Does Preschool Tips the Balance in favour of Mothers in the Labour Market? Evidence for Brazil.[†]

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Abstract

This paper examines the impact of preschool enrollment on maternal labour market outcomes in Brazil, focusing on the effect of sending the youngest child to preschool and how this varies with the presence of other female family members. Using a fuzzy regression discontinuity design to exploit changes in preschool-entry age regulations, I find that enrolling the youngest child in preschool increases the probability of employment or job search by 33% and weekly hours worked by 15 hours, increasing the likelihood of holding a full-time job by 30 percentage points. These effects are not observed for mothers enrolling their non-youngest children. Notably, the employment effects are more pronounced for mothers without other female relatives in the household, highlighting the role of informal childcare in alleviating maternal childcare responsibilities.

JEL Classification: J13, J16, J22

Keywords: Gender inequality, preschool, regression discontinuity.

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1 Introduction

Women's increased participation in the labour market has contributed positively to narrowing gender gaps. However, their domestic and childcare responsibilities have largely remained unchanged. Despite the convergence of men and women in labour markets, women still shoulder the majority of caregiving duties, limiting their ability to fully engage and progress in the workforce. Recent evidence shows that the arrival of children accounts for roughly 40% of the remaining gender earnings gap in Latin America (Marchionni & Pedrazzi, 2023). In this context, public policies that reduce this burden, such as the expansion of access to childcare at an early age, could not only encourage more mothers to enter the labour market but also improve their performance in it. Indeed, Garcia et al. (2023) finds that the expansion of public childcare services in São Paulo, Brazil, resulted in a significant and lasting reduction in the motherhood effect: each additional seat per child led to a 20% increase in mothers' formal employment after the birth of their first child.

This paper examines whether children's preschool enrolment has a causal impact on maternal labour market outcomes in Brazil. Exploiting variation in preschool attendance induced by a school-entry age regulation, I estimate a fuzzy regression discontinuity model to assess the effects of sending children to preschool on their mother labour market outcomes and how this changes with the presence of other female family members.

In the past few years, Brazil has undergone several changes to provide more equal educational opportunities. Originally, compulsory education in Brazil started at age 7 and lasted 8 years. In 2006, a major reform lowered the minimum age for school entry from 7 to 6 years old and increased the duration of mandatory education from 8 to 9 years. In 2009, the compulsory school entry age was lowered even further to 4 years old, and the duration was extended to a total of 14 years. This last expansion includes preschool ages and is the change I will focus on to assess the impact on mothers' labour force participation.

A substantial body of literature has investigated how maternal labour supply responds to increased childcare provision facilitated by preschool education. In developed countries, studies on the impact of preschool attendance on maternal labour market outcomes reveal overall positive effects, but primarily for mothers with no other younger child and single mothers. In the United States, Gelbach (2002) found a 6% to 24% increase in maternal employment when 5-year-olds enrolled in school. Later on, Fitzpatrick (2010) found a significant effect only for single mothers without additional young children. In Canada, enhanced childcare access in Quebec led to a 7.7 percentage point increase in maternal employment (Baker et al., 2008; Lefebvre & Merrigan, 2008). Conversely, in Norway, Havnes and Mogstad (2011) observed a nearly null effect on maternal employment due to significant crowding out of informal childcare. In Europe, studies in France (Goux & Maurin, 2010), Germany (Bauernschuster & Schlotter, 2015), Hungary (Lovász & Szabó-Morvai, 2019), and Italy (Carta & Rizzica, 2018) consistently show increases in maternal employment, particularly among single mothers or those with the youngest child at home, with employment gains ranging from 6 to 11.7 percentage points depending on the context.

Less is known about the impact on developing countries, particularly in Latin America and the Caribbean (LAC). To the best of my knowledge, Berlinski et al. (2009) were the first to provide evidence from a Latin American country. Results from Argentina show that a large expansion of public preschools boosted preschool attendance by about 7.5 percentage points. According to their results, this expansion led to an increase in maternal employment ranging from 7 to 14 percentage points, although the effect on the intensive margin (i.e., hours worked) was less precise. Later on, Berlinski et al. (2011), in a more closely related setting to this study, find that mothers with access to preschool are more likely to be employed and tend to work more hours. The availability of preschool care reduces the need for mothers to stay at home, thus enabling them to take on full-time or more stable jobs. Other evidence for Brazil has asses the effect of childcare on the labour market outcomes of mothers. For instance, Evans et al. (2017) shows that access to free daycare did not affect the mothers but notably increased the labour supply and income of grandparents (primarily grandmothers) living in the same household as the child attending daycare. Building on this, Ryu (2019) found that preschool enrolment significantly increased the time spent working rather than performing household chores among mothers living without additional younger children and other relatives.

In this paper, I advance the literature in two key ways. First, I provide new causal evidence on the effects of preschool enrollment on mothers' labour market outcomes in a developing country, utilizing the most recent methods in regression discontinuity analysis. By extending the analysis to a broader set of years and states within Brazil, my study offers robust evidence on the local causal impact of childcare policy in a developing country context. While Evans et al. (2017) focused on a lottery program for daycare access in Rio de Janeiro, and Ryu (2019) examined a school reform in 2009 across multiple Brazilian states, my study builds upon these contributions by offering a more comprehensive analysis of preschool policies across a broader range of states and years. Secondly, given the pervasiveness of informal childcare systems in Brazil, I assess whether the introduction of formal childcare options, such as preschool, might be particularly beneficial in households with no other female relative present to help alleviate the mother's childcare responsibilities. To address this question, I examine the effects within households consisting solely of the mother compared to households where an additional female aged 18 or older (such as a sister, aunt, or grandmother) resides. Finally, the study analyzes the effects of fathers on children who are enrolled in preschool.

I find that the probability of being employed or looking for a job increases by 33% for mothers enrolling their youngest child in preschool. Additionally, on the intensive margin, weekly hours worked increase by 15 hours, raising the probability of having a full-time job by 30 percentage points. In contrast, no effect is found for mothers enrolling their non-youngest child. This is unsurprising, as having another younger child to care for may limit mothers' labour supply even after their eligible child is enrolled in preschool.

Moreover, the effects on employment rise to 44%, and weekly hours worked increase by 20 hours for mothers enrolling their youngest child without other female relatives in the household. In contrast, the results reveal no significant impact on labour market outcomes for mothers living with another female relative. These findings suggest that the positive effects observed for mothers enrolling their youngest child are primarily driven by the absence of support from other household members. This raises the question of the effect on fathers; however, they do not appear to be affected, as no impact on their labour outcomes is found.

The rest of this paper is organized as follows: Section 2 details the data, the empirical approach, and validity checks. Section 3 presents and discusses the results and robustness checks related to mothers, while Section 4 focuses on the findings for other household members. Finally, Section 5 concludes with some final remarks.

2 Data and Empirical Strategy

2.1 Methodology

I use a fuzzy regression-discontinuity design to assess the causal relationship between children's preschool enrolment and maternal labour market outcomes. Initially, I would be interested in estimating the following equation:

$$Y_{ist} = \beta_0 + \beta_1 E_{\text{ist}} + f\left(X_{ist} - c\right) + v_{\text{ist}} \quad -h_n \leq \left(X_{ist} - c\right) \leq h_n, \tag{1}$$

where Y_{ist} represents the labour market outcomes of woman i in state s in year t and E_{ist} is the preschool enrolment of the 4-year-old child. However, estimations using conventional OLS to measure the relationship between these two variables would be biased and inconsistent, as mothers often simultaneously decide on their children's school enrolment and their participation in the labour force. For instance, more career-motivated women are more likely to choose to send their children to schools and participate in the workforce. To sort out this problem, I exploit the cutoff date for preschool enrolment enforced by the Brazilian government as a source of exogenous variation in school attendance. In Brazil, children have to turn 4 years old before the cutoff date in the school year in which they enrol in preschool. Those born one day after the cutoff must wait another year to be enrolled in that grade.

I model the probability of mothers enrolling their children in preschool as follows:

$$E_{ist} = \gamma + \delta T_{ist} + f\left(X_{ist} - c\right) + \varepsilon_{ist} \quad -h_n \leq \left(X_{ist} - c\right) \leq h_n, \tag{2}$$

where E_{ist} is a variable indicating preschool enrolment of a child i in state s in year t, with a value of 1 if the child enrolled in preschool and 0 otherwise. T_i is an indicator variable, which is equal to 1 for students who turn 4 years old after the cutoff date and are thus ineligible to start preschool and 0 for those who were born before the cutoff date and are eligible to start preschool. The primary coefficient of interest in Equation (2) is δ, which captures the discontinuity in the probability of school enrolment at the cutoff. I anticipate that $\delta < 0$ since children born after the cutoff date do not fulfil the minimum age requirement for preschool enrollment. In practice, the point estimate is likely between -1 and 0 since younger children may already be enrolled in the previous preschool level, and some older children may ignore compulsory attendance rules. $f\left(X_{ist} - c\right)$ is a linear function of the running variable that can vary on either side of the cutoff date. The running variable indicates the distance between the child's birthdate and the school cutoff date, c. The bandwidth selected for the estimation is given by $|h_n|$.

Once estimating Equation (2), I can consistently estimate Equation (1) by replacing the enrollment rate with the estimated $\hat{E_{ist}}$. I am interested in β_1 from equation (1) that represents the Local Average Treatment Effect of a child's enrolment in preschool on the maternal labour outcome. The underlying assumption for the validity of the above strategy is that maternal outcome variables would be continuous if there was no discontinuity of school enrolment around the cutoff date. In the next sections, I conduct several tests to assess the validity of this assumption.

The most recent methods in regression discontinuity use local polynomials to approximate the regression function near the cutoff (Cattaneo & Titiunik, 2022). Therefore, I estimate both stages using a shared bandwidth chosen to minimize the mean squared error. Within this bandwidth, it is common practice to adopt a weighting scheme to ensure that the observations closer to the cutoff receive a higher weight than those further away. In line with standard practice in this literature, I use a triangular kernel function in all main specifications. Additionally, I follow Calonico et al. (2020) for robust inference.

2.2 Data

The analysis is based on Brazil's main national cross-sectional household surveys from 2001 to 2015. The *Pesquisa Nacional por Amostra de Domicílios* (PNAD) is managed by the Brazilian Institute of Geography and Statistics (IBGE) and was conducted annually until 2015, except for 2010 due to the census.[1] To ensure consistent definitions and adjustments over time, I followed the Socioeconomic Database for Latin America and the Caribbean (SEDLAC) protocol, a collaborative effort between CEDLAS at the Universidad Nacional de La Plata and the World Bank (CEDLAS and The World Bank, 2024).

From the PNAD, I am able to obtain social, labour, and demographic variables at the individual level. Specifically, I focus on five key labour market outcomes, namely: (i) participation in the labour market (coded as 1 if an individual is employed or looking for a job, and 0 otherwise), (ii) employment (coded as 1 if an individual is employed, and 0 otherwise), (iii) weekly working hours, (iv) full-time job (coded as 1 if an individual is employed and working 30 or more hours a week, and 0 otherwise), and (v) informality (coded as 1 if an individual is an informal worker, and 0 otherwise) where outcomes (iii) to (v) are coded as 0 if the person is not working. Workers are classified as informal if they are wage workers without access to social security benefits, low-skilled self employees, or unpaid workers. In addition, the data provides every household member's exact date of birth as well as the mother's identifier for each child, which allows me to identify both the child who is eligible for preschool entry and her mother.

For my main results, I use a sample of women between the ages of 18 and 49 who have at least one child around the age eligibility rule in the survey year. The final sample includes mothers of children who were either 4 or 3 years old as of the cutoff date. Children who were 4 years old by the cutoff were eligible to start preschool in that survey year, while

[1]Subsequent years are excluded from the sample due to a modification in the PNAD school attendance question, which is now asked to children who are 5 years old or above.

those who were 3 years old must wait an additional year before beginning that preschool level. This setup enables a comparison between children who could start preschool as soon as they turn 4 and those who experienced a one-year delay in their entry due to being only 3 years old at the cutoff.

In Brazil, like in many countries, a cutoff date is established for those who can enrol in a given academic year. The Law of Guidelines and Bases of National Education (Lei de Diretrizes e Bases da Educação) grants teaching and administrative autonomy to the different states and municipalities in Brazil. Before the 2009 reform, this implied significant heterogeneity in the admission criteria for preschool and primary education, as well as in how strictly these rules were enforced. After the reform and to address this variation between states, the Basic Education Chamber of the National Education Council attempted to standardize the cutoff date across states by establishing that students must be 4 years old by March 31 to enter preschool education.[2][3] Despite this, some states appealed the decision and adopted different cutoff dates.[4] Further efforts were made to enforce uniformity, such as the enactment of Law No. 12.796 in 2013, which required all states and municipalities to adopt the new system by 2016. Ultimately, in 2018, the Basic Education Chamber of the National Education Council mandated March 31 as the uniform cutoff date for all states, effectively ending the variation across the country.

To obtain information about the cutoff date used in every state and over time, I obtained official resolutions from the Basic Education Chamber of the National Education Council and resolutions from Subnational Educational Ministries. Thereafter, cutoff dates were rescaled to unify enrollment rules to generate a continuous variable indicating dates of birth relative to the cutoff date established by each state and period. Table A.1 in the Appendix shows a list of the thresholds used for each state.[5]

2.3 Validity of the Empirical Strategy

One potential concern about the validity of the fuzzy regression discontinuity design I adopt is the potential manipulation of the running variable, for example, if mothers can manipulate the birthdate of their children. To evaluate this, I first explore the distribution of birthdates using a histogram. Figure 1a shows the frequency of birthdates in the sample.

[2] See CNE/CEB N° 5/2009, N° 20/2009, N° 6/2010, 12/2010, N°17/2012.

[3] Other cutoff dates that have worked as threshold points are June 30 or the beginning of the school year.

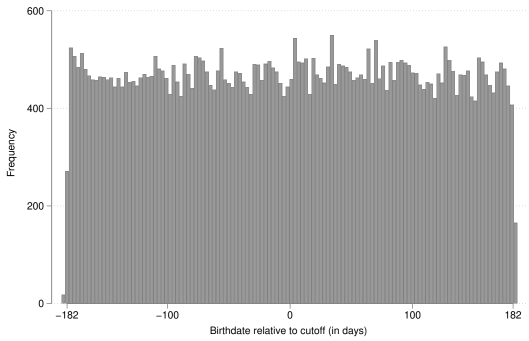
[4] RJ state has maintained the June 30 cutoff until 2018, for example. Check Table A.1 for a detailed review of enrolment rules by state.

[5] The most common cutoff date is March 31, which was followed by 75% of the states during the period under analysis.

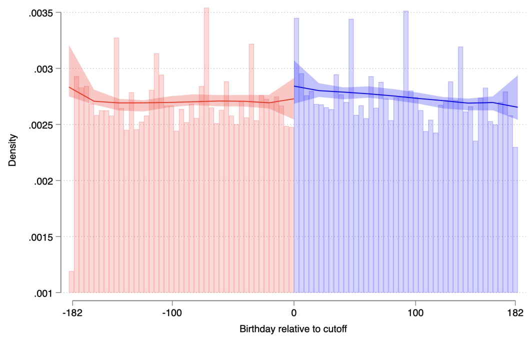
Although there are some jumps, there is no evidence of any discontinuity in the distribution of birthdates around the cutoff dates.

In addition, I formally test for the presence of manipulation around the cutoff dates using a density test constructed using local polynomial density estimators proposed by Calonico et al. (2017). Figure 1b shows the density of birthdates around the cutoff for the distribution on either side of the cutoff. I fail to reject the null hypothesis of no discontinuity—the t-statistic is 0.73, and the corresponding p-value is 0.46—providing suggestive evidence that results are unlikely driven by sorting or systematic manipulation of birthdate around the cutoff point.

Figure 1. Histogram and Estimated Density of birthdates



(a) Histogram



(b) Estimated Density

Notes: In (a) the bars represent the frequency of the birthdate relative to the cutoff dates in my sample, grouped in 3-day intervals. Figure (b) shows the manipulation tests based on density discontinuity proposed in Cattaneo et al. (2018).

As a second validation strategy, I assess whether discontinuities exist in the mother's predetermined characteristics around the cutoff date. This analysis tests the balance of observable characteristics to evaluate whether mothers just above the cutoff are comparable to those just below it, suggesting that any observed effects are not confounded by differences in these predetermined variables. Table 1 presents the results from estimating discontinuities around the cutoff on predetermined characteristics of the mother's samples. Except for the years of education, all predetermined covariables are smooth around the threshold date, suggesting that treated and control mothers do not differ systematically in these characteristics. In Section 3.3, I show that my results do not appear to be influenced by differences in education but rather by the discontinuity in enrollment generated by the eligibility criteria.

Table 1. Balance analysis of predetermined characteristics of mothers

Variables	**MSE optimal bandwidth**	**RD estimator**	**Robust Inference**		**Observations Left,Right**
			p-value	**Confidence Interval**	
Age	62.23	0.019	0.93	[-0.45 ; 0.49]	[9614, 10073]
Married	53.07	-0.011	0.47	[-0.05 ; 0.02]	[6805, 7257]
Years of education	46.25	-0.496	0.00	[-0.89 ; -0.20]	[7074, 7529]
Child is male	59.53	-0.025	0.13	[-0.07 ; 0.01]	[9170, 9614]
No. children	57.83	0.084	0.10	[-0.02 ; 0.19]	[8857, 9309]
Youngest child	63.17	0.011	0.38	[-0.02 ; 0.05]	[9771, 10263]
Other female (+18) at home	73.55	0.004	0.73	[-0.02 ; 0.03]	[11346, 11896]

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. Bandwidth is the MSE optimal based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff.

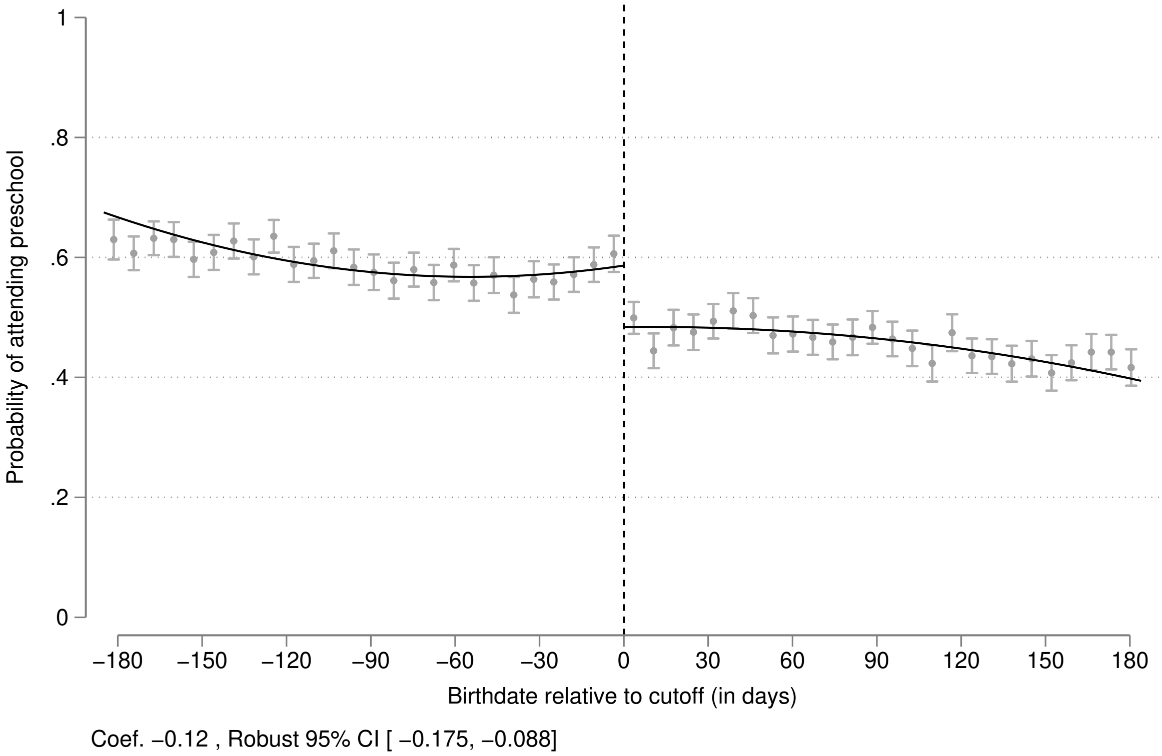
3 Main Results

3.1 Preschool Enrolment

To examine the relevance of the eligibility rule, Figure 2 illustrates the discontinuity in the probability of preschool enrolment for eligible children, as presented in Equation (2). Specifically, a child who turned 4 years old before the cutoff date is approximately 12 percentage points more likely to be enrolled in preschool than a child who did not meet the minimum age requirement. Given that the average preschool enrolment rate for non-eligible children between 2001 and 2015 was approximately 48%, these estimates suggest an increase in enrolment rates of about 19% to 36%. Figure A.1 in the Appendix shows similar results when splitting the sample of mothers according to whether it is the youngest child or another child, but not the youngest, who turns 4 years old around the cutoff. The significant discontinuity in both cases suggests that compliance with the enrollment rule does not change with this aspect of family structure.

Additionally, similar to the weak instruments problem in the IV literature, if the eligibility criteria has a non-zero but very small effect on the probability of being enrolled in preschool, the estimates become unreliable and statistical inferences turns invalid when examining the Local Average Treatment Effect (LATE). I address this concern using standards weak instrument tests, and all F-statistics exceed the standard values (see Table A.2).

Figure 2. Effect of preschool eligibility on the probability of enrolment



Notes: Second-order polynomial approximation using a triangular kernel and 95% confidence intervals. The dots in the scatterplots represent the average value of school enrollment rates in 7-day birthdate bins. This figure is based on the total sample of mothers aged 18 to 49.

3.2 Preschool Effects on Mothers

In this subsection, I present and discuss the estimated effects of preschool on mothers' labour market outcomes. First, Table 2 shows the results for the reduced form. Panel A refers to the sample of mothers whose youngest child is between 4 and 3 years old relative to the cutoff, while Panel B refers to mothers whose non-youngest child falls within this age range.

Columns (1) to (5) from Table 2 show the effects of the eligibility rule on mothers. Results in Panel B confirm that despite the significant discontinuity in preschool enrolment rate, the eligibility rule has no significant effect on maternal labour market outcomes if the child is not the youngest. In contrast, for mothers with the youngest child just above the cutoff, there is a significant effect on labour market outcomes. Mothers of children below the age requirement are approximately 6.5 percentage points less likely to participate in the labour force and almost 7 percentage points less likely to be employed. In addition to the negative impact on the extensive margin of labour supply, the eligibility rule also affects hours worked. Column (3) shows that women with uneligible children works, on average, 2.5 hours less per week. This is also reflected in the 5 percentage points drop in the probability of having a full-time job. Finally, I find no effect on the probability of having an informal job.

Table 2. Effects of preschool eligibility on mothers' labour market outcomes

	Intention to Treat				
	Participation	Employment	Hours worked	Full time job	Informal job
	(1)	(2)	(3)	(4)	(5)
PANEL A: Youngest child					
RD Estimate	-0.065***	-0.069***	-2.490***	-0.049**	0.003
	(0.024)	(0.024)	(0.933)	(0.022)	(0.017)
Observations	[3626, 3922]	[3934, 4277]	[4855, 5258]	[4967, 5354]	[6963, 7415]
Mean outcome	0.67	0.58	20.91	0.42	0.30
Robust 95% CI	[-.128 ; -.023]	[-.132 ; -.024]	[-4.931 ; -.693]	[-.105 ; -.005]	[-.032 ; .046]
Robust p-value	0.00	0.00	0.01	0.03	0.73
Bandwidth (h)	34.10	37.22	46.16	47.47	66.56
PANEL B: Non-youngest child					
RD Estimate	-0.013	-0.001	-0.168	-0.001	-0.017
	(0.030)	(0.029)	(1.102)	(0.026)	(0.024)
Observations	[2595, 2686]	[2808, 2881]	[2808, 2881]	[2654, 2728]	[3577, 3641]
Mean outcome	0.51	0.42	13.42	0.25	0.29
Robust 95% CI	[-.087 ; .055]	[-.074 ; .061]	[-2.998 ; 2.094]	[-.065 ; .058]	[-.076 ; .034]
Robust p-value	0.65	0.85	0.73	0.92	0.45
Bandwidth (h)	53.25	57.22	57.09	54.40	72.17

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff. *** p<0.01, ** p<0.05, * p<0.1

I now turn to the effect on the subgroup of mothers who are induced to enrol their children after the eligibility rule. Table 3 rescales the intent-to-treat effect by dividing it by the estimate obtained in the first stage. Under the monotonicity assumption, this is known as the Local Average Treatment Effect (LATE). Once again, statistically significant impacts are present only for the group of mothers enrolling their youngest child. Columns

(2) to (6) show that mothers who are influenced by the cutoff date to enrol their children in preschool are almost 27 percentage points more likely to be employed or looking for a job. In addition, mothers are 33 percentage points more likely to have a job and 44 percentage more likely to work full-time, because, on average, these mothers work 15 hours per week more as a consequence of having their youngest child attending school. As mentioned before, I find no effect on the probability of having an informal job as the coefficient for informality is not statistically different from zero. The conclusions hold as well when including controls for year and state (see Table A.3).

Table 3. Effects of preschool enrolment on mothers' labour market outcomes

	First Stage	Local Average Treatment Effect				
	Attendance	Participation	Employment	Hours worked	Full time job	Informal job
	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Youngest child						
RD Estimate	-0.139***	0.267*	0.335**	15.446**	0.305*	-0.041
	(0.023)	(0.132)	(0.141)	(6.063)	(0.138)	(0.130)
Observations	[4141, 4499]	[6363, 6732]	[6175, 6530]	[6254, 6629]	[6657, 7947]	[6175, 6530]
Mean outcome	0.63	0.67	0.58	20.91	0.42	0.30
Robust 95% CI	[-.201 ; -.096]	[-.01 ; .591]	[.039 ; .696]	[1.937 ; 30.08]	[-.003 ; .638]	[-.345 ; .227]
Robust p-value	0.00	0.06	0.03	0.03	0.05	0.69
Bandwidth (h)	39.38	60.42	58.48	59.29	62.88	58.89
PANEL B: Non-youngest child						
RD Estimate	-0.097***	0.120	0.011	2.448	0.038	0.181
	(0.028)	(0.288)	(0.301)	(10.881)	(0.251)	(0.270)
Observations	[2913, 2990]	[3354, 3430]	[2808, 2881]	[3481, 3539]	[3414, 3483]	[3698, 3733]
Mean outcome	0.51	0.51	0.42	13.42	0.42	0.29
Robust 95% CI	[-.169 ; -.037]	[-.486 ; .874]	[-.655 ; .767]	[-18.278 ; 31.973]	[-.445 ; .714]	[-.417 ; .857]
Robust p-value	0.00	0.58	0.88	0.59	0.65	0.50
Bandwidth (h)	59.42	68.02	57.04	70.04	69.53	74.80

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the cutoff's main bandwidth to the right and left.
*** p<0.01, ** p<0.05, * p<0.1

3.3 Is Education Driving the Results?

As years of education seem to present some discontinuity around the cutoff, I want to rule out that changes in mothers' educational attainment are driving the effects. Since women with more years of education face better labour market conditions, this could be behind the observed impacts. While one could consider controlling for education, this strategy is not recommended as it cannot restore identification of the treatment effect (Cattaneo et al., 2023). To assess that schooling is not driving the effects, I estimate equations (1) and (2) for a subsample of mothers for whom all characteristics are balanced around the cutoff.

I estimate results for a subset of years in which the number of years of mothers' education is balanced. After further inspecting the data, it appears that the imbalance in years of education occurs only in years 2004, 2005, and 2007 (the results of the balance analysis by year is presented in Figure A.2 in the Appendix). Therefore, Table 4 presents the results for compliant mothers excluding those years from the sample. Except for labour force participation, which, although positive, is not significant at usual levels, the effect on the probability of being employed, the weekly hours worked, and the likelihood of working more than 30 hours a week are similar to the effects found for the entire sample and significant at usual levels. The fact that the effects found on this subsample are similar to those in the entire sample suggests that the labour market impact on mothers is not driven by differences in education.[6]

Table 4. Effects of preschool enrolment on mothers' labour market outcomes for the subsample with balanced characteristics

	First Stage	Local Average Treatment Effect				
	(1)	(1)	(2)	(3)	(4)	(5)
	Attendance	Participation	Employment	Hours worked	Full time job	Informal job
PANEL A: Youngest child						
RD Estimate	-0.127***	0.218	0.314*	14.757**	0.480***	0.005
	(0.024)	(0.156)	(0.171)	(7.398)	(0.182)	(0.162)
Observations	[4012, 4314]	[5640, 5944]	[5073, 5303]	[4919, 5131]	[4705, 4961]	[4610, 4883]
Mean outcome	0.63	0.66	0.58	20.43	0.49	0.30
Robust 95% CI	[-.187 ; -.077]	[-.102 ; .632]	[-.021 ; .785]	[-1.211 ; 33.75]	[.115 ; .964]	[-.372 ; .394]
Robust p-value	0.00	0.16	0.06	0.07	0.01	0.96
Bandwidth. (h)	48.08	67.16	60.18	58.05	56.08	55.62
PANEL B: No youngest child						
RD Estimate	-0.096***	0.350	0.243	5.745	0.143	0.336
	(0.031)	(0.336)	(0.349)	(12.495)	(0.309)	(0.309)
Observations	[2358, 2444]	[2320, 2405]	[2042, 2144]	[2215, 2300]	[2258, 2344]	[2546, 2642]
Mean outcome	0.51	0.51	0.42	13.42	0.32	0.29
Robust 95% CI	[-.175 ; -.028]	[-.355 ; 1.231]	[-.478 ; 1.16]	[-20.663 ; 37.926]	[-.447 ; .973]	[-.311 ; 1.135]
Robust p-value	0.01	0.28	0.41	0.56	0.47	0.26
Bandwidth (h)	63.07	62.10	55.53	59.44	60.96	68.94

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff.
*** p<0.01, ** p<0.05, * p<0.1

[6] I conducted a second exercise focusing on the subperiod from 2011 to 2015, with the hypothesis that compulsory preschool would balance the sample. While the results are qualitatively similar, I do not find statistically significant effects, likely due to the reduction in sample size.

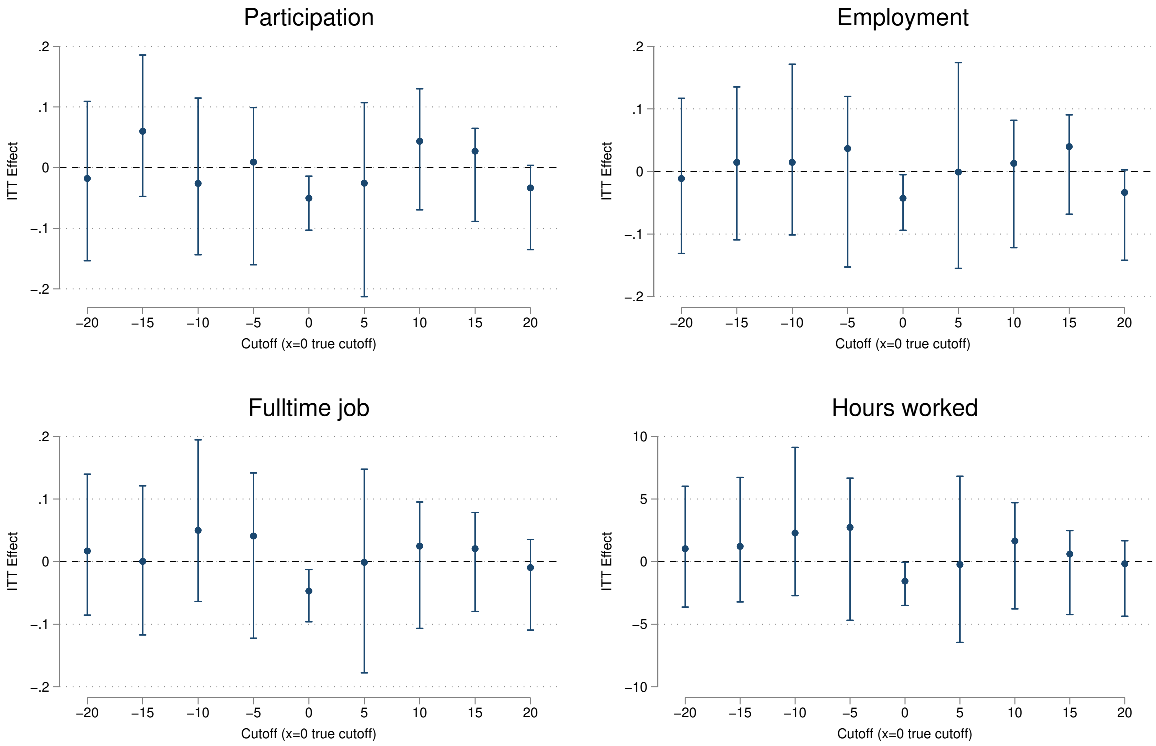
3.4 Robustness

This subsection reports a series of robustness checks to increase the confidence in the results obtained using the fuzzy regression discontinuity approach.

First, one useful robustness exercise is to examine the treatment effects at artificial or placebo cutoff values. This test replaces the true cutoff value with another value at which the treatment status does not change, such as 5 days, 10 days, or 15 days before or after the actual cutoff. The expectation is that no significant treatment effect will occur at placebo cutoff values.

The formal implementation of this test is depicted in Figure 3, which presents the estimates for each outcome derived from various placebo cutoffs. The figure clearly shows that the estimate corresponding to the true cutoff date differs from those obtained using false cutoff dates. Except for the estimate at the true cutoff, all other RD estimators are not statistically different from zero. Consequently, it can be concluded that the outcomes of interest do not exhibit discontinuous jumps at the artificial cutoffs evaluated.

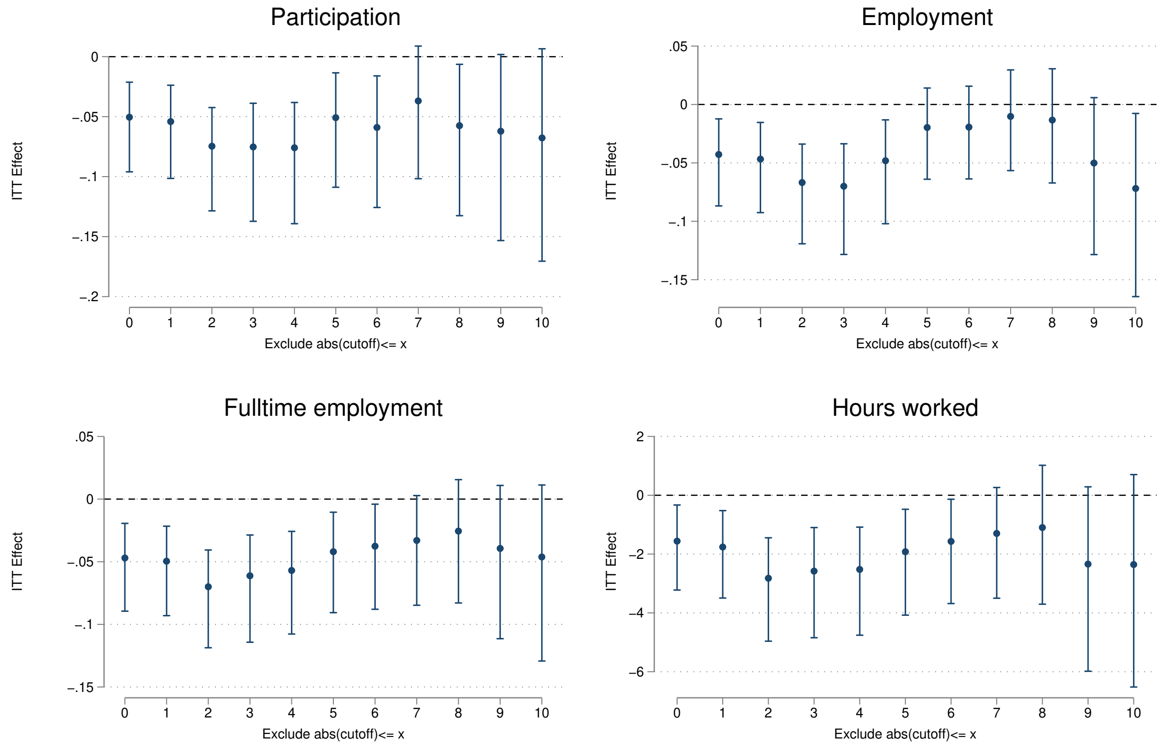
Figure 3. Estimates from artificial cutoff dates



Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. For artificial cutoffs above the real cutoff I only use treated observations, and for artificial cutoffs below the real cutoff I only use control observations. Bandwidth is the MSE optimal based on Calonico et al. (2014).

Another falsification approach examines the sensitivity of results to the exclusion of units located very close to the cutoff. This strategy, commonly referred to as the "Donut Hole" method, involves estimating the unknown regression function while excluding observations within a specific narrow range around the threshold. This approach is also valuable for evaluating how sensitive the results are to the inherent extrapolation required in local polynomial estimation. Figure 4 reports the RD estimates of gradually excluding observations below and above the cutoff. The results of the analysis remain robust. The newly estimated effects continue to be significant at the 10% level, even after excluding children within one week on either side of the cutoff.

Figure 4. Sensitivity to the exclusion of observations around cutoff date



Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. Bandwidth is the MSE optimal based on Calonico et al. (2014).

4 The Role of and Effects on Other Household Members

4.1 Effect of Additional Female in the Household

As mentioned before, in settings with high levels of informal childcare, the preschool enrolment of the youngest child may free up time not only for mothers of young children but also for other relatives who might have been previously taking care of children in the household, such as grandmothers (Evans et al., 2017; Pinto, 2023). If this is the case, then one might expect the effect on the labour outcomes of mothers to be larger in households where there are no other female relatives who can provide childcare. Because of that, I explore the heterogeneity in the effect of the presence or absence of other 18-year-old or older female relatives in the household.

Results presented in Table 5 show strong and significant employment effects only for mothers of youngest children with no other female help at home.[7] Turning to the local effect on mothers who are induced to enrol their youngest child, the point estimates are slightly larger than the findings of the previous section. More precisely, results from Table 6 indicate that mothers in nuclear households, who now have free time as their children attend preschool, are 29 percentage points more likely to be employed or looking for a job. The probability of being employed increases by 44 percentage points. On the intensive margin, weekly hours worked increased by approximately 19 hours. Consistent with previous findings, there seems to be no effect on their informal work status.

On the contrary, the results reveal no significant impact on labour market outcomes for the subsample of mothers living with another female relative, despite a statistically significant 13 percentage point discontinuity in the probability of enrolling children in preschool (Panel B in Tables 5 and 6). These results suggest that the findings from the previous section are primarily driven by the impact on mothers who lack support from other women in the household. The absence of significant effects raises important questions about the dynamics within these households, particularly regarding whether changes are occurring for other women in the household.

[7]Even in the absence of other female relatives residing in the household, mothers may receive support from non-cohabiting relatives, such as a grandmother who does not live in the same home. However, these findings suggest that the critical factor is the presence of someone within the household who can provide assistance.

Table 5. Effects of preschool eligibility on mothers' labour market outcomes by presence of other women (18+) in the household

	Intention to Treat				
	(1)	(2)	(3)	(4)	(5)
	Participation	Employment	Hours worked	Full time job	Informal job
PANEL A: No other female (+18) at home					
RD Estimate	-0.068***	-0.085***	-3.305***	-0.078***	-0.003
	(0.026)	(0.026)	(1.025)	(0.025)	(0.020)
Observations	[3039, 3291]	[3290, 3546]	[3970, 4221]	[3732, 3981]	[4981, 5229]
Mean outcome	0.66	0.58	20.42	0.40	0.30
Robust 95% CI	[-.136 ; -.02]	[-.153 ; -.037]	[-5.996 ; -1.365]	[-.143 ; -.031]	[-.051 ; .044]
Robust p-value	0.01	0.00	0.00	0.00	0.89
Bandwidth (h)	36.87	39.85	47.04	44.41	59.27
PANEL B: Other female (+18) at home					
RD Estimate	-0.008	0.023	0.676	0.048	0.037
	(0.038)	(0.044)	(1.936)	(0.046)	(0.040)
Observations	[1361, 1521]	[1192, 1328]	[1223, 1355]	[1101, 1245]	[1118, 1267]
Mean outcome	0.72	0.59	22.70	0.47	0.29
Robust 95% CI	[-.1 ; .077]	[-.084 ; .122]	[-3.695 ; 5.411]	[-.045 ; .166]	[-.048 ; .137]
Robust p-value	0.80	0.72	0.71	0.26	0.34
Bandwidth (h)	63.99	56.21	57.29	52.63	53.80

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Effects of preschool enrolment on mothers' labour market outcomes by presence of other women in the household

	First Stage	Local Average Treatment Effect				
	(1)	(2)	(3)	(4)	(5)	(6)
	Attendance	Participation	Employment	Hours worked	Full time job	Informal job
PANEL A: No other female (+18) at home						
	-0.146***	0.295*	0.436**	18.997**	0.444**	-0.002
	(0.025)	(0.145)	(0.155)	(6.577)	(0.155)	(0.145)
Observations	[3498, 3749]	[5298, 5568]	[5703, 5997]	[5703, 5997]	[5369, 5662]	[4463, 4734]
Mean outcome	0.66	0.66	0.58	20.42	0.40	0.30
Robust 95% CI	[-.212 ; -.098]	[-.001 ; .674]	[.099 ; .822]	[4.709 ; 35.6]	[.115 ; .846]	[-.337 ; .339]
Robust p-value	0.00	0.05	0.01	0.01	0.01	0.99
Bandwidth (h)	41.90	63.23	68.06	68.43	64.59	53.74
PANEL B: Other female (+18) at home						
	-0.132**	0.146	-0.161	-6.888	-0.495	-0.244
	(0.048)	(0.319)	(0.361)	(16.871)	(0.479)	(0.323)
Observations	[968, 1097]	[1143, 1287]	[1101, 1245]	[1032, 1176]	[938, 1057]	[1032, 1176]
Mean outcome	0.51	0.72	0.59	22.70	0.47	0.29
Robust 95% CI	[-.256 ; -.042]	[-.552 ; .925]	[-.931 ; .743]	[-45.151 ; 32.222]	[-1.605 ; .579]	[-.964 ; .560]
Robust p-value	0.01	0.62	0.83	0.74	0.36	0.60
Bandwidth (h)	47.21	54.58	52.89	49.28	44.38	49.02

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff. *** p<0.01, ** p<0.05, * p<0.1

4.2 What About Fathers?

In this subsection, I present the results concerning labour market outcomes for fathers. For this analysis, I restrict the sample to those households where the mother of the child is either the household head or the household head's spouse, and thus, the household head or spouse is expected to be the child's father.[8]

Overall, the father's labour market choices in Table 7 show that estimated effects are not statistically significant in participation, employment, hours worked or informality rates. In contrast to the substantial changes observed in mothers—who experienced nearly a 40% increase in participation relative to the mean outcome (see Table 3)—fathers did not exhibit any notable changes when children were enrolled in preschool. In this context, where the employment rate for fathers tends to be very high, it is unlikely to find that childcare has an appreciable effect as in mothers. These results suggest that caregiving responsibilities are primarily viewed as a task for mothers, reflecting a persistent allocation of gender roles within the household.

[8]Within my sample, 75% of households have the father as the head.

Table 7. Effects of preschool enrolment on father's labour market outcomes

	First Stage	Local Average Treatment Effect				
	(1)	(2)	(3)	(4)	(5)	(6)
	Attendance	Participation	Employment	Hours worked	Full time job	Informal job
PANEL A: Youngest child						
RD Estimate	-0.163***	0.100	0.096	-0.947	0.063	-0.080
	(0.029)	(0.057)	(0.074)	(5.197)	(0.087)	(0.138)
Observations	[2549; 2808]	[3326; 3573]	[3702; 3983]	[3407; 3662]	[4418; 4710]	[4525; 4795]
Mean outcome	0.46	0.96	0.93	42.97	0.89	0.40
Robust 95% CI	[-.245 ; -.108]	[-.03 ; .232]	[-.07 ; .258]	[-13.027 ; 10.071]	[-.121 ; .261]	[-.399 ; .218]
Robust p-value	0.00	0.13	0.26	0.80	0.47	0.57
Bandwidth (h)	37.50	42.17	47.03	43.67	56.13	57.91
PANEL B: Non youngest child						
RD Estimate	-0.124***	-0.221	-0.220	-3.571	-0.284	-0.208
	(0.038)	(0.119)	(0.158)	(9.842)	(0.212)	(0.299)
Observations	[1571; 1676]	[2573; 2648]	[2526; 2601]	[2573; 2648]	[2059; 2147]	[2097; 2183]
Mean outcome	0.36	0.97	0.93	42.97	0.88	0.53
Robust 95% CI	[-.224 ; -.053]	[-.484 ; .063]	[-.568 ; .157]	[-26.288 ; 19.07]	[-.78 ; .194]	[-.856 ; .547]
Robust p-value	0.00	0.13	0.27	0.76	0.24	0.67
Bandwidth (h)	49.48	70.21	69.01	70.43	57.93	58.36

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff.
*** p<0.01, ** p<0.05, * p<0.1

5 Concluding Remarks

In this paper, I contribute to the growing literature on the effectiveness of formal childcare as a public policy to tip the balance in favour of mothers in the labour market. Exploiting variation in preschool attendance induced by the school-entry age regulation, I estimate a fuzzy regression discontinuity model to assess the effects of sending children to preschool on their mother labour market outcomes and how this changes with the presence of other female family members in a developing country context with high levels of informal childcare arreingments.

The findings reveal positive and important increases in the labour decisions following the enrolment of the youngest child in the household. Mothers enrolling their youngest child in preschool are 29 p.p. more likely to be participation in the labour market, corresponding to a 33% increase, and a proportional increase in hours worked. On the contrary, no effect was found between mothers with other youngest child at home as having another child to care for limit mothers' labour supply even after their eligible child is enrolled in preschool.

The effects found are larger within household where there is no other female relative raising up to a 44% increase on mothers labour force participation and leveraging weekly hours worked up to 19 hours. The absence of significant effects between mothers with no other female relatives in the household raises important questions about the dynamics within these households, particularly regarding whether changes occur for other women. Future research should delve deeper into understanding the underlying mechanisms behind these caregiving arrangements, contributing to the rigidity of gender gaps.

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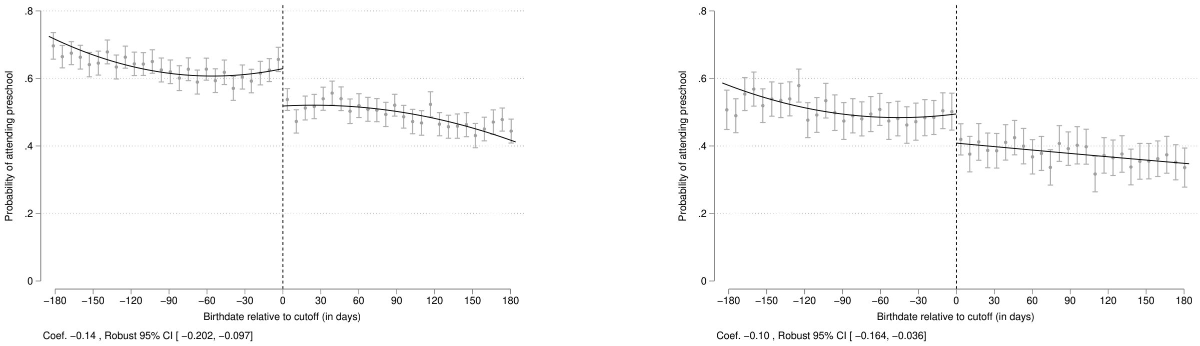
A Appendix

Table A.1. Changes in cutoff dates for Brazilian states (2001-2009 and 2011-2015)

State	**2001-2009**	**2011-2015**
Acre	December 31	March 31
Alagoas	June 30	March 31
Amapá	March 31	March 31
Amazonas	December 31	March 31
Bahia	March 31	March 31
Ceará		March 31
Espírito Santo	December 31	March 31
Federal District	March 31	March 31
Goiás	March 31	March 31
Maranhão	March 31	March 31
Mato Grosso		March 31
Mato Grosso do Sul		March 31 (until 2013)
Minas Gerais	June 30	June 30
Pará	December 31	March 31
Paraíba	December 31	
Paraná		December 31
Pernambuco	December 31	March 31
Piauí		March 31
Rio de Janeiro	June 30	December 31
Rio Grande do Norte	June 30	March 31
Rio Grande do Sul		March 31
Rondônia	March 31	March 31 (until 2013)
Roraima	June 30	June 30
Santa Catarina	December 31	March 31
São Paulo	December 31	June 30

Source: Compilation of resolutions from the National Council of Education - Chamber of Basic Education of Brazil and various state ministries of education.
Notes: Sergipe and Tocantins were excluded due to lack of information about the eligibility rule.

Figure A.1. Effect of preschool eligibility on the probability of enrolment



(a) Youngest child

(b) Non-youngest child

Notes: Second-order polynomial approximation using a triangular kernel with a 95% confidence interval. The dots in the scatterplots represent the average value of school enrollment rates in 7-day birthdate bins. Figure A.1a is based on the subsample of mothers with the youngest child eligible to enrol and Figure A.1b with the subsample of mothers with non-youngest children eligible for preschool.

Table A.2. Weak Identification Test Results

F-statistic	**Value**
Montiel-Pflueger Robust	56.50
Cragg-Donald Wald	62.19
Kleibergen-Paap rk Wald	61.75

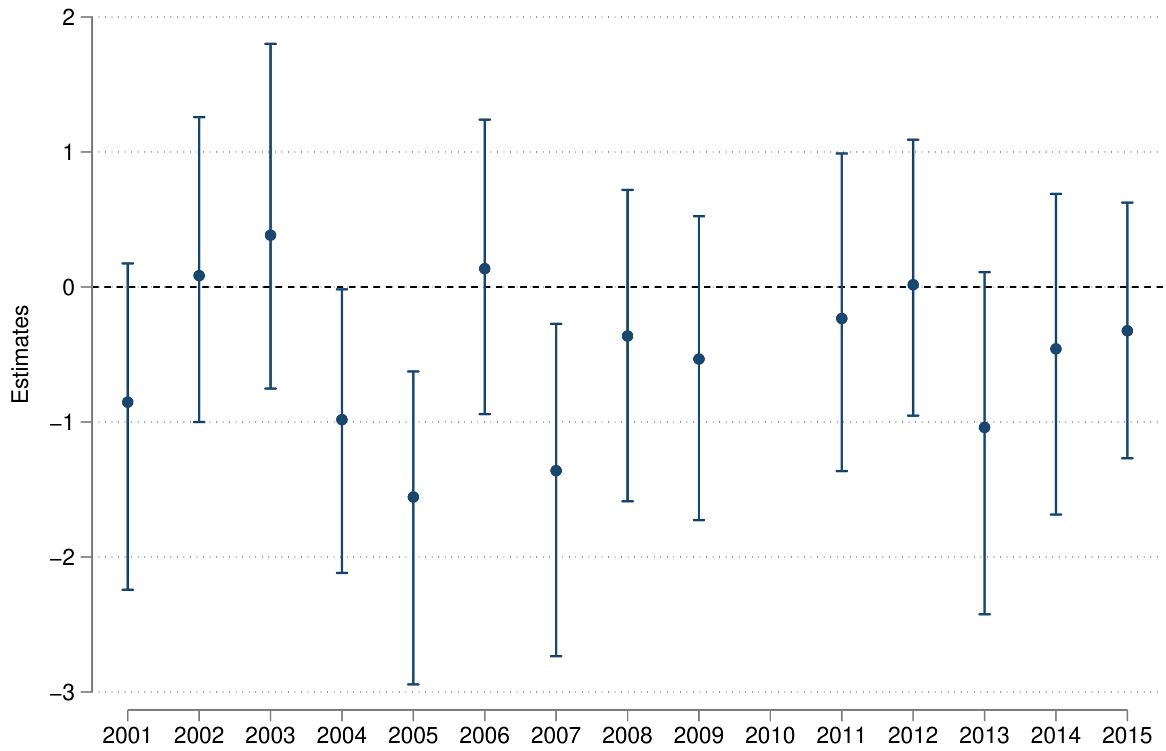
Notes: The estimates are for mothers between 18 and 49 years of age.

Table A.3. Effects of Preschool Enrolment on Mothers' Labour Market Outcomes

	Local Average Treatment Effect				
	(1)	(2)	(3)	(4)	(5)
	Participation	Employment	Hours worked	Full time job	Informal job
PANEL A: Youngest child					
RD Estimate	0.317**	0.376***	16.949***	0.497***	-0.077
	(0.131)	(0.141)	(6.068)	(0.143)	(0.128)
Observations	[5484, 5898]	[5154, 5587]	[5061, 5472]	[5384, 5808]	[5484, 5898]
Robust 95% CI	[.048 ; .634]	[.089 ; .738]	[3.655 ; 31.083]	[.204 ; .86]	[-.367 ; .19]
Robust p-value	0.02	0.01	0.01	0.00	0.53
Bandwidth (h)	52.75	49.26	48.63	51.38	52.04
FE Year and State	YES	YES	YES	YES	YES
PANEL B: Non-youngest child					
RD Estimate	0.070	-0.044	0.236	-0.071	0.152
	(0.262)	(0.266)	(9.950)	(0.251)	(0.242)
Observations	[3351, 3430]	[2965, 3039]	[3574, 3641]	[3574, 3641]	[3694, 3733]
Robust 95% CI	[-.484 ; .746]	[-.617 ; .632]	[-18.861 ; 27.676]	[-.553 ; .626]	[-.387 ; .758]
Robust p-value	0.68	0.98	0.71	0.90	0.53
Bandwidth (h)	68.12	60.40	72.28	72.16	74.15
FE Year and State	YES	YES	YES	YES	YES

Notes: Results from local linear polynomial estimation with a triangular kernel and robust inference. h is the MSE optimal main bandwidth based on Calonico et al. (2014). Observations are sample sizes within the main bandwidth to the right and left of the cutoff. *** p<0.01, ** p<0.05, * p<0.1

Figure A.2. Estimations on Years of Education



Notes: Figure presents the point estimates and 95% confidence intervals from regressing years of education on birthdates, relative to the cutoff date, by year. Each estimates corresponds to a different regresion. The estimates are based on a local linear polynomial with a triangular kernel and robust inference. Each year, the bandwidth is established as the optimal MSE according to Calonico et al. (2014).