Child Marriage Bans and Its Effect on Female Health, Education, and Empowerment Outcomes: Evidence from the SCMRA in Pakistan

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Abstract

Child marriage remains a pervasive issue in South Asia, despite legislative efforts to curb the practice. This paper evaluates the short-term impacts of the Sindh Child Marriage Restraint Act (SCMRA), enacted in Pakistan in 2013, which criminalises marriages of girls under 18. Using a Regression Discontinuity Design (RDD), the study examines the immediate effects of the ban on female education, health, and empowerment outcomes. Leveraging data from the Multiple Indicator Cluster Survey (MICS-6), I find that while the SCMRA effectively raises the average age at marriage by approximately 6 months, it has limited impact on broader health and empowerment indicators. Affected women experience increased pressure to have children soon after marriage, reflecting a trade-off between delayed marriage and diminished reproductive agency. These findings suggest that legal reforms, when implemented without complementary socioeconomic incentives, may have unintended consequences that undermine women's empowerment and well-being. This research contributes to the literature by providing quantitative evidence on the short-term effectiveness of large-scale child marriage bans and highlights the need for multifaceted approaches to effectively promote gender equity and agency.

1 Introduction

An estimated 650 million girls and women worldwide were married before their 18th birthday, with South Asia contributing over 40% of this global burden. Despite a decreasing trend in early marriage rates—down from nearly 50% a decade ago to 30% today—early marriage remains prevalent, adversely affecting labour force participation as well as women and infant health. To address this issue, non-governmental organisations and governments have implemented various programs and regional bans. These initiatives range from provincial bans and policy changes to incentives such as cash transfers and microfinance to encourage later marriages.

Due to the efforts of the United Nations, in recent years more countries have enacted large scale legislation in accordance with the recommendations of the United Nations Children Fund (UNICEF) Assembly (1989) , which include safeguarding young people from early marriages. However, the effectiveness of such legislation remains in question, especially in the absence of other multifaceted approaches to behaviourally change the status-quo.

To address these concerns, I focus on the specific context of the province of Sindh in Pakistan. In 2013, the provincial government of Sindh enacted the Sindh Child Marriage Restraint Act, criminalising marriages of girls under 18, with severe penalties for those involved. However, the effectiveness of such bans is questioned due to enforcement challenges and poor documentation. Critics argue that these laws often delay official marriage registration rather than preventing the marriages themselves. Furthermore, the dualism of legislative and religious powers in Pakistan complicates the efficacy of the law. Marriages are often solemnised by religious leaders (Qazi) who are not affiliated with the state, particularly in rural areas, creating a conflict between legislative authority and cultural practices.

Understanding the interplay between these forces is crucial for developing effective policies to eliminate underage marriages in Pakistan and similar South Asian countries, such as Bangladesh, which enacted the Bangladesh Child Marriage Restraint Act of 2017 (BCMRA). Despite existing literature on providing incentives to delayed marriages, there is limited research on the impact of country or regional bans, especially given the prevalence of unofficial marriage practices.

In this paper, I intend to study the immediate impact of the ban on child marriages imposed by the SCMRA on women education, health and empowerment outcomes, additionally, I intend estimate the level of adherence to the ban and by extension the magnitude by which it is being circumvented through unofficial channels of marriage solemnisation. This would contribute to the limited literature on the effect of large-scale early marriage bans and to utilising natural experiments over a temporal discontinuity to measure the effect of policies pertaining to early marriages. This would also contribute to overcoming a significant challenge for researchers, which is to find and exploit natural experiments in terms of policy changes to better measure its effect.

To do this I use a regression discontinuity design around the month the SCMRA was passed to see the initial impact in marriage behaviours, and the resulting impact in health and empowerment of women. By doing this, we can find similar people close to the discontinuity on either side with them randomly being assigned to the control and treatment groups based on when they were born.

I use the Multiple Indicator Survey Data Round 6 (MICS-6) published by the United Nations Children's Fund (UNICEF), which contains observations for 7200 women between the ages of 15 and 21 at the time the SCMRA was put into effect. The MICS-6 also contains data on education, marriage, children, maternal health, domestic abuse, life satisfaction and wealth. In addition, I redo the analysis on the Demographic Health Survey (DHS) data on Pakistan for 2017 and 2018, which contains similar data for 650 women.

This methodology presents some threats to identification, most significantly any tampering around the cutoff. However, as the cutoff used is the age of the subject at the time the law was passed, self-selection is highly unlikely. Using this method employs the conditional independence assumption as it is unlikely the birth of girls was planned with the foresight of the SCMRA being passed 15 years later. This has been verified using McCrary (2008) density tests to test bunching around the cutoff as well as pooled t-tests for individual characteristics by treatment, which will further be explored later in the paper. Other threats to accurate estimation would be inaccuracy of the collected data, which pertaining to the MICS-6 data for Sindh has been a point of contention among researchers.

I find that even though the ban has a significant effect on age at marriage, the only other significant effects are reduced agency in deciding when to have a child and a reduction in the health of the child at birth. This creates a narrative where the band causes women to get married later, however, to compensate for the time lost they are forced by families or husbands into having children before they themselves want to. This analysis is robust to manipulation around the cutoff in addition to bandwidth manipulation to account for the sensitivity of the selected bandwidth, additionally, placebos for cutoff are also employed.

2 Contribution

In this section I will discuss existing literature on policy interventions surrounding child marriages while highlighting how this paper adds to the existing research.

The adverse health outcomes associated with child marriage have been extensively documented. Nasrullah, Muazzam, Bhutta & Raj 2014, Nasrullah, Zakar, Zakar, Abbas, Safdar, Shaukat & Krämer 2014, Nasrullah 2015 and Lee-Rife et al. (2012) provide substantial evidence of significant maternal and child health complications arising from early marriages, such as higher rates of maternal mortality, obstetric fistula, and low birth weight. These foundational studies underscore the profound health risks young brides face, establishing a critical link between child marriage and adverse health outcomes. Additionally, Abdullah et al. (2015) and Bhanji & Punjani (2014) highlight the compounded health disadvantages young brides experience, including limited access to reproductive health services and increased vulnerability to domestic violence. This paper adds to this evidence by showing short term changes in child health at birth and views on domestic violence as a result of limiting child marriages.

The detrimental effects of child marriage on educational attainment are well-established in the literature.Parsons et al. (2015) and Wodon et al. (2017) demonstrate that early marriage often truncates girls' education, reducing their opportunities for future economic independence and empowerment. This is corroborated by studies such as those by Chow & Vivalt (2022) and Naveed & Butt (2020), which show that child marriage significantly diminishes educational outcomes and perpetuates cycles of poverty. Bellés-Obrero & Lombardi (2023) and Buchmann et al. (2023) further elaborate on the long-term economic repercussions of child marriage, emphasising the loss of human capital and the perpetuation of gender inequality. This paper also provides evidence of increased time in school as a result of banning child marriages, providing an account of why such results may not be an accurate representation of education attainment.

Beyond education, the socioeconomic consequences of child marriage are significant. Research by Bellés-Obrero & Lombardi (2023) and Chow & Vivalt (2022) emphasises the broader socioeconomic impacts, such as reduced labour market participation and increased vulnerability to poverty. Studies by Kakal et al. (2023) and Shahbaz et al. (2021) focus on community-based interventions and their role in shifting societal norms and empowering young women, illustrating the multifaceted nature of child marriage and its pervasive effects on socioeconomic outcomes. Furthermore, Garcia-Hombrados (2022) and Scolaro et al. (2015) explore the effectiveness of educational programs designed to delay marriage and empower girls, highlighting the importance of education in mitigating the impacts of child marriage.

Evaluations of policy interventions and legal reforms are crucial for understanding the effectiveness of measures aimed at curbing child marriage.Muzaffar et al. (2018) and Naveed & Butt

(2020) examine the cultural and socioeconomic determinants of child marriage and the efficacy of local initiatives. Dadras et al. (2022) and Javed & Mughal (2021) evaluate the effectiveness of specific local initiatives, while Raj et al. (2014) and Rasmussen et al. (2019) assess the broader implications of legal reforms. However, these studies often lack a rigorous quantitative approach to assess the immediate effects of large-scale legislative interventions.

While there is significant research evaluating various interventions, detailed, quantitative analysis of the immediate impacts of comprehensive legislative reforms remains scarce. Abdullah et al. (2015) and Hussain (2021) provide insights into the broader implications of child marriage bans, but a rigorous evaluation of the immediate outcomes is still needed.

My paper makes several significant contributions to the existing literature on child marriage and its impact on female health, education, and empowerment. By examining the immediate effects of the Sindh Child Marriage Restraint Act (SCMRA) in Pakistan through a Regression Discontinuity Design (RDD), this study addresses a critical gap in the literature. Unlike previous studies that focus on small-scale or localised interventions, this paper evaluates a significant legislative reform, offering insights into the effectiveness of large-scale policy measures.

This research fills a critical gap by focusing on the immediate aftermath of the SCMRA, providing timely evidence on the short-term impacts of child marriage bans on female health, education, and empowerment outcomes. The use of Regression Discontinuity Design (RDD) represents a methodological advancement in the study of child marriage, enhancing the precision of impact estimates and strengthening causal inference, thereby setting a new standard for future research in this area.

While existing research predominantly concentrates on broader South Asian or African contexts, this study provides a detailed analysis specific to Pakistan, contributing to a more nuanced understanding of regional dynamics and the effectiveness of child marriage legislation in this particular setting. The findings of this paper have significant implications for policymakers and practitioners working in the field of child marriage prevention. By demonstrating the immediate impacts of legislative reforms, this research offers valuable evidence to inform the design and implementation of future policies aimed at eradicating child marriage and promoting gender equity.

This paper extends the existing literature by addressing a previously under-explored dimension of child marriage research and sets a precedent for the use of advanced quantitative methods in evaluating the effectiveness of large-scale policy interventions. Through this comprehensive analysis, it contributes to a deeper understanding of the immediate effects of child marriage bans on female health, education, and empowerment, with a specific focus on the SCMRA in Pakistan.

3 Background

The SCMRA was passed in October of 2013, placing heavy fines and imprisonment of 2-3 years for parents of the children under 18 years of age involved and any parties involved in solemnising the marriage. This created a clear cutoff for the existence of child marriages in the province of Sindh in Pakistan. Due to the law's implementation, girls around 18 were divided randomly into two separate groups based on when they were born. Women who were under the age of 18 during October 2013 were affected by the law, while those who had crossed the age barrier were not.

This presents a policy driven natural experiment for this paper to utilise in getting a comparable sample of women around the cutoff to estimate the immediate effect of the SCMRA on women health, empowerment and education. Additionally, as legal age is very difficult to change, I argue that self-selection around the cutoff is statistically non-existent, which would enable the estimates to have high internal validity.

As the law was passed on a provincial level, it allows us to estimate the effect of the law itself, and control the regional variation in religious influences, allowing a cleaner estimate of the effect of the child marriage ban itself. By isolating one aspect of the dualism of legislative and religious powers, it presents an opportunity to gauge the impact of such bans in an isolated setting, allowing for much better external validity.

The SCMRA provides an ideal setting to evaluate these outcomes as it creates an environment where people do not have the ability to self-select into the program and are randomly allocated based on birth. This also provides a setting where the treatment is provided to a large area and people have very little ability to escape the law imposed on them as that would require either a new birth certificate or to change their residence to a different province on their domicile, which is an official document issued by their local council board.

4 Data

I use the Multiple Indicator Cluster Survey 2018-2019 Round 6 (MICS-6) survey data collected for Sindh Pakistan. This contains individual level data on women health, maternal health, education, and domestic abuse of for a randomised sub-sample of the population. To validate its findings, I also use the Demographic Health Survey (DHS) 2018 data for Pakistan, which collects the same data albeit for a smaller randomised sample.

The MICS-6 data is collected as a set of multiple surveys administered at the same time based on relevance. The data is collected individually for each household member. For the purposes of this study, I use the women dataset and merge the household-individual level dataset to then match each woman to their household variables by merging with the household level dataset. This provides me with an individual level dataset allowing me to cluster at an individual level. The DHS dataset provides all relevant variables in a single data set on an individual level and was therefore used without any further construction.

The Multiple Indicator Cluster Survey (MICS-6) dataset for Sindh, Pakistan, was collected through a household survey conducted by the Sindh Bureau of Statistics in collaboration with UNICEF. The survey employed a two-stage stratified sampling method to ensure representations across urban and rural areas. Data collection focused extensively on women, capturing a range of indicators pertinent to their well-being and socioeconomic status. Key areas included educational attainment, employment status, reproductive health, maternal and child health, domestic violence, and access to healthcare services. Interviews were conducted face-to-face with women aged 15-49, providing comprehensive insights into their living conditions and facilitating targeted policy interventions.

Similarly, the 2018 Pakistan Demographic and Health Survey (DHS) for Sindh was conducted by the National Institute of Population Studies (NIPS). Utilising a two-stage stratified sampling design, the survey aimed to ensure a representative sample of households across urban and rural regions. Data collection focused significantly on women aged 15-49, encompassing a wide range of health and demographic indicators. The survey gathered detailed information on women's reproductive health, contraceptive use, maternal and child health, nutritional status, anaemia prevalence, and experiences of domestic violence. Interviews were administered face-to-face, providing valuable data to inform health policies and programs aimed at improving women's health and well-being in Sindh.

For all analysis, the running variable used for the RDD was women age at time of SCMRA. This was a discrete variable constructed by calculating the age in months of each woman during October of 2013. Next, this age is adjusted to reflect the age as of October 2013. The sample is then restricted to women who were between 15 and 21 years old as of October 2013. Finally, the running variable is computed to measure the deviation in months from the exact age of 18 (216 months) in October 2013, allowing us to normalise the running variable.

For the outcome variables, I used a similar process. The eight outcome variables used were age at marriage in months (age_married), number of children ever born (num_children), child survival rates for mother (child_survival), a 5-point scale of women's empowerment based on the survey (empow), the age at first childbirth in months (first_birth), size of the last child at birth (size_child), a binary variable if for if the woman wanted to have her last child (wanted_child), and an ordinal variable for level of achieved schooling (schooling), respectively. Below is an explanation of how each variable is derived.

The outcome variables for number of children ever born, size of the last child at birth, and a binary variable if for if the woman wanted to have her last child were used as provided in the MICS-6 dataset with some minor re-coding. Age at marriage in months and age at first childbirth in months was constructed similarly to our running variable. Child survival rate was calculated by dividing the number of surviving children, by all children ever born to a woman. Schooling was constructed by assigning ordinal levels to level of schooling creating a 6 point scale from 0, no education, to 5, higher education.

An important consideration made in using the dataset was that around the cutoff there were many women who had not been married at the time of the interview. However, as we have no way of estimating whether these women will marry in the future or not, we lose significant power for our estimations. We currently do not have a way to add this feature in our estimation equation without adding significant bias. Additionally, a 5-point scale for empowerment may not provide a sufficient level of accuracy to gauge changes in largely similar cohorts. A better comparison of the cohorts around the cutoff can be seen in Table 1.

To consider is that given the design of this study and the limitations of the data, I am unable to measure the effectiveness of the law over a large period. What this study looks at is the immediate effect of the law and the immediate effect it has on empowerment health care and education.

Table 1: Descriptive Statistics by cutoff

	Control (N=3,037) (49.3%)	Treatment (N=3,118) (50.7%)	Total (N=6,155) (100.0%)	Test
age_in_oct13	235.31 (10.57)	197.64 (10.88)	216.23 (21.68)	<0.001
age_married	228.42 (38.42)	211.96 (31.12)	221.37 (36.40)	<0.001
Combined wealth score	0.13 (0.95)	0.09 (0.95)	0.11 (0.95)	0.102
Education				
Pre-primary or none	1,510 (49.7%)	1,529 (49.1%)	3,039 (49.4%)	0.149
Primary	397 (13.1%)	369 (11.8%)	766 (12.4%)	
Middle	220 (7.2%)	211 (6.8%)	431 (7.0%)	
Secondary	353 (11.6%)	364 (11.7%)	717 (11.7%)	
Higher	557 (18.3%)	644 (20.7%)	1,201 (19.5%)	
Area				
Urban	1,634 (53.8%)	1,619 (51.9%)	3,253 (52.9%)	0.140
Rural	1,403 (46.2%)	1,499 (48.1%)	2,902 (47.1%)	
If she goes out with out telling husband: wife beating justified				
YES	612 (20.2%)	598 (19.2%)	1,210 (19.7%)	0.115
NO	2,368 (78.0%)	2,434 (78.1%)	4,802 (78.0%)	
DK	56 (1.8%)	84 (2.7%)	140 (2.3%)	
NO RESPONSE	1 (0.0%)	2 (0.1%)	3 (0.0%)	
Native language of the Respondent				
ENGLISH	2 (0.1%)	1 (0.0%)	3 (0.0%)	0.603
URDU	764 (25.2%)	772 (24.8%)	1,536 (25.0%)	
SINDHI	1,493 (49.2%)	1,550 (49.7%)	3,043 (49.4%)	
SARAIKI	237 (7.8%)	237 (7.6%)	474 (7.7%)	
PUSHTO	73 (2.4%)	62 (2.0%)	135 (2.2%)	
PUNJABI	92 (3.0%)	88 (2.8%)	180 (2.9%)	
BALOCHI	146 (4.8%)	135 (4.3%)	281 (4.6%)	
OTHER LANGUAGE	230 (7.6%)	273 (8.8%)	503 (8.2%)	
Ever attended school				
YES	1,535 (50.5%)	1,598 (51.3%)	3,133 (50.9%)	0.311
NO	1,500 (49.4%)	1,520 (48.7%)	3,020 (49.1%)	
NO RESPONSE	2 (0.1%)	0 (0.0%)	2 (0.0%)	
Children ever born	1.75 (1.35)	1.20 (1.10)	1.52 (1.28)	<0.001
Ever had child who later died				
YES	134 (6.5%)	83 (5.4%)	217 (6.0%)	0.160
NO	1,919 (93.5%)	1,455 (94.6%)	3,374 (94.0%)	
Any member have a mobile telephone				
YES	2,612 (86.0%)	2,687 (86.2%)	5,299 (86.1%)	0.981
NO	422 (13.9%)	428 (13.7%)	850 (13.8%)	
NO RESPONSE	3 (0.1%)	3 (0.1%)	6 (0.1%)	
Household owns the dwelling				
OWN	2,469 (81.3%)	2,528 (81.1%)	4,997 (81.2%)	0.060
RENT	382 (12.6%)	360 (11.5%)	742 (12.1%)	
OTHER	184 (6.1%)	230 (7.4%)	414 (6.7%)	
NO RESPONSE	2 (0.1%)	0 (0.0%)	2 (0.0%)	
Any household member own land that can be used for agriculture				
YES	416 (13.7%)	406 (13.0%)	822 (13.4%)	0.583
NO	2,615 (86.1%)	2,708 (86.9%)	5,323 (86.5%)	
NO RESPONSE	6 (0.2%)	4 (0.1%)	10 (0.2%)	

The table contains descriptive statistics for observations around the cutoff of 216 months of age. Control indicates women who were less than 18 when the law was passed, while Treated indicates women who were older. For continuous variables, means are provided with standard deviation in parenthesis, whereas, for categorical variables, counts are provided with group level contribution in parenthesis. It also contains pooled t-tests to identify significant differences between groups.

5 Empirical Strategy

To estimate the effect of the SCMRA, I will use a Strict Regression Discontinuity Design with the cutoff being age 18 years (216 months) when the act was passed. I first normalise the age around the cutoff value. For A_i is the age of observation i in months when the SCMRA was passed.

$$X_i = A_i - 216$$

Therefore, our estimates can be obtained by using Ordinary Least Squares (OLS) to estimate the following functional form:

$$Y_i = \alpha + \tau D_i + f(X_i) + \epsilon_i$$

with

$$D_i = \begin{matrix} 1, & \text{if } X_i \geq 0 \\ 0, & \text{if } X_i < 0 \end{matrix}$$

Where Y_i is the outcome variable, which is the age at marriage, health outcomes, education outcomes, empowerment outcomes or age at first birth of individual i, D_i is the treatment indicator, which equals 1 if the individual was 18 or older at the time the law was passed, X_i is the normalised running variable, representing the age in months of individual i at the time the law was passed, centred around the cutoff age of 18, f(X_i) is a function of the normalised running variable, τ is the treatment effect, measuring the impact of the ban on the outcome variable, α is the intercept term and ϵ_i is the error term, capturing unobserved factors affecting the outcome variable.

For the main results in this paper we use a quadratic f(X_i) resulting in out local linear regression taking the following parametric form:

$$Y_i = \alpha_0 + \alpha_1 D_i + \alpha_2 X_i + \alpha_3 X_i^2 + \alpha_4 X_i D_i + \alpha_5 X_i^2 D_i + \epsilon_i$$

with

$$D_i = \begin{matrix} 1, & \text{if } X_i \geq 0 \\ 0, & \text{if } X_i < 0 \end{matrix}$$

Where Y_i is the outcome variable, which is the age at marriage, health outcomes, education outcomes, empowerment outcomes or age at first birth of individual i, D_i is the treatment indicator, which equals 1 if the individual was 18 or older at the time the law was passed, X_i is the normalised running variable, representing the age in months of individual i at the time the law was passed, centred around the cutoff age of 18, X_i^2 is the squared normalised running variable, representing the age squared in months of individual i at the time the law was passed, centred around the cutoff age of 18,, α is the intercept term and ϵ_i is the error term, capturing unobserved factors affecting the outcome variable.

Using this method employs the conditional independence assumption as it is unlikely the birth of girls was planned with the foresight of the SCMRA being passed 15 years later. This has been verified using McCray density tests to test bunching around the cutoff. There seems to be no bunching around the cutoff and no manipulation of the running variable as can be seen in figure 1, p-values of 0.0000 were obtained for conventional, robust and binomial tests. Additionally, the sample of women are also similar in observable traits which further reinforces the conditional independence assumption as traits seem to be distributed randomly between either side of the cutoff, as seen in table 1.

For robustness the stated estimation will be conducted on two independent datasets collected in the same time-frame, and the direction and magnitude will be compared with each other to verify the results. The estimation equation will also be estimated using a variety of kernels and with varying degrees of form for f(X_i).

A major limitation with the empirical design of this study is that women who turned 18 years old very close to the cutoff date were only affected by the law for a very short period. Alternatively, women who turned 18 years of age much before the law was passed very subjected to it for a longer period, which would have allowed them more time to exercise agency and consciously try to improve education or working conditions. Given the use of a regression discontinuity design, the long- and medium-term effect of this law on the agency of women cannot be measured without adding bias due to cohort effects as women born in different time frames are likely to be different due to immeasurable environmental effects.

6 Results

In this section I outlined the main results of this study going into further depth of the magnitude of those results and their importance, which will then be holistically analysed with the mechanisms discussed in the following section. Threats to identification, manipulation around the cutoff and sensitivity to bandwidth selection are addressed in detail in the Robustness section following results and mechanisms.

Table 2: RD Estimates of P(2) using Uniform Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Estimates	6.113*	-0.229**	0.0283	-0.153	-3.196	-0.199	-0.146**	1.134***
	(3.01)	(-4.01)	(0.01)	(-1.72)	(1.68)	(0.52)	(-4.09)	(12.53)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the Conventional coefficients, Bias-Corrected standard error in the parenthesis, and Robust p-values as per convention. The estimates are reported using the STATA rdrobust package with polynomials of degree 2, uniform kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Age of Marriage

I found that the SCMRA was effective in increasing the age of marriage for young women by almost 6 months, however this is not very surprising as registration of marriage was nearly impossible given the legislation put into place.

Number of Children

Women who were affected by the law, on average had fewer children then who were married early and were not affected by the law. It is important to note that this reduced number of children is it direct effect of the law and not due to women reaching the age of menopause as all women in the sample were under the age of 25 when the survey was conducted.

Reproductive Agency

Women who were affected by the law were less likely to have wanted a child when they conceived it. This indicates that women then required by law to marry later are influenced by their husbands or families to have children earlier or more frequently to compensate for the time lost in childbearing. This is also supported by the fact that we did not find any significant change in child survival rates, age of the women at first birth, women empowerment, or the size of children at birth.

Education

Another interesting finding was that schooling in women affected by the law was much higher, however, this result is not as impacting as it may seem. The SCMRA was passed in October of 2013, where women around the cutoff would be moving from Secondary to Higher schooling, therefore this marked jump in schooling can be attributed to women on the left of the cutoff allowed to complete that year of schooling.

Detrimental Impacts

These results indicate that even though the SCMRA, like many other legislative tools for increasing the age of marriage, effective in increasing the average age of marriage for women, however families are quick to cope with this change even a short while after the law has been put into place by influencing women to have children earlier and more often. There is little to no effect on women health, empowerment, or child health of this law in the short run. These findings are supported by literature on minimum marriage age as without the presence of incentives pertaining to education or labour market outcomes, women merely enter marriage contracts later and are forced to compensate for the time lost by having children quicker when they do not want to themselves. This brings in questions the efficacy of minimum marriage age as it, if not implemented appropriately, can significantly impact the agency of women in deciding when to bear children.

7 Mechanisms

Leveraging the results from the discontinuity design, this paper suggests that by placing a minimum marriage age for women without any other incentives into education or work opportunities, the ban has a negative effect on female agency after marriage. In this section I will present two potential mechanisms through which this change can be explained, while also drawing policy comparisons with other treatments which proved more favourable than just a ban alone.

The first mechanism through which this might be possible is that due to the duality of religious agents and state agents in the rural Pakistani landscape, informal marriage contract may exist which parties subscribe to with state registration being postponed to after the ban is no longer constraining. A result that supports this hypothesis is that we found no significant change in the age of first childbirth among the women who were affected by the law compared to those who are not. This indicates that due to the law women are having children no later than they usually did, and the only difference as a result being more women are forced into having children earlier by their husbands or their families.

Another potential reason for the ineffectiveness of this law in female empowerment, health, education outcomes is the push nature of this law. Treatment studies conducted by Buchmann et al. (2018) showed that when a viable incentive was given to women to delay marriages, they responded by increasing employable skills and increasing their education which allowed them to delay their marriage by more than the time frame in which they were being provided an incentive. This brings the case for a stick and carrot approach, whereby in addition to placing a bad on early marriages, policies should also create opportunities for women to become productive members of their society to alleviate pressures of marriage even after the ban no longer applies to an individual.

8 Robustness

To address any threats to identification, Cattaneo et al. (2020) test for manipulation was conducted to find any manipulation around the cutoff. No manipulation was found around the cutoff, which is inline with the difficulty of changing registered age after the childhood in Pakistan. This is evident in Figure 1.

Additionally, the McCrary (2008) test for manipulation was also conducted, where the p-value was close to 0. This allows us to reject the hypothesis that our running variable was manipulated near the cutoff. These tests help support the use of a RDD as it allows for accurate estimation given that there has been no manipulation around the cutoff. This is less obvious in Figure 2 due to the scale of the y-axis.

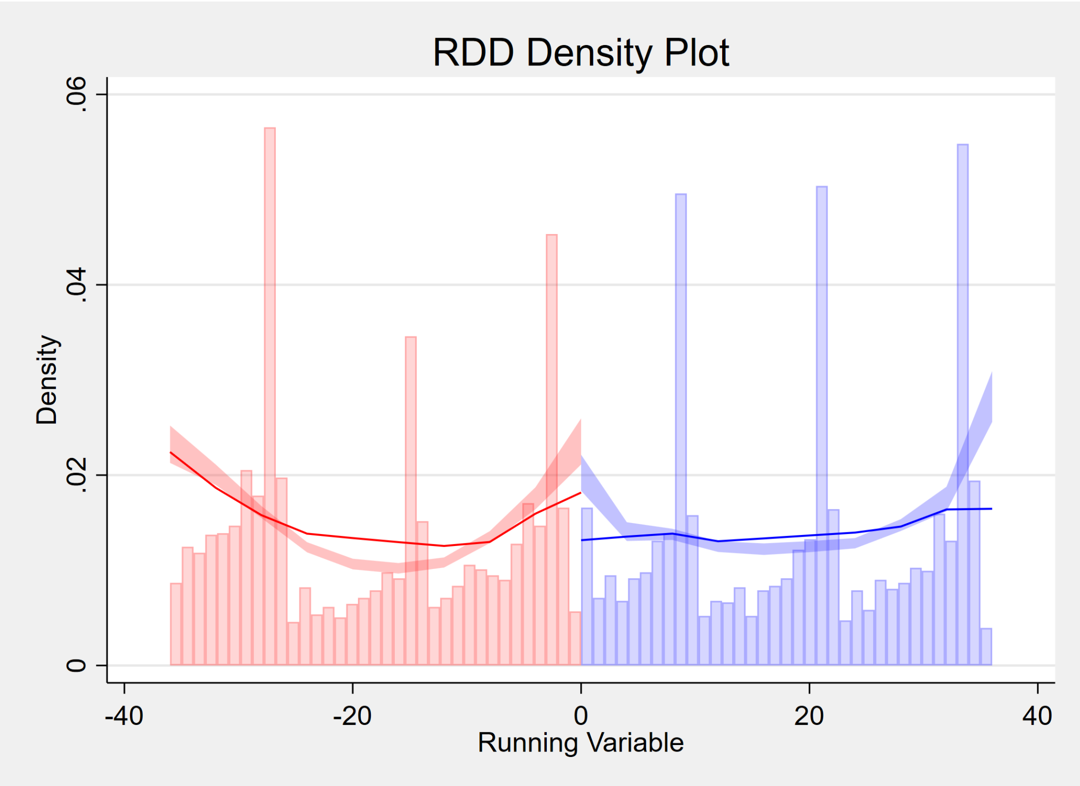

Figure 1: Constructed using the STATA command RDDensity which uses Cattaneo et al. (2020) test procedures to generate density plots. The figures show that there has not been any manipulation in the running variable around the cutoff at a 95% confidence interval.

The estimation was also redone after deviating from the optimal bandwidth. I found that results remained significant even when the bandwidth was incremented by 10 periods in either direction. This indicates that the results are not overly sensitive to the choice of bandwidth made in the analysis. This can be seen in Table 3 and Table 4.

Lastly, for robustness we also conducted the same analysis with a placebo, we altered the cut off to 8 weeks before the law was passed. We found that none of our original results persisted. This is visable in Table 5.

Additional tests, plots and regression estimates using alternative kernels and polynomials are available in the appendix. All robustness and appendix tables are provided in their entirety, deviating from convention to better represent small changes in obtained estimates, standard errors and p-values.

To ensure the quality of the data provided by the MICS-6 dataset we hoped to repeat the analysis on the data made available by the DHS. However, due to the small effective sample

Table 3: RD Estimates of P(2) with Smaller Bandwidth

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	9.308	-0.274	0.0189	-0.119	3.146	0.370	-0.138	1.710***
	(1.27)	(-1.64)	(0.58)	(-0.48)	(0.44)	(1.40)	(-1.10)	(5.52)
Bias-corrected	-4.733	0.417*	0.0358	0.612*	3.284	1.272***	-0.243	0.356
	(-0.65)	(2.50)	(1.10)	(2.46)	(0.46)	(4.83)	(-1.93)	(1.15)
Robust	-4.733	0.417	0.0358	0.612	3.284	1.272**	-0.243	0.356
	(-0.39)	(1.74)	(0.79)	(1.60)	(0.28)	(2.89)	(-1.09)	(0.71)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 2, uniform kernel and bandwidths of 13 months on the left of the cutoff and 12 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: RD Estimates of P(2) with Larger Bandwidth

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	2.092	-0.129	0.0346	-0.125	0.709	0.0196	-0.134*	1.034***
	(0.55)	(-1.27)	(1.13)	(-0.87)	(0.19)	(0.13)	(-2.11)	(6.12)
Bias-corrected	8.955*	-0.392***	0.0355	-0.467**	-0.195	-0.249	-0.192**	2.109***
	(2.35)	(-3.88)	(1.16)	(-3.26)	(-0.05)	(-1.60)	(-3.02)	(12.49)
Robust	8.955	-0.392**	0.0355	-0.467*	-0.195	-0.249	-0.192*	2.109***
	(1.66)	(-2.89)	(0.79)	(-2.38)	(-0.04)	(-1.26)	(-2.16)	(8.96)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 2, uniform kernel and bandwidths of 33 months on the left of the cutoff and 32 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: RD Estimates of P(2) with Placebo Cutoff

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	-4.694	0.250*	0.0365	0.352	4.121	0.630**	0.194*	-0.692**
	(-0.90)	(2.32)	(0.99)	(1.90)	(0.78)	(2.77)	(2.01)	(-2.96)
Bias-corrected	-3.892	0.151	0.0631	0.197	9.408	0.861***	0.232*	-0.994***
	(-0.75)	(1.40)	(1.72)	(1.07)	(1.79)	(3.79)	(2.40)	(-4.25)
Robust	-3.892	0.151	0.0631	0.197	9.408	0.861**	0.232	-0.994**
	(-0.56)	(1.03)	(1.31)	(0.79)	(1.34)	(3.22)	(1.75)	(-3.11)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 2, uniform kernel, modified cutoff of -8 and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

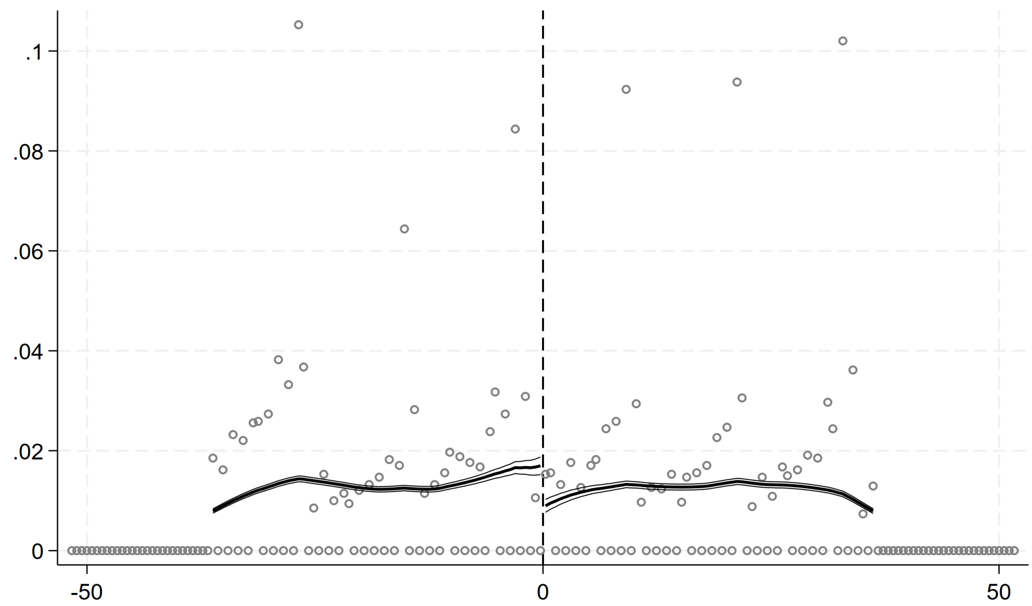

Figure 2: Constructed using the STATA command DCDensity which uses McCrary (2008) test procedures to generate density plots. The figures show that there has not been any manipulation in the running variable around the cutoff at a 95% confidence interval.

size and differences in survey practices we decided to refrain from drawing any conclusions as the descriptive statistics between the two datasets were not very similar.

9 Conclusion

In this paper I analyse the short run effects of the SCMRA, which placed a floor on legal age of marriage in Sindh, using a regression discontinuity design. I found that even though the SCMRA was able to increase the average age of marriages in women, it did not cause any other benefits for women empowerment, education or health outcomes. The law is shown to harm female reproductive agency and child health at birth.

These findings shed light on the harmful nature of laws pertaining to minimum marriage age without due consideration of other policy measures to guide available women to better outcomes through education and work opportunities. Additionally, this paper also is novel in that it looks at the short to medium run effects of large-scale policy measures designed to protect minors in developing countries.

These findings are crucial for designing and revising policies put into place to protect young women as the SCMRA, which on paper seems like a good idea to protect minors, is resulting in adverse effects for young women and their children. I push for a two-pronged approach where policies such as marriage age bans should be supplemented with reforms in education and labour market access to allow women to use the extra time granted by the ban to educate and up-skill themselves to improve their lives as well as those of their families and children.

In this paper I was unable to expand my sample into other provinces in Pakistan due to limitations on time and resources which I would like to explore next. In the future I would also like to explore how such regional legislation effects marriage migration, especially as a response of regional flooding. Currently unsubstantiated claims of rise in child marriages as a result of mass flooding and resulting migration in order for families to receive dowry payments have been reported in mass media such as Janjua (2024). It is crucial to determine the effects of such shocks on child safety and migration in order to design pro-active policy measures.

Additionally, with the BCMRA passed in 2018, this also presents an interesting opportunity to study comparisons between the two policies, given the joint history the two countries share.

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Appendix

Descriptive Statistics

Table 6: Descriptive Statistics

	Summary (N=6,155)
age_in_oct13	216.23 (21.68)
age_married	221.37 (36.40)
Combined wealth score	0.11 (0.95)
Education	
Pre-primary or none	3,039 (49.4%)
Primary	766 (12.4%)
Middle	431 (7.0%)
Secondary	717 (11.7%)
Higher	1,201 (19.5%)
Area	
Urban	3,253 (52.9%)
Rural	2,902 (47.1%)
If she goes out with out telling husband: wife beating justified	
YES	1,210 (19.7%)
NO	4,802 (78.0%)
DK	140 (2.3%)
NO RESPONSE	3 (0.0%)
Native language of the Respondent	
ENGLISH	3 (0.0%)
URDU	1,536 (25.0%)
SINDHI	3,043 (49.4%)
SARAIKI	474 (7.7%)
PUSHTO	135 (2.2%)
PUNJABI	180 (2.9%)
BALOCHI	281 (4.6%)
OTHER LANGUAGE	503 (8.2%)
Ever attended school	
YES	3,133 (50.9%)
NO	3,020 (49.1%)
NO RESPONSE	2 (0.0%)
Children ever born	1.52 (1.28)
Ever had child who later died	
YES	217 (6.0%)
NO	3,374 (94.0%)
Any member have a mobile telephone	
YES	5,299 (86.1%)
NO	850 (13.8%)
NO RESPONSE	6 (0.1%)
Household owns the dwelling	
OWN	4,997 (81.2%)
RENT	742 (12.1%)
OTHER	414 (6.7%)
NO RESPONSE	2 (0.0%)
Any household member own land that can be used for agriculture	
YES	822 (13.4%)
NO	5,323 (86.5%)
NO RESPONSE	10 (0.2%)

The table contains descriptive statistics for the sample.

Additional Robustness Checks

Table 7: RD Estimates of P(1) using Uniform Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	0.466	-0.0324	-0.00292	-0.156	0.640	0.0703	-0.0734	0.763***
	(0.16)	(-0.41)	(-0.20)	(-1.38)	(0.23)	(0.57)	(-1.45)	(5.90)
Bias-corrected	6.113*	-0.229**	0.0283	-0.153	-3.196	-0.199	-0.146**	1.134***
	(2.08)	(-2.88)	(1.93)	(-1.36)	(-1.13)	(-1.60)	(-2.89)	(8.76)
Robust	6.113	-0.229	0.0283	-0.153	-3.196	-0.199	-0.146	1.134***
	(1.25)	(-1.85)	(1.15)	(-0.88)	(-0.67)	(-1.15)	(-1.87)	(5.36)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 1, uniform kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: RD Estimates of P(2) using Uniform Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	6.113	-0.229	0.0283	-0.153	-3.196	-0.199	-0.146	1.134***
	(1.25)	(-1.85)	(1.15)	(-0.88)	(-0.67)	(-1.15)	(-1.87)	(5.36)
Bias-corrected	14.69**	-0.494***	0.000134	-0.301	8.016	0.0898	-0.319***	2.649***
	(3.01)	(-4.01)	(0.01)	(-1.72)	(1.68)	(0.52)	(-4.09)	(12.53)
Robust	14.69*	-0.494**	0.000134	-0.301	8.016	0.0898	-0.319**	2.649***
	(2.03)	(-2.94)	(0.00)	(-1.20)	(1.14)	(0.34)	(-2.59)	(8.52)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 2, uniform kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: RD Estimates of P(3) using Uniform Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	14.69*	-0.494**	0.000134	-0.301	8.016	0.0898	-0.319**	2.649***
	(2.03)	(-2.94)	(0.00)	(-1.20)	(1.14)	(0.34)	(-2.59)	(8.52)
Bias-corrected	1.420	0.111	0.0419	0.284	-0.0119	1.171***	-0.147	1.175***
	(0.20)	(0.66)	(1.20)	(1.13)	(-0.00)	(4.41)	(-1.20)	(3.78)
Robust	1.420	0.111	0.0419	0.284	-0.0119	1.171**	-0.147	1.175**
	(0.13)	(0.50)	(0.91)	(0.81)	(-0.00)	(2.65)	(-0.77)	(2.59)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 3, uniform kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: RD Estimates of P(4) using Uniform Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	1.420	0.111	0.0419	0.284	-0.0119	1.171**	-0.147	1.175**
	(0.13)	(0.50)	(0.91)	(0.81)	(-0.00)	(2.65)	(-0.77)	(2.59)
Bias-corrected	-21.41*	1.084***	0.00201	1.237***	-0.710	1.493***	-0.297	-1.633***
	(-1.99)	(4.87)	(0.04)	(3.54)	(-0.07)	(3.38)	(-1.55)	(-3.60)
Robust	-21.41	1.084***	0.00201	1.237**	-0.710	1.493**	-0.297	-1.633**
	(-1.43)	(3.81)	(0.03)	(2.61)	(-0.05)	(2.69)	(-1.04)	(-2.62)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 4, uniform kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: RD Estimates of P(1) using Triangular Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	2.538	-0.112	0.00862	-0.161	-1.092	-0.0244	-0.107*	0.943***
	(0.77)	(-1.27)	(0.58)	(-1.30)	(-0.34)	(-0.19)	(-2.03)	(6.39)
Bias-corrected	9.977**	-0.348***	0.0163	-0.222	1.739	-0.0762	-0.223***	1.797***
	(3.04)	(-3.93)	(1.10)	(-1.80)	(0.54)	(-0.61)	(-4.25)	(12.18)
Robust	9.977	-0.348**	0.0163	-0.222	1.739	-0.0762	-0.223*	1.797***
	(1.84)	(-2.63)	(0.67)	(-1.18)	(0.33)	(-0.41)	(-2.57)	(7.76)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 1, triangular kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: RD Estimates of P(2) using Triangular Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	9.977	-0.348**	0.0163	-0.222	1.739	-0.0762	-0.223*	1.797***
	(1.84)	(-2.63)	(0.67)	(-1.18)	(0.33)	(-0.41)	(-2.57)	(7.76)
Bias-corrected	9.299	-0.247	0.0159	-0.0622	4.488	0.504**	-0.248**	2.053***
	(1.72)	(-1.87)	(0.65)	(-0.33)	(0.85)	(2.71)	(-2.85)	(8.86)
Robust	9.299	-0.247	0.0159	-0.0622	4.488	0.504	-0.248	2.053***
	(1.16)	(-1.39)	(0.52)	(-0.23)	(0.59)	(1.73)	(-1.81)	(6.05)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 2, triangular kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: RD Estimates of P(3) using Triangular Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	9.299	-0.247	0.0159	-0.0622	4.488	0.504	-0.248	2.053***
	(1.16)	(-1.39)	(0.52)	(-0.23)	(0.59)	(1.73)	(-1.81)	(6.05)
Bias-corrected	-10.34	0.592***	0.0212	0.764**	-0.192	1.344***	-0.227	-0.242
	(-1.29)	(3.33)	(0.69)	(2.87)	(-0.03)	(4.61)	(-1.66)	(-0.71)
Robust	-10.34	0.592*	0.0212	0.764*	-0.192	1.344**	-0.227	-0.242
	(-0.85)	(2.50)	(0.48)	(2.01)	(-0.02)	(3.06)	(-1.01)	(-0.48)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 3, triangular kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: RD Estimates of P(4) using Triangular Kernel

	(1) age_married	(2) num_children	(3) child_survival	(4) empow	(5) first_birth	(6) size_child	(7) wanted_child	(8) schooling
Conventional	-10.34	0.592*	0.0212	0.764*	-0.192	1.344**	-0.227	-0.242
	(-0.85)	(2.50)	(0.48)	(2.01)	(-0.02)	(3.06)	(-1.01)	(-0.48)
Bias-corrected	-29.40*	1.161***	-0.0638	1.282***	-10.64	0.986*	-0.533*	-1.492**
	(-2.41)	(4.90)	(-1.46)	(3.38)	(-0.94)	(2.25)	(-2.37)	(-2.97)
Robust	-29.40	1.161***	-0.0638	1.282*	-10.64	0.986	-0.533	-1.492*
	(-1.79)	(3.92)	(-1.23)	(2.53)	(-0.73)	(1.77)	(-1.63)	(-2.22)
N	3591	6155	2702	6080	2702	1760	1748	6153

The table is generated by estimating the effect of the SCMRA on the 8 outcome variables present in each column. The reported values are the estimated coefficients and the standard error in the brackets. Three separate estimates are reported for Conventional, Bias-corrected and Robust estimators using the STATA rdrobust package with polynomials of degree 4, triangular kernel and bandwidths of 23 months on the left of the cutoff and 22 months on the right of the cutoff.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

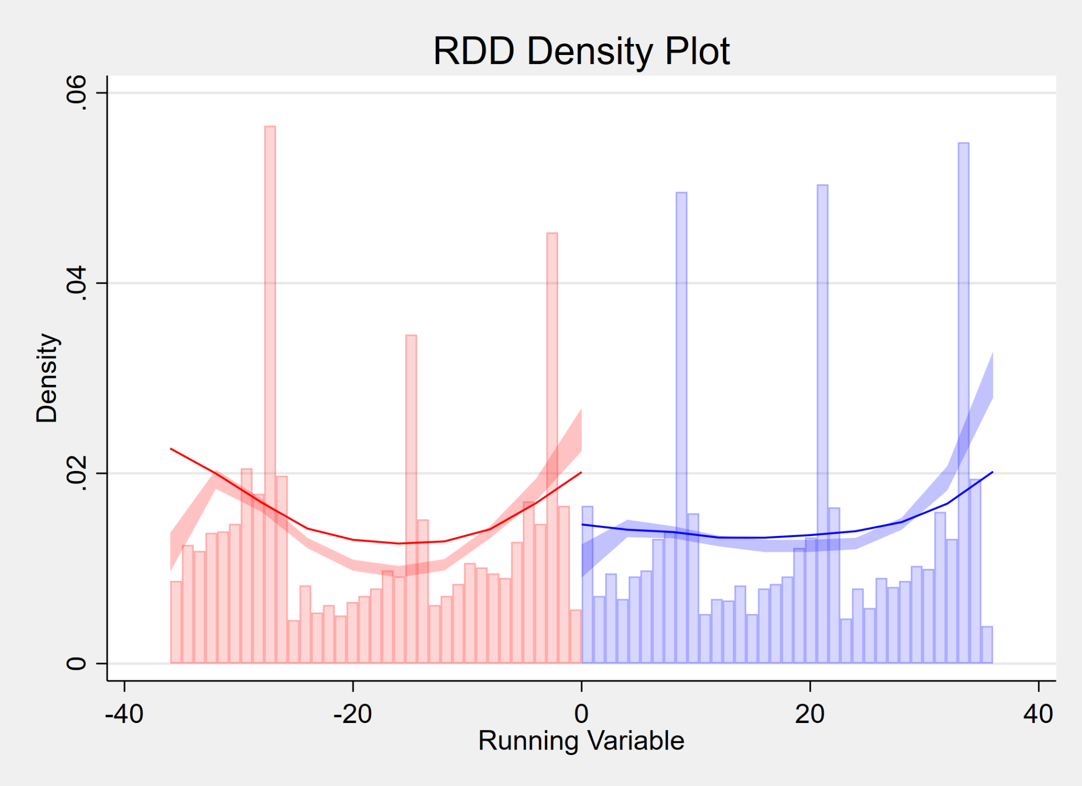

Figure 3: Constructed using the STATA command RDDensity which uses Cattaneo et al. (2020) test procedures to generate density plots. The figures show that there has not been any manipulation in the running variable around the cutoff at a 95% confidence interval. This uses a triangular kernel.

Outcome Variables Generation

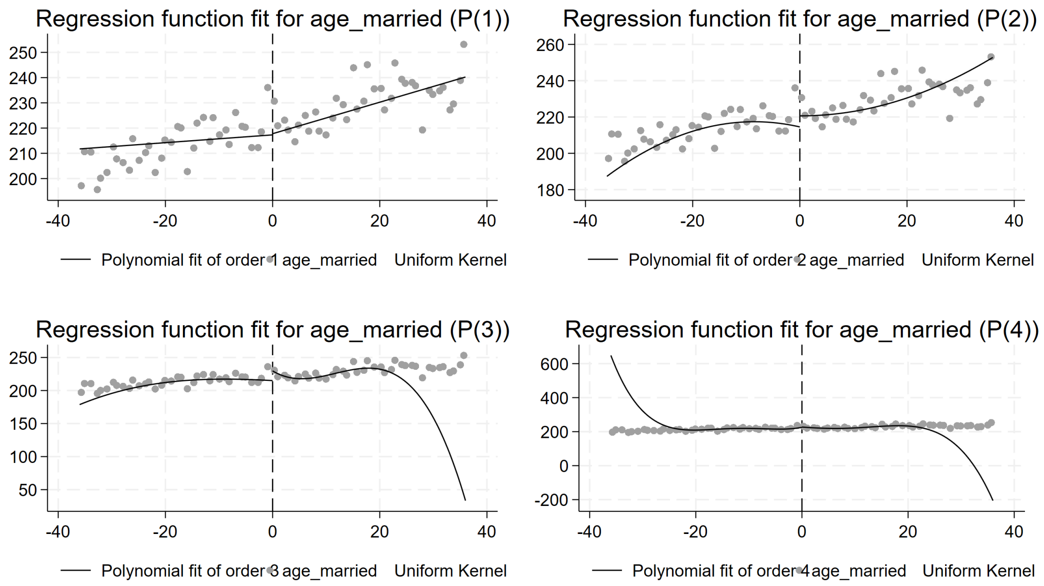

Figure 4: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

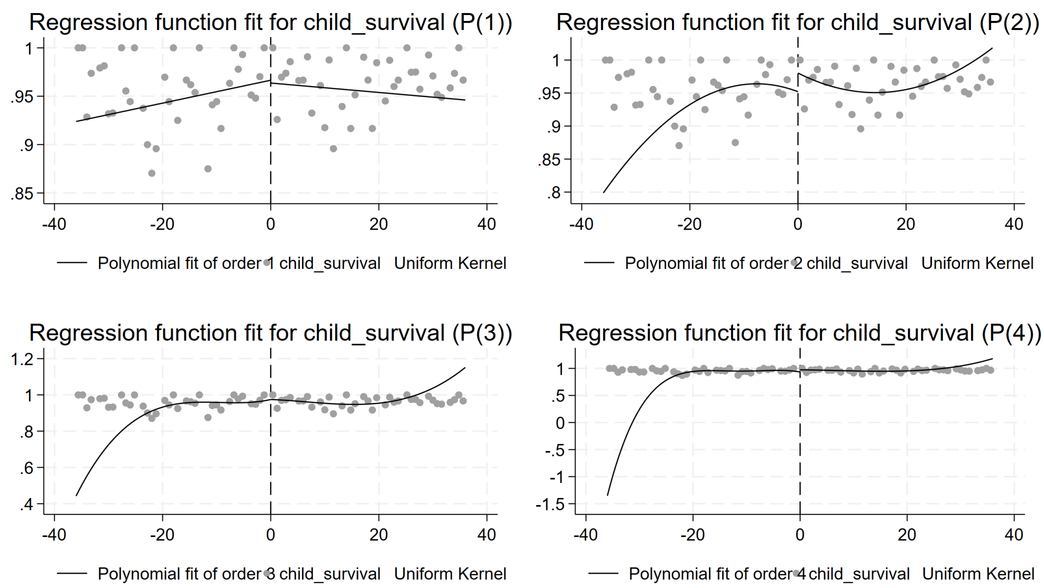

Figure 5: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

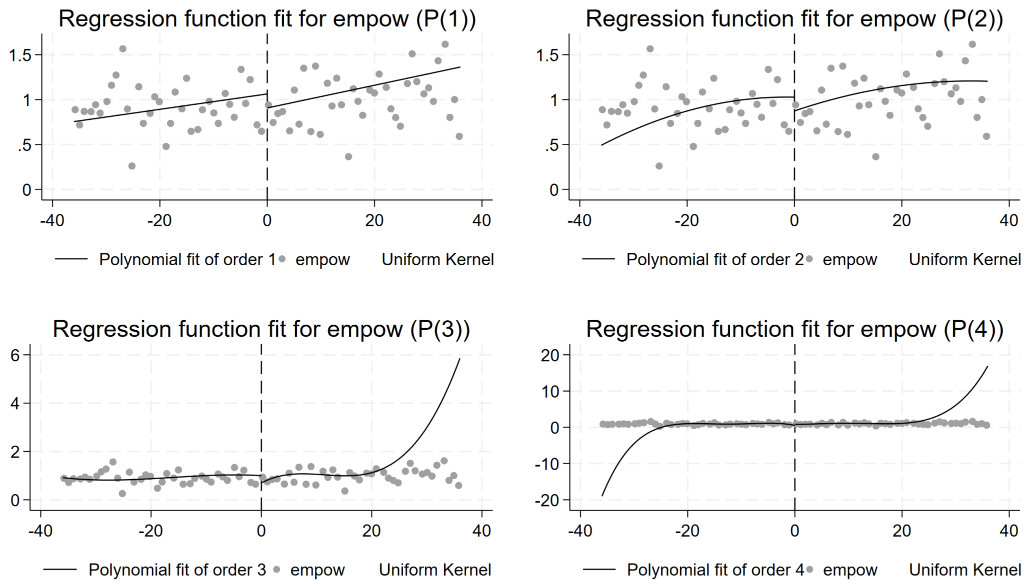

Figure 6: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

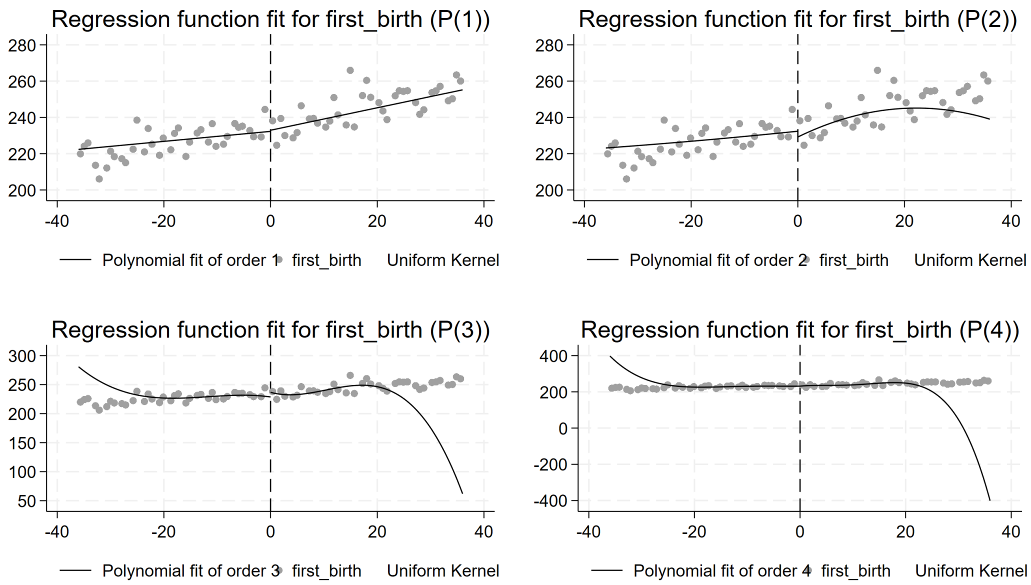

Figure 7: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

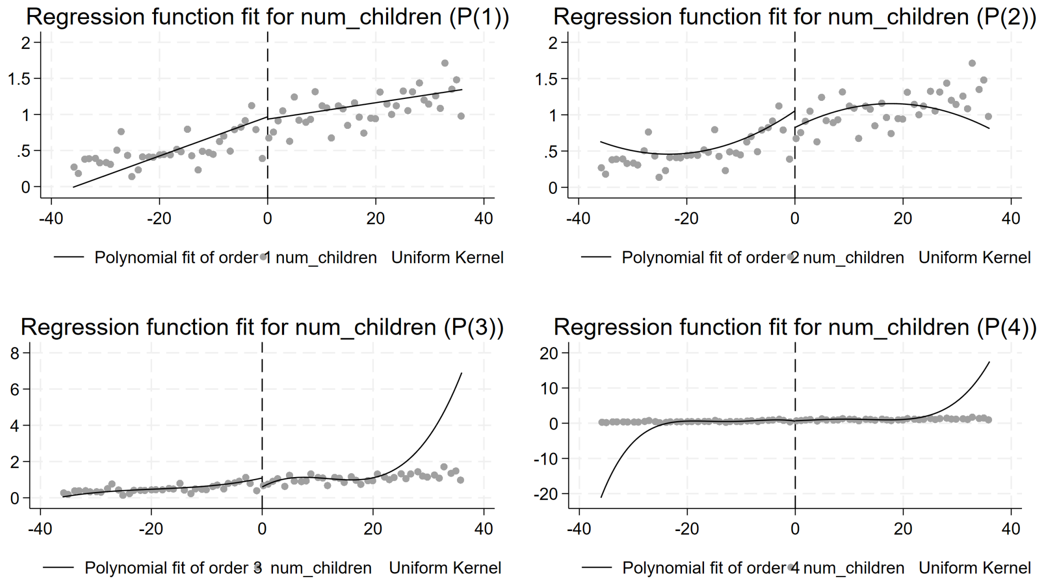

Figure 8: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

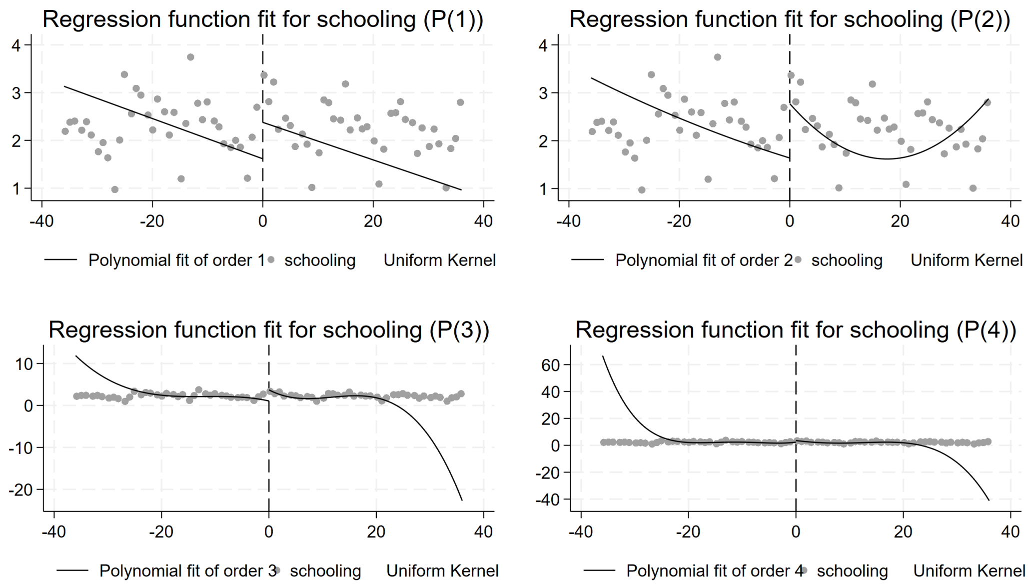

Figure 9: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

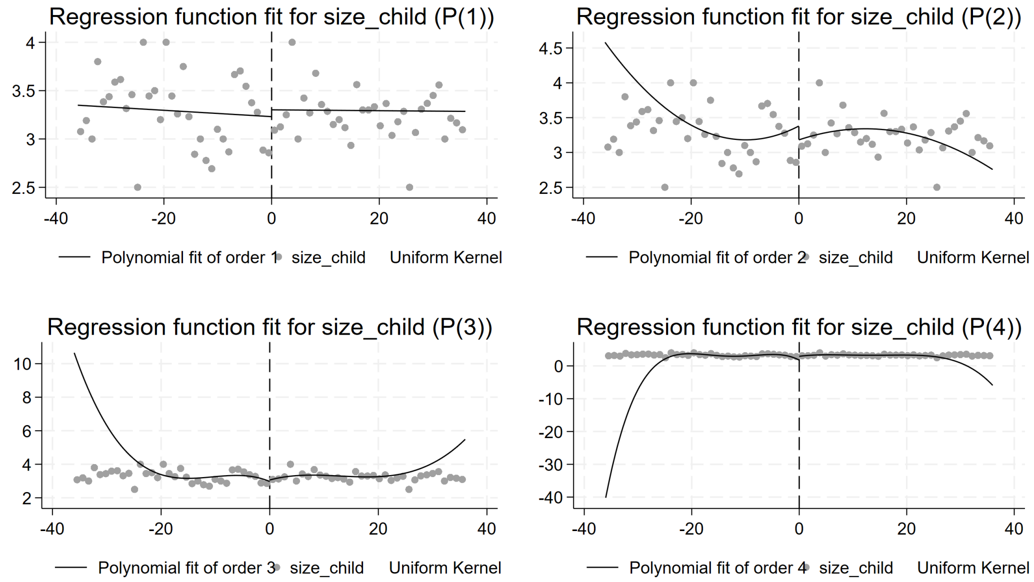

Figure 10: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

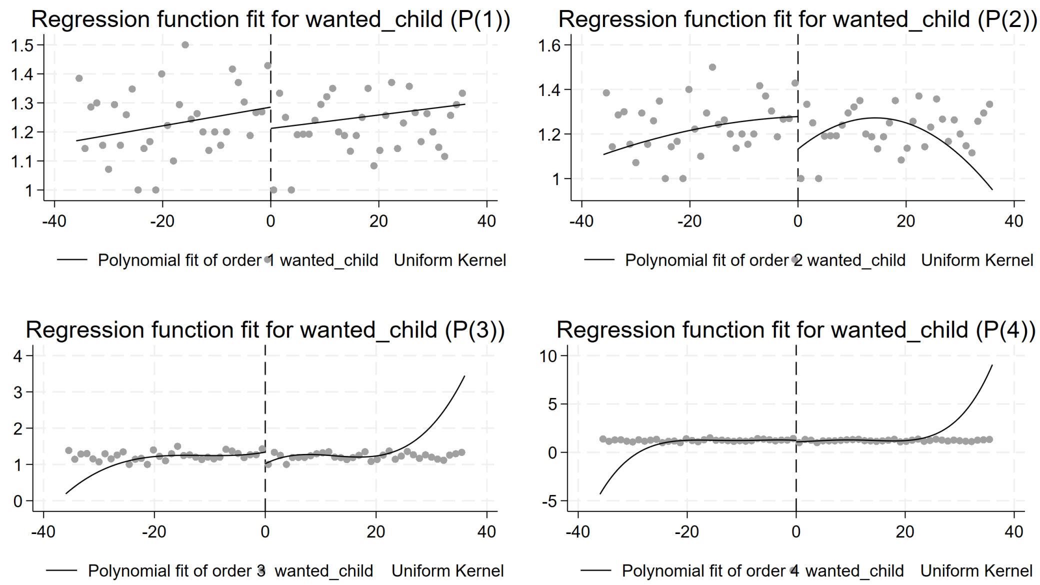

Figure 11: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

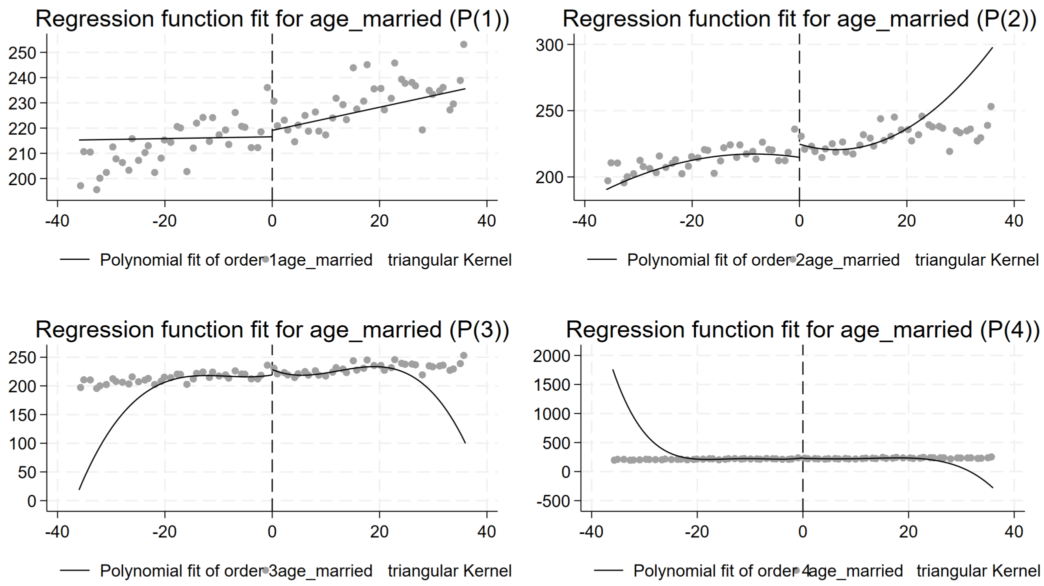

Figure 12: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

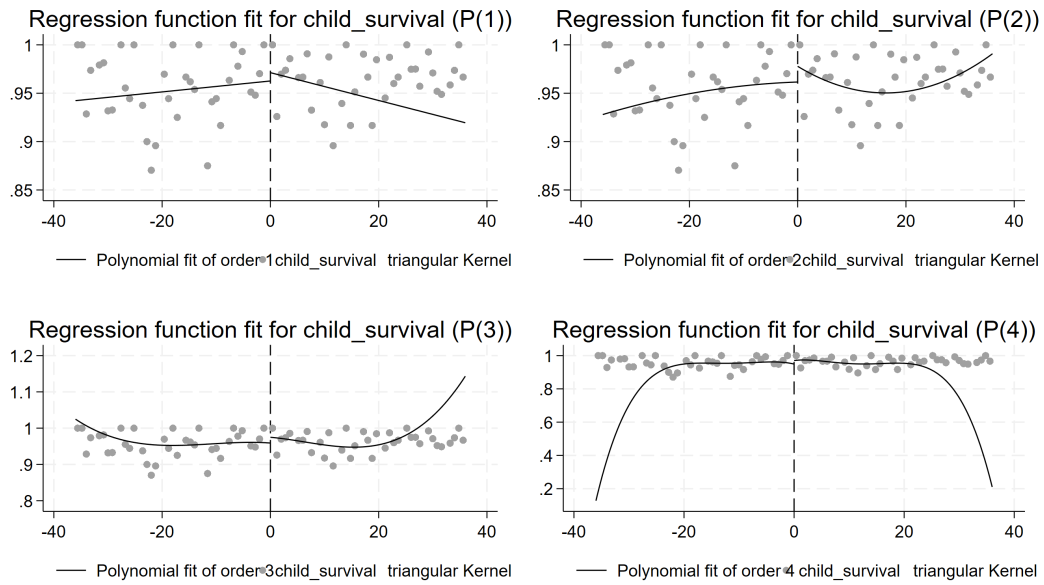

Figure 13: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

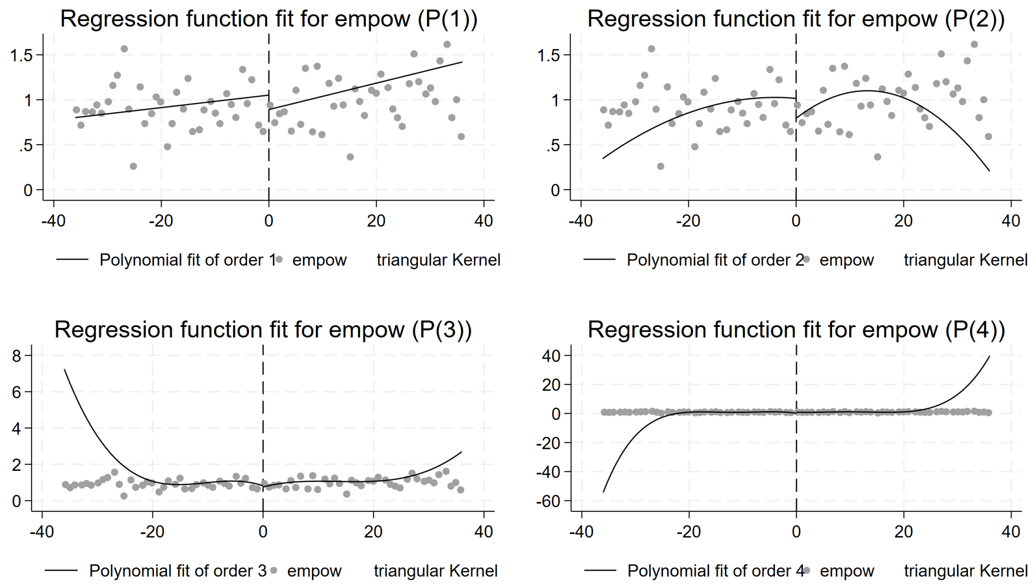

Figure 14: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

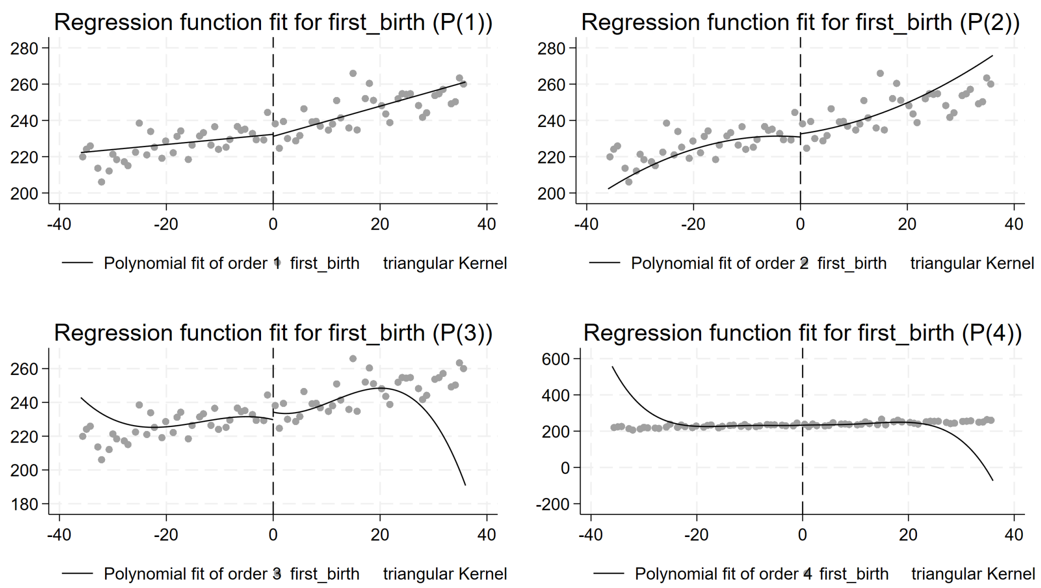

Figure 15: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

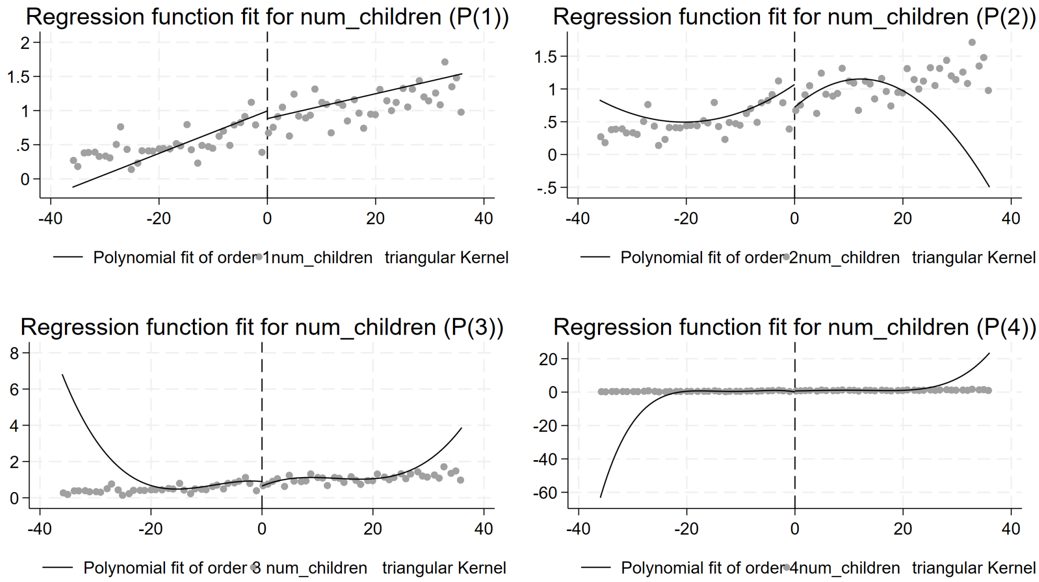

Figure 16: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

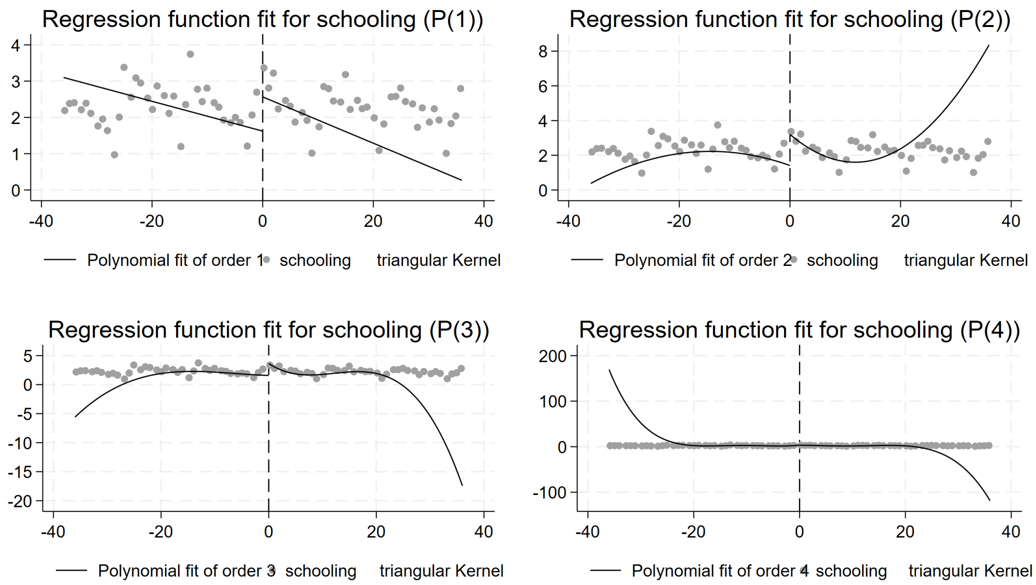

Figure 17: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

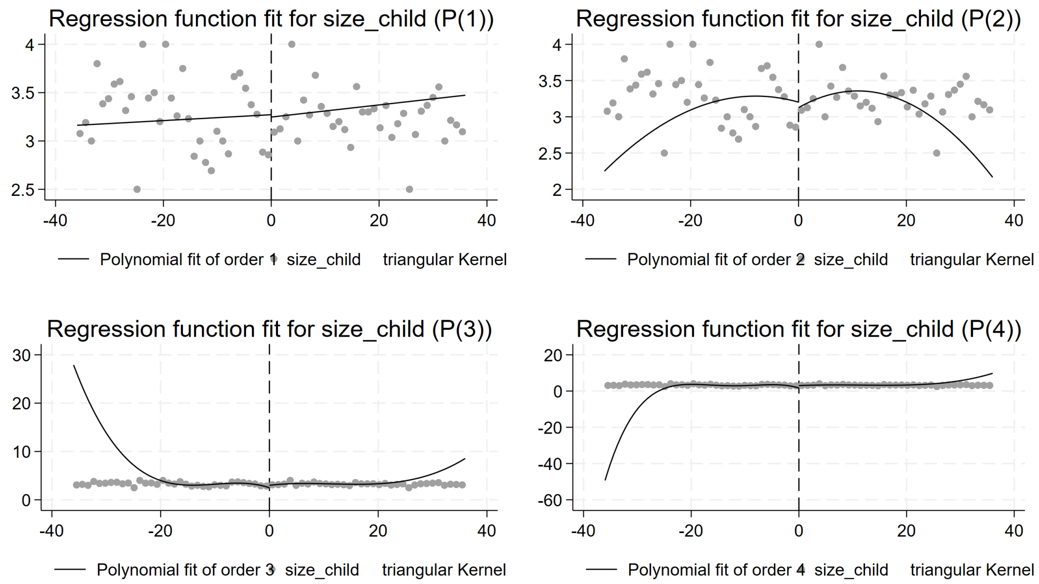

Figure 18: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.

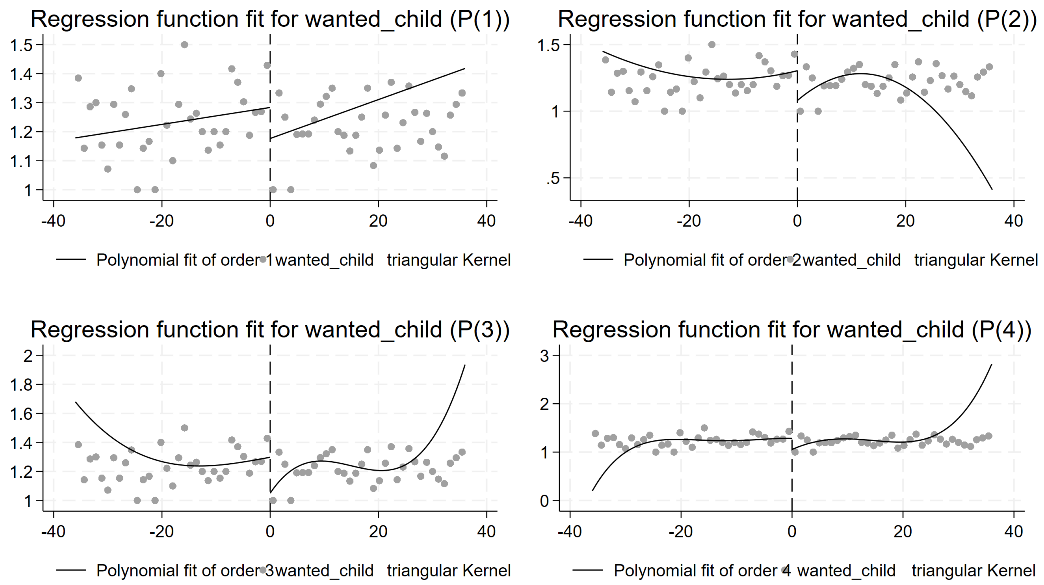

Figure 19: Constructed using the STATA command RDPLOT which uses Cattaneo et al. (2020) test procedures to generate density plots.