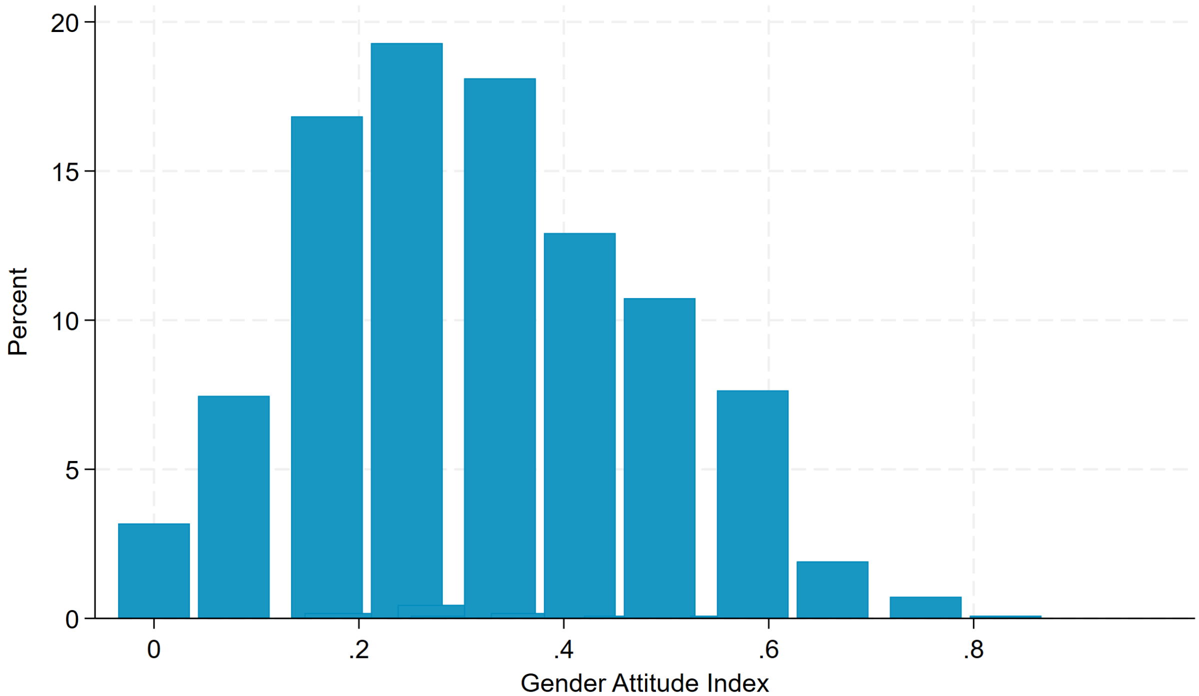
Note: Data is from the Peru Continuous DHS from 2004 to 2016. This table reports the impact of Juntos on fathers' participation in the labor force and three categories of occupations: agricultural self-employment, white-collar, and service and manual work. The coefficients represent intent-to-treat effects at the district level. *Workforce Participation* equals 1 if a father has worked in the past 12 months, and 0 otherwise. *Agricultural self-employment* equals 1 if a father is self-employed in agriculture, and 0 otherwise. *White-collar* equals 1 if a father works in professional, technical, managerial, clerical, or sales occupations, and 0 otherwise. *Service & Manual* equals 1 if a father works in household and domestic, services or in skilled or unskilled manual labor, and 0 otherwise. Individual characteristics include the father's age, age squared, household size, an indicator for residence in a rural area, and dummy variables for educational attainment and wealth index. All regressions include DHS sampling weights. Standard errors are clustered at the district level. Asterisks denote significance: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Appendix Table A11. Effects on Household Expenditure Per Capita by Child Gender Composition, Alternative Mechanism

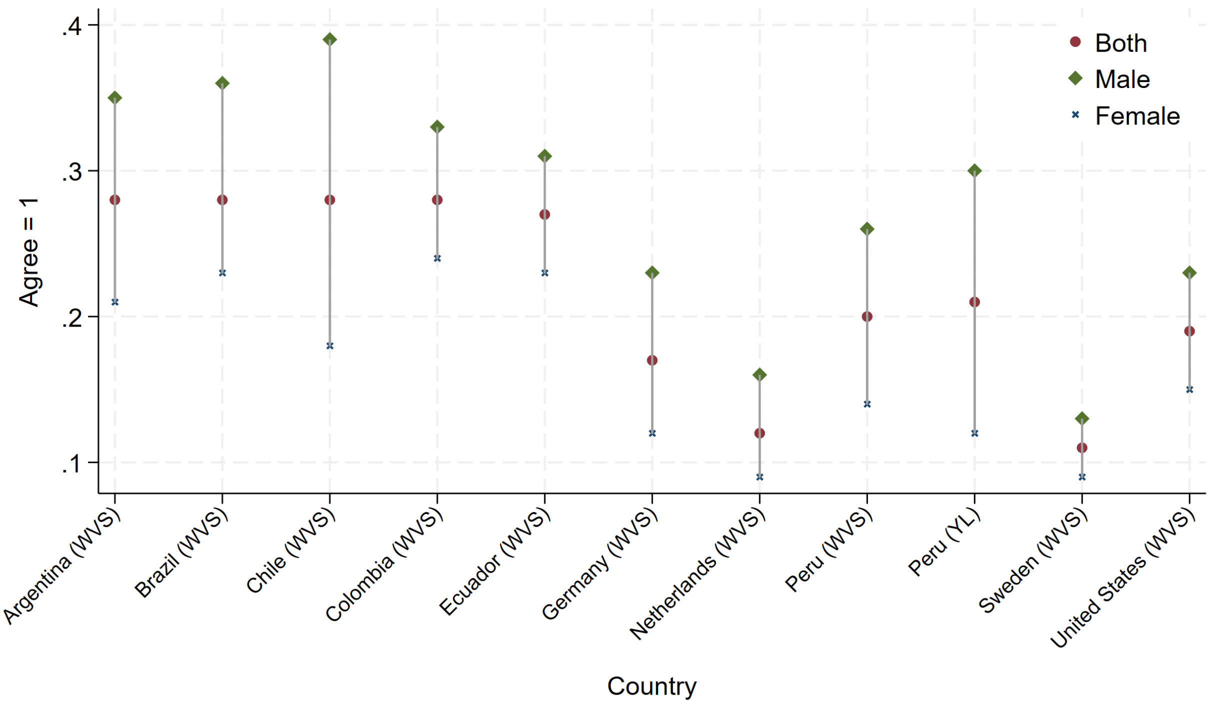
	Total Expenditure	Food	Non-food
	(1)	(2)	(3)
Juntos (Y=1)	-158.029	-62.755	-103.035*
	(104.464)	(59.437)	(59.210)
Juntos × Female	98.320	37.467	65.371
	(63.502)	(28.914)	(46.353)
Juntos × Only child	70.365	16.506	58.171
	(79.075)	(50.312)	(44.037)
Juntos × Has brother(s)	16.524	-2.882	21.340
	(32.166)	(20.316)	(16.139)
Juntos × Has sister(s)	134.043**	49.198	86.683***
	(57.382)	(35.447)	(30.230)
Juntos × Female × Only child	-125.903	-46.034	-80.938*
	(80.751)	(41.970)	(47.513)
Juntos × Female × Has brother(s)	-43.390	-6.817	-36.680*
	(27.307)	(14.120)	(20.672)
Juntos × Female × Has sister(s)	-82.427*	-41.633**	-42.390
	(43.282)	(19.969)	(30.780)
Female	12.749	5.104	5.444
	(12.621)	(8.619)	(6.451)
Only child (Y=1)	-18.027	1.959	-21.595**
	(25.808)	(19.668)	(10.499)
Has brother(s) (Y=1)	-30.598**	-15.113**	-16.159***
	(12.199)	(7.669)	(5.373)
Has sister(s) (Y=1)	-89.063***	-37.750**	-51.525***
	(22.617)	(15.370)	(10.671)
Observations	593	593	593
R-squared	0.240	0.169	0.207

Note: Data is from Round 3 of the household survey from the YLS. The dependent variables are household per capita total expenditure, per capita food expenditure, and per capita non-food expenditure. *Food expenditure* includes both purchased items and food obtained from own production or other own sources. *Non-food expenditure* encompasses spending on clothing and footwear, education, healthcare, entertainment, and other non-food-related items. Each column in the table reports estimates from a separate regression. The estimation uses a parametric specification with a bandwidth of 0.144. Al regressions control for the district fixed effects. Standard errors, clustered at the district level, are reported in parentheses.

Appendix Figure A1. Distribution of Gender Attitude Index (Mean: 0.32, SD: 0.16)

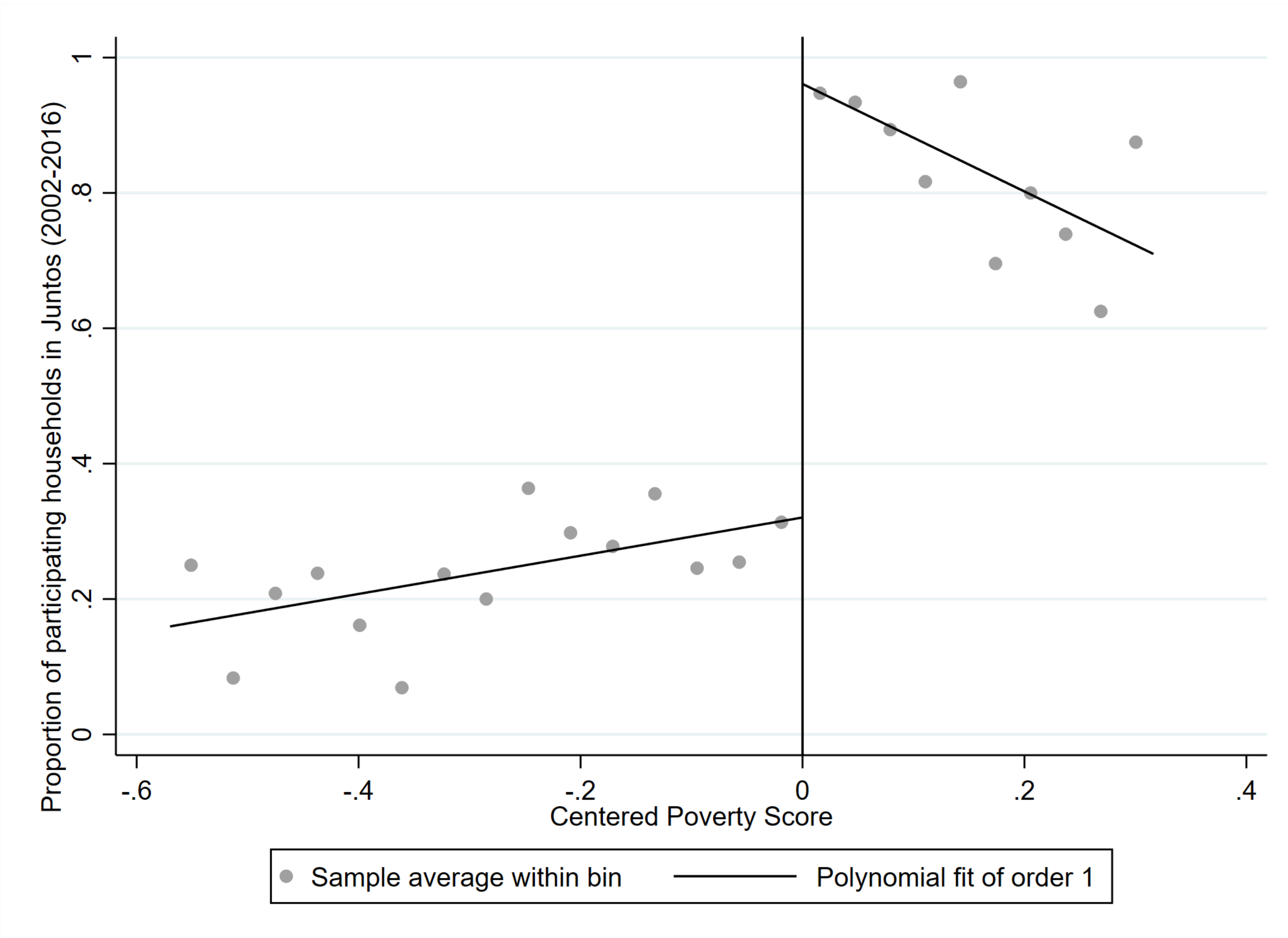


Appendix Figure A2. Comparison of YLS's question with WVS in Peru and other countries



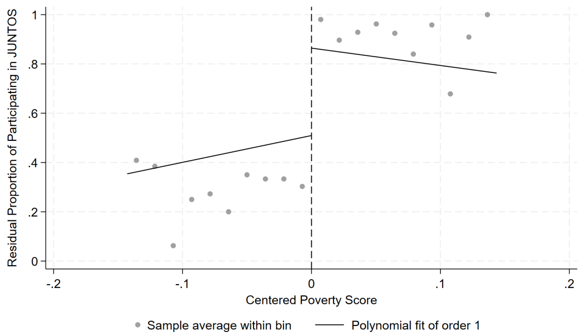
Note: This graph compares the average response to the statement *Men make better political leaders than women do* in the WVS in Peru and some other countries with the average response to the statement *Men are better leaders than women* in the YLS. Despite the age difference of respondents (ranging from 18 to 88 years old) in the WVS, the mean responses of the YLS and the Peruvian WVS are highly similar. Peru exhibits a more progressive stance compared to neighboring countries, similar to the United States but less progressive than some European countries. The WVS (`www.worldvaluessurvey.org`) is an international scholarly endeavor aimed at investigating the dynamics of changing values and their influence on social and political realms. Commencing in 1981, the survey employs robust research methodologies tailored to individual countries. It includes almost 100 countries, covering about 90% of the world's population. Using a standard questionnaire, this non-commercial, cross-national, and long-term study has surveyed nearly 400,000 people, making it the largest academic project examining global differences—from poor to rich countries—across all major cultures.

Appendix Figure A3. Discontinuity in the Share of Participating Households (Excluding Top 2% and Bottom 2% of the Centered Poverty Score)

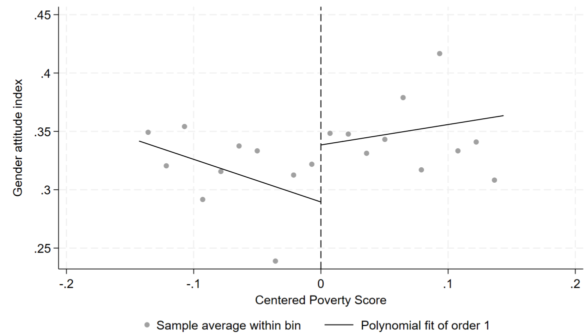


Note: In this graph, the support of the running variable (centered poverty score) is divided into disjoint bins. The observations situated to the right of the vertical line are considered eligible for Juntos. Including all values of the centered poverty score also reveals a clear jump at the threshold. For visual clarity, the top and bottom 2% of the running variable are excluded from the plot. I use the full sample to identify the optimal bandwidths for the RDD estimation.

Appendix Figure A4. First Stage and Intention-to-Treat of Gender Attitude Index (within the optimal bandwidth)

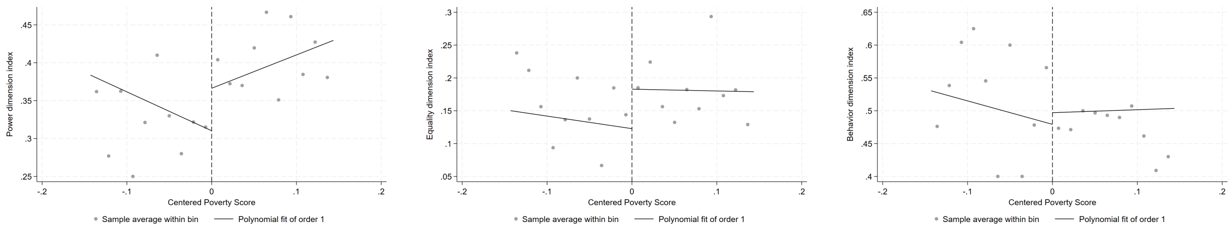


(a) First Stage



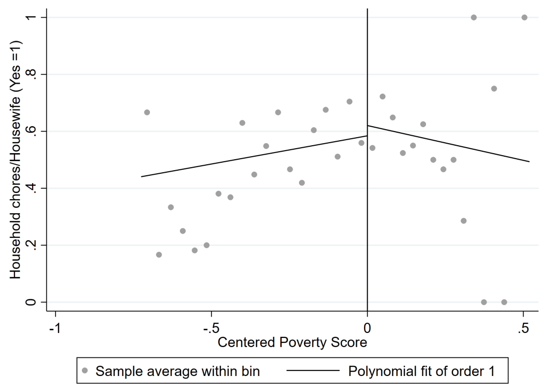
(b) Intention-to-Treat (Gender Attitude Index)

Appendix Figure A5. Intention-to-Treat of Power Dimension, Equality Dimension and Behavior Dimension (within the optimal bandwidth)

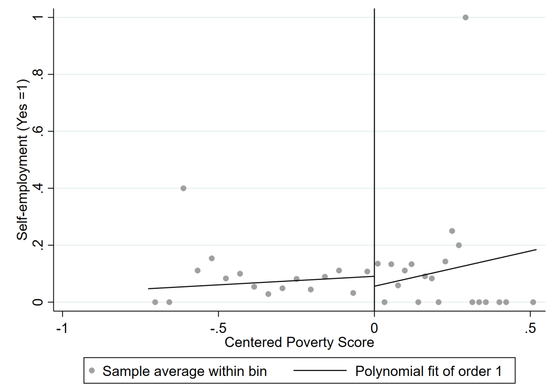


(a) Power Dimension **(b) Equality Dimension** **(c) Behavior Dimension**

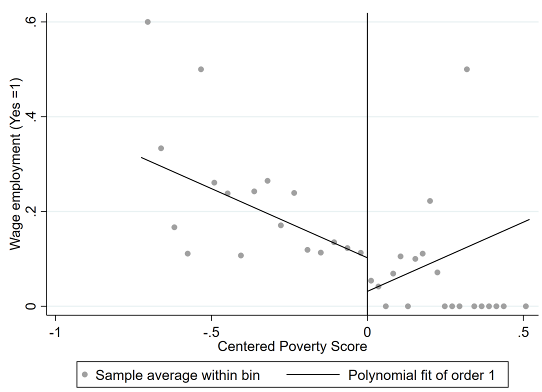
Appendix Figure A6. Discontinuity Test of Maternal Time Priority Around the Threshold in Round 2 (Mother Sub-sample)



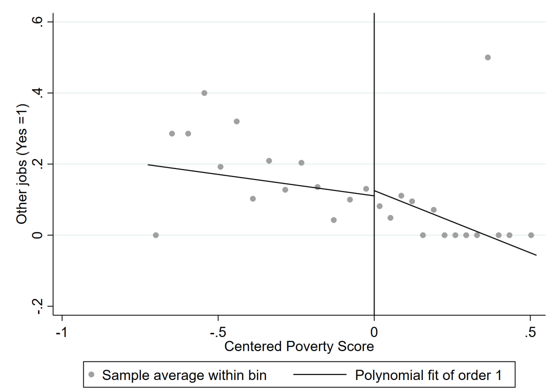
(a) Household chores (Robust p-value: 0.693)



(b) Self-employment (Robust p-value: 0.208)

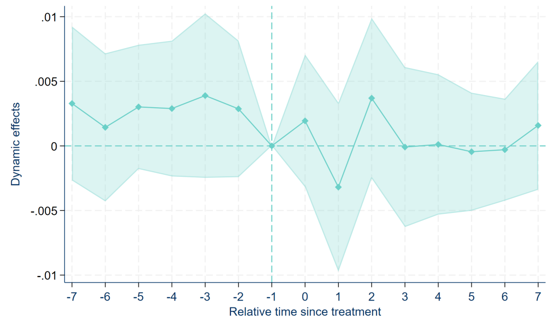


(c) Wage-employment (Robust p-value: 0.361)

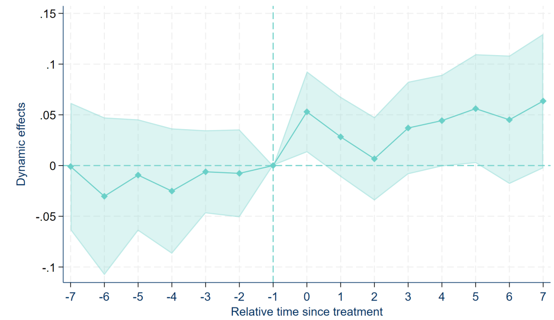


(d) Other jobs (Robust p-value: 0.831)

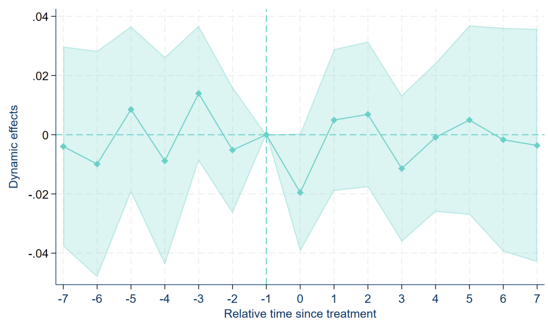
Appendix Figure A7. Testing the Plausibility of the Parallel Trend Assumption (DHS 2004-2016), Fathers' Outcomes



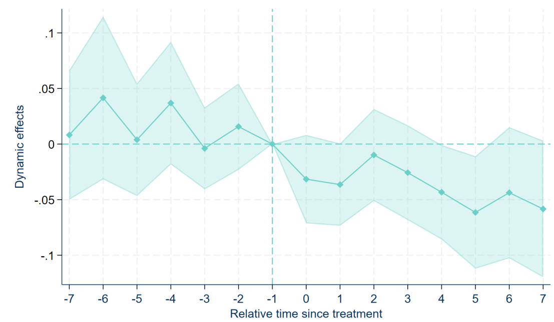
(a) Fully Dynamic Event Study: Workforce participation. Leads joint significance F-test p-value: 0.905. Pre-Juntos average effect p-value: 0.248



(b) Fully Dynamic Event Study: Self-employment. Leads joint significance F-test p-value: 0.970. Pre-Juntos average effect p-value: 0.515



(c) Fully Dynamic Event Study: White-collar jobs. Leads joint significance F-test p-value: 0.490. Pre-Juntos average effect p-value: 0.934



(d) Fully Dynamic Event Study: Services & manual jobs. Leads joint significance F-test p-value: 0.541. Pre-Juntos average effect p-value: 0.364

B Further Details on Constructing the Household Poverty Score

B.1 Household Poverty Score (2005-2011)

From 2005 to 2011, the Peruvian government conducted logistic regression analysis using household data sourced from the National Household Survey, specifically covering the period between 2001 and 2004:

$$Y = \alpha + \beta X + \mu \quad (6)$$

where $Y = 1$ if the household was consider as poor, and $Y = 0$ if the household was not poor. α is the constant, μ is the error term. X are explanatory variables including: analf_m, edu_men, combust0, no_equip, serv3, tipom2, tipom3, tipom4.

Below is the result of the regression:

Appendix Table B1. Result of the Logistic Regression

Variable	Coefficient
analf_m	1.1832 [12.66]***
edu_men	0.2276 [5.13]***
combust0	-0.7624 [12.84]***
no_equip	0.4446 [27.40]***
serv3	-0.3769 [3.23]***
tipom2	-0.2593 [5.55]***
tipom3	-0.8584 [14.86]***
tipom4	-1.3172 [17.53]***
Constant	-1.3461 [12.48]***

The steps involved in producing the household poverty score are as follows:

1. Identifying the variables in the equation:

   The dummy variables tipom2, tipom3, and tipom4 correspond to housing type groups 2, 3, and 4, respectively, which result from distinct combinations of wall, roof, and floor materials. From an initial pool of 294 material combinations, 22 selections (91.1%) were chosen and organized into the subsequent variables:

Appendix Table B2. The list of variables used to produce household poverty score

Variable	Definition
Total illiterate female adults	The sum of all female adults (over 18 years of age) in the household who do not know how to read and write
Total adults	The sum of all household members aged over 18
Total minors in school	The sum of all minors (below the age of 18) in the household who currently attends a regular educational center or program
Total minors	The sum of all minors (below the age of 18) in the household
analf_m	The ratio between total illiterate female adults and total adults
edu_men	The ratio between total minors in school and total minors
combust0	Equals 1 if the primary fuel used for cooking in the household is of industrial origin (gas, electricity, kerosene), and 0 otherwise.
no_equip	The quantity of equipment unavailable within a household. The value ranges from 1 to 7, corresponding to the following appliances: black and white television, color television, refrigerator, electric iron, gas stove, motorized vehicle, and pedal-powered vehicle
serv3	The value ranges from 1 to 3, depending on whether the household has access to electricity connected to the grid, public network water supply, and sanitary toilet facilities.

Appendix Table B3. Housing type groups

Variable	Type	Wall material	Roof material	Floor material
Group 1	102	Adobe	Tiles	Land
	126	Adobe	Straw	Land
	294	Mat	Straw	Land
	210	Stone with mud	Straw	Land
	114	Adobe	Woven cane	Land
	168	Rushes covered with mud	Straw	Land
Group 2	108	Adobe	Calamine	Land
	150	Rushes covered with mud	Calamine	Land
	252	Wood	Straw	Land
	276	Mat	Calamine	Land
	113	Adobe	Woven cane	Concrete
	101	Adobe	Tiles	Concrete
	192	Stone with mud	Calamine	Land
Group 3	234	Wood	Calamine	Land
	107	Adobe	Calamine	Concrete
	250	Wood	Straw	Planks
	106	Adobe	Calamine	Planks
	24	Brick	Calamine	Land
Group 4	232	Wood	Calamine	Planks
	23	Brick	Calamine	Concrete
	5	Brick	Concrete	Concrete
	233	Wood	Calamine	Concrete

2. All the variables previously generated are multiplied by their corresponding coefficients obtained in the regression in Table B1. The result signifies the probability that a household is poor. Considering that poverty in the rural area stands at 65.9% in the household pool of 2001-2004, the threshold associated with that percentage is 0.7567447.

B.2 Household Poverty Score - IHF Index (2012 on-wards)

As described in Section 2, from 2012 and beyond, a new poverty score - *Indice de Focalizacion de Hogare (IFH index)* and 15 regional-specific thresholds were established following the integration of all social protection programs under MIDIS. The IFH index has a scale from 0 to 100, with higher scores indicating greater wealth. Below, I explain how the index is calculated.

Initially, the responsible entity utilized data from ENAHO 2009 to determine the collection of factors involved in the computation. They applied the Sommers test to assess the correlation between potential explanatory variables and a poverty measurement. Subsequently, they chose significant variables and implemented a Principal Component analysis targeting discrete variables. The selected variables, which were statistically significant at the 10% level in the Sommers test, fall into five categories, including: household assets, education, housing characteristics, labor and social security characteristics. Finally, they calculated the weights of each component variable in the equation. The method was applied separately across three geographic zones: the Lima Province, other urban areas, and all rural areas.

The equation to calculate the IFH index is as follows:

$$IFH_{ij} = v_{j1}X_{i1j} + ... + v_{jp}X_{ipj} \tag{7}$$

where IFH_{ij} is the poverty score of household *i* in cluster *j*, X_{inj} is the nth selected variable in the computation in cluster *j*, v_{jn} is the corresponding weight of the variable X_{inj} in cluster *j*.

Table B4 provides the list of selected variables and their corresponding weights in three geographic areas. Using those weights, I can calculate the raw index IFH_{ij} and then I standardize the index to obtain the standardized index. The value range of the standardize index is between 0 and 100 in each cluster. The formula to standardize the raw index is as follows:

$$IFH'_{ij} = 100 * \frac{IFH_{ij} - IFH_j^{\min}}{IFH_j^{\max} - IFH_j^{\min}} \tag{8}$$

where IFH'_{ij} is the standardized IFH of household *i* in cluster *j*, $IFH_j^{\min}$ and $IFH_j^{\max}$ are the minimum and the maximum values of the raw IFH index in cluster *j*, respectively.

Appendix Table B4. Variables and weights to construct IFH index

Variables	**Metropolitan Lima**	**Remaining urban areas**	**Rural areas**
Fuel used to cook			
Do not cook	-0.49	-0.67	-0.76
Other	-0.40	-0.50	-0.38
Firewood	-0.37	-0.33	0.05
Carbon	-0.33	-0.22	0.36
Kerosine	-0.29	-0.19	0.37
Gas	0.02	0.12	0.52
Electricity	0.43	0.69	0.52
Water supply in the home			

Other	-0.78	-0.58	
River	-0.65	-0.42	
Well	-0.62	-0.37	
Water tanker	-0.51	-0.34	
Pipe	-0.41	-0.32	
Outside	-0.35	-0.25	
Inside	0.10	0.12	
Wall material			
Other	-0.70	-0.80	
Wood or mat	-0.48	-0.55	
Stone with mud	-0.44	-0.46	
Rushes covered with mud	-0.41	-0.43	
Clay	-0.39	-0.38	
Sun-dried brick or adobe	-0.37	-0.20	
Stones, lime or concrete	-0.33	-0.07	
Brick	0.10	0.25	
Type of drainage			
None	-0.89	-0.68	
River	-0.75	-0.49	
Sinkhole	-0.59	-0.40	
Septic tank	-0.46	-0.30	
Drainage system outside the house	-0.39	-0.21	
Drainage system inside the house	0.10	0.20	
Number of members with health insurance			
None	-0.26	-0.25	-0.10
One	-0.04	0.06	0.50
Two	0.06	0.17	0.59
Three	0.14	0.27	0.66
More than three	0.32	0.48	0.86
Goods that identify household wealth			
None	-0.47	-0.35	-0.11
One	-0.17	0.05	0.64
Three	0.15	0.40	0.90
Four	0.25	0.52	1.09

Five	0.47	0.75	1.09
Has fixed phone			
Yes	-0.32		
No	0.20		
Roof material			
Other	-0.86	-0.90	
Straw	-0.74	-0.72	
Mat	-0.67	-0.62	
Woven cane	-0.38	-0.23	
Tiles	-0.23	0.03	
Wood or mat	-0.21	0.07	
Concrete	0.17	0.32	
Education of the Household head			
None	-0.51	-0.57	-0.59
Preschool	-0.43	-0.25	-0.08
Primary	-0.28	0.01	0.35
Secondary	-0.06	0.19	0.59
Vocational education (VET)	0.10	0.33	0.68
Undergraduate	0.22	0.55	0.88
Postgraduate	0.40	0.55	0.88
Floor material			
Other	-0.97	-1.12	
Land	-0.60	-0.47	
Concrete	-0.16	-0.01	
Wood	0.08	0.30	
Tiles	0.16	0.40	
Vinyl sheets	0.28	0.51	
Parquet	0.51	0.71	
Overcrowding			
More than six	-0.68		
Between four and six	-0.51		
Between two and four	-0.31		
Between one and two	-0.07		
Less than one	0.24		

Highest level of education in the house	
None	-0.35
Primary	0.11
Secondary	0.41
Vocational education (VET)	0.62
Undergraduate	0.83
Electricity	
No	-0.29
Yes	0.22
Floor made of earth	
Yes	-0.17
No	0.47

Note: Taken from SISFOH (2010).

To determine whether a household is eligible, there are specific cluster thresholds. The households that have an index below or equal to the threshold are eligible for the Juntos program. Table B5 present the cluster-thresholds. The 15 clusters were obtained by combining areas with similar monetary poverty in 2009. Generally, each of these clusters comprises multiple geographically distinct areas that are not connected to each other.

Appendix Table B5. Eligibility Thresholds by Cluster (Taken from SISFOH (2010))

Cluster	Threshold	Population	Per capita income (soles)	Per capita spending (soles)	Poverty status
1	33	208,101	2,184	1,815	0.5159
2	36	1,907,122	2,116	1,697	0.5994
3	34	2,284,876	2,332	1,937	0.5404
4	38	2,646,680	2,282	1,916	0.5389
5	35	634,472	2,067	1,595	0.6410
6	34	212,723	5,941	4,045	0.2606
7	52	2,544,448	5,141	4,260	0.2565
8	42	2,134,993	5,667	4,428	0.2397
9	44	3,740,611	6,403	5,050	0.1352
10	50	2,229,638	5,997	4,673	0.1620
11	44	490,207	5,498	4,015	0.2725
12	43	101,993	8,632	4,638	0.1645
13	43	1,636,740	5,045	4,024	0.2116
14	33	93,527	8,961	6,178	0.0261
15	55	9,342,700	8,712	6,612	0.1546
Peru	-	30,208,831	5,793	4,501	0.2764

Note: Taken from SISFOH (2010).

C Variables Description

In this appendix, I provide further details on the list of items used to measure gender role attitudes (taken from Round 5 of the Child Survey).

Gender attitudes. Indicate whether a child: Strongly disagree, disagree, agree, or strongly agree about each statement.

(i) Swearing is worse for a girl than for a boy.

(ii) On a date, the boy should be expected to pay all expenses.

(iii) On the average, girls are as smart as boys.

(iv) More encouragement in a family should be given to sons than daughters to go to college.

(v) It is all right for a girl to want to play rough sports like football.

(vi) In general, the father should have greater authority than the mother in making family decisions.

(vii) It is all right for a girl to ask a boy out on a date.

(viii) It is more important for boys than girls to do well in school.

(ix) If both husband and wife have jobs, the husband should do a share of the housework such as washing dishes and doing the laundry.

(x) Boys are better leaders than girls.

(xi) Girls should be more concerned with becoming good wives and mothers than desiring a professional or business career.

(xii) Girls should have the same freedoms as boys.