From Means-Tested to Universal Antipoverty Programs: Distributional and School Dropout Consequences

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Abstract

We study distributional and educational impacts of shifting from means-tested to semi-universal antipoverty programs, leveraging a natural experiment in Mexico. In 2019, the Mexican program PROGRESA was replaced by the semi-universal Benito Juarez Scholarships (BBJ), resulting in an eligibility base expansion at the cost of transfer amounts. We give evidence that this resource reallocation was regressive, but that the marginal households that benefited from the new targeting strategy might display educational benefits. Using a difference-in-differences and a regression discontinuity design, we employ a variation in the BBJ targeting design to compare a semi-universal to a proxy-means strategy. Employing administrative and survey information, we focus on the basic education level since BBJ employs both targeting strategies at this level. Our DiD findings suggest that the semi-universal targeting reduces dropout rates by 0.76 percentage points at the elementary level, while having non-significant reductions in middle school. Our RDD estimates do not display significant changes.

Keywords: Targeting, Conditional Cash Transfers, poverty alleviation, education.

JEL: H52, H53, I28

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1 Introduction

For the last two decades, conditional cash transfer programs (CCTs) have been widely implemented across the globe as social protection policies. Supported by a randomization study and rich data collection, the Mexican program PROGRESA[1] led the available evidence surrounding the implementation of this type of programs (Parker and Todd 2017). Despite its international popularity, in 2019 it was replaced by *Benito Juarez Scholarships* (BBJ for its Spanish acronym), which seek to simplify targeting by extending benefits semi-universally based on school location and private-public status.

This transition to BBJ and BBJ's design offers a unique setting to evaluate a relevant social policy change. One would expect that the transition by itself, which involves canceling a long standing program, loosening the conditionalities and reducing the cash disbursement should result in an increase in school dropouts—an outcome both programs aimed to reduce. Nonetheless, at the same time, the coverage expanded in specific regions as a result of different targeting strategies being implemented under BBJ. Some regions kept a finely targeted mechanism, as employed under PROGRESA while others moved to a semi-universal delivery.

This paper studies the consequences of replacing PROGRESA with BBJ under a semi-universal format vis-à-vis under a means-tested selection of recipients. Employing a marginalization index[2] of their geographical location, BBJ classified elementary and middle public schools (grades 1–9 in Mexico) into *priority* and *susceptible* for the program's rollout. Households with students in *priority* schools would be eligible to receive a universal cash transfer while those in *susceptible* schools would be subject to a proxy-means test (PMT) set to incorporate low-income households. Interestingly, the PMT procedure emulates the same strategy that PROGRESA followed for almost twenty years. Aside from this targeting difference, BBJ established changes with respect to PROGRESA that were homogeneously implemented and include a reduction in conditionalities,[3] lower cash transfer amounts, the cash delivery is now gender neutral, and a reduced community involvement.

By comparing *priority* and *susceptible* schools, two estimates are calculated using an event study and a regression discontinuity design. The event study design compares before and after the program

[1]PROGRESA was also known later as *Oportunidades* and *Prospera*. The name changed precisely after national elections that resulted in political party transitions. For the purpose of the present paper, we keep the original and wider known name.

[2]This poverty index has been calculated since 1995 and is updated every five years using the Census or Inter-Census data. Its calculation method was not created nor modified for the purposes of the BBJ program. See CONAPO's website for more information.

[3]BBJ only established that children must be signed up in school at the beginning of the school term. PROGRESA had a frequent school attendance revision, required all the household members to attend regular preventive visits to the clinic, and required the female household head to attend regular workshops (usually twice per year) which most often were used to distribute information.

transition while the regression discontinuity employs a rule established to define *priority* and *susceptible* schools. The event study design estimates a 0.76 percentage point (*pp*) decrease in elementary school dropout as a result of universal targeting. As for the RDD, at the elementary level, it results in a 1.1*pp* (not significant (NS)) increase. In the case of middle school, the event study design results in a 0.3*pp* (NS) increase in dropout, but we observe differential pre-trends. The RDD for middle school also points to a 1.7*pp* (NS) increase in dropout rates. Unfortunately, our identification strategies do not allow us to estimate an impact on high school dropouts, since BBJ implemented an almost universal cash transfer at that level.[4]

Our results complement Marquez-Padilla et al. (2025) who focus on the rollback of PROGRESA by comparing municipalities based on the intensive margin of PROGRESA's implementation before versus after it was canceled. Their estimates result in a generalized decline in enrollment rates that range between 1.3, 3.6 and 8.9 percentage point decreases in enrollment for full PROGRESA coverage in elementary, middle and high school, respectively. They can also be related to previous PROGRESA literature that consistently estimated increments in school enrollment, mainly at the high and middle school levels (Schultz 2004; Parker and Vogl 2023).[5]

Nonetheless, our main contribution results from isolating and quantifying the heterogeneous effect of the targeting strategy during the policy transition. The PMT strategy implemented under PROGRESA was evaluated close to the start of the program and confirmed to be a proper methodology to identify the households below the poverty line (Skoufias et al. 2001). PMT strategies are employed in a wide variety of contexts and are commonly used in social programs (Hanna and Karlan 2017a). Some work in the literature underlines some concerns in its implementation, including possible vulnerability to information missreporting (Martinelli and Parker 2009; Camacho and Conover 2011; Banerjee et al. 2020), the use of an inadequate target (de Janvry and Sadoulet 2006; Haushofer et al. forthcoming; Beuermann et al. 2025), and PMT algorithm limitations (Alatas et al. 2012; Brown et al. 2018). Some alternatives that have been put forward and discussed in the literature are self-targeting strategies (Alatas et al. 2016), geographical targeting (Smythe and Blumenstock 2022), and universal distribution of resources (Niehaus and Suri forthcoming; Hanna and Olken 2018a).

Our paper provides evidence that contributes to this literature. In addition, we show that in the transition from PROGRESA to BBJ, the cash delivery became less progressive. Not only the distribution of resources is geographically more concentrated in more developed localities (as discussed also by Marquez-Padilla et al. (2025)), but became more evenly distributed according to households' income

[4]At the high school level, every student attending a public high school is eligible for the program. The cash transfer is delivered directly to the student. The transfer amount is equivalent to that delivered to households under the BBJ being described in this paper.

[5]Parker and Todd (2017) provide a comprehensive literature review on the program.

distribution. As expected, this affects poor households disproportionately. For instance, the cash delivery as a proportion of expenditure is reduced by close to 20 percentage points for the lowest quintile and less than 5 percentage points for the highest quintile.

The rest of the paper is organized as follows. Section 2 describes in detail the policy transition; section 3 describes our data sources; section 4 presents an analysis of how the transition affected households in different parts of the income ladder; section 5 details the identification strategies while section 6 presents the main results. Finally, section 7 concludes.

2 The transition of PROGRESA to Becas Benito Juarez

Since 1997 PROGRESA was the flagship antipoverty program of the Mexican federal government. The program included three different components: one for education, one for health and one for social development (see Levy (2006) for details of the program's design). The program was implemented throughout four presidential terms under two different political parties. Before PROGRESA was canceled, it had reached more than 6.5 million households—about 26 million beneficiaries—, which amounts to 21.6% of the Mexican population (Secretaría de Desarrollo Social 2018). By the end of 2017, its annual budget was about US$4.2 billion, out of which US$1.5 billion were allocated to the education component of the program. The transfer amount was, on average, US$592 (about 54% of the yearly minimum wage) per household per year. This was equivalent to 74% of the yearly food expenditure for the lowest income decile, according to data from the Mexican official income and expenditure survey from 2018. In the transitions across the party in power the program was renamed, but its design and main components remained almost unchanged.

In July 2018, the left-wing candidate Andres Manuel Lopez Obrador (AMLO) was elected in the Mexican presidential elections with an overwhelming majority after receiving 53.2% of the votes.[6] The elected president's campaign was strongly focused on a progressive distribution of resources to reduce social inequality.[7] One year after the new administration took office, PROGRESA was terminated, and the government announced the creation of a new program of cash transfers to students and families called *Benito Juarez Scholarships* (Stok 2019). The main argument to cancel PROGRESA was a non-proved claim of corruption within the program,[8] and the argument that after 20 years of PROGRESA's

[6]This is the highest proportion of votes received by a candidate in a presidential election since 1982, when elections in Mexico were perceived to be controlled by the ruling party and doubted to be democratic.

[7]In his inauguration ceremony, AMLO proclaimed 100 commitments, out of which 25 were related to poverty or corruption. One of his main campaign and government slogans was: "For our country's sake, we put the poor first." (authors' translation).

[8]In various daily press conferences, AMLO argued that the use of intermediaries resulted in incomplete cash transfers to program recipients. He also claimed that the list of beneficiaries included "ghost beneficiaries." Numerous times the president assured that his government was going to publish a document with all the evidence to back up his decision, but to

operation, it was not effective at reducing poverty and inequality as intended in its main objectives (Lambert and Park 2019).[9]

By late 2024, BBJ accounted for a total of over 10 million recipient households and an annual budget of about US$3.5 billion (2018 USD). This means that, in terms of its education component, it has surpassed PROGRESA on the extensive margin (see Figure 1a). The program is available at the national level and shares some similarities with PROGRESA in its design. In companion to this program, the new administration also created three cash transfer programs for college students and young professionals that were released between 2019 and 2020.[10] Additionally, in 2024 a new extension of the BBJ program was released.[11] The analysis of those programs, which are often mentioned with BBJ, is beyond the scope of this paper.

Figure 1b shows the number of beneficiaries and budget evolution for PROGRESA and BBJ separated by education level. As for basic education, the number of beneficiaries decreased by 20% in the first year of BBJ—relative to the last year of PROGRESA—, with gradual increases of about 10% the two following years, resulting in a similar number of program recipients by 2022. In the case of high school there was an immediate and large increase in the number of beneficiaries. Just one year after the transition to BBJ, in 2020, it increased by almost 300% relative to the number of PROGRESA beneficiaries in 2018, clear evidence of the program focusing on the expansion of recipients at the high-school level.[12] Table OA-1 summarizes the differences between both programs by comparing PROGRESA in 2018—its last year of operation—to BBJ during the 2024 fiscal year.

2.1 Targeting strategy

Both PROGRESA and BBJ established as their purpose to benefit the individuals from the lowest part of the income distribution. With this goal in mind, both programs include in their rules of operation a clear methodology for selecting program recipients. Nonetheless, even when both programs share some similarities, the targeting strategy and the theory of change through which the programs are designed differ in important aspects.

At its beginning, PROGRESA had a strong emphasis on targeting families residing in rural localities

our knowledge evidence to back up these claims has not been published. We were only able to find this report by Animal Politico, a Mexican online media source "intended to create content with rigor, precision and thought to serve the citizens."

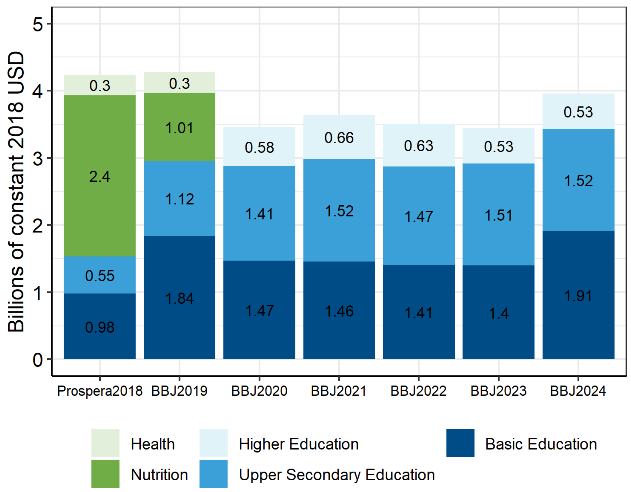
[9]See e.g., this video and this video for examples of such claims.

[10]The official name for those programs are: *Young Students Writing the Future* (authors' translation for: "Jóvenes Escribiendo el Futuro"), *Elisa Acuña Scholarship* (authors' translation for: "Beca Elisa Acuña") and *Young Professionals Building the Future* (authors' translation for: "Jóvenes Construyendo el Futuro"), respectively.

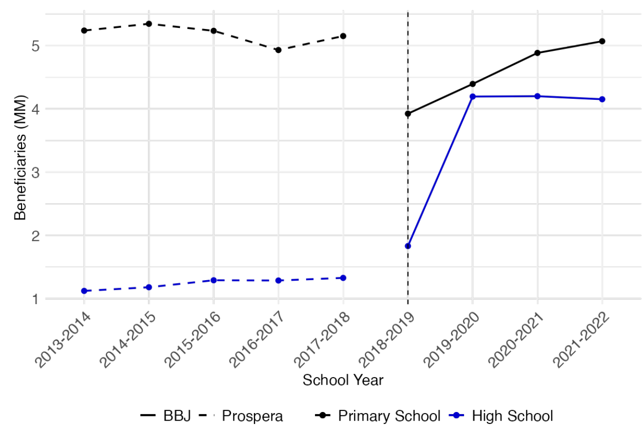
[11]The government rebranded the BBJ program for students in middle school (secundaria), making it more similar to the high school design of BBJ. It is now known as *Rita Cetina Scholarship* (authors' translation for: "Beca Rita Cetina").

[12]In a separate study Aguilar, González-Téllez and Simpser (2025) study whether the expansion toward this demographic had electoral consequences in the 2021 and 2024 elections.

Figure 1. Beneficiaries and Budget of PROGRESA/BBJ Over Time



(a) Budget (2018 MXN)



(b) Beneficiaries

Notes: Panel (a) presents the allocated budget, adjusted to 2018 pesos and then converted to U.S. dollars using the average 2018 exchange rate. The higher education budget includes both *Jóvenes Escribiendo el Futuro* and *Elisa Acuña*. Panel (b) shows the evolution of recipient households for PROGRESA between 2013-2018 and BBJ between 2018-2024. Sources: Federal Expenditure Budget and Administrative Information.

(Skoufias et al. 2001). In 2004, the program went through a reform which relaxed this focus on rural localities in order to incorporate urban localities as well (Parker et al. 2007).[13] Thereon, the targeting was done exclusively based on a household's proxy of wealth. A PMT strategy was implemented in which household's self-reported assets—which sometimes went through a verification process (Martinelli and Parker 2009)—and demographic characteristics were the main input of a needs-based index that was employed to discriminate eligible households (see, e.g., Grosh and Baker (1995); Clert and Wodon (2001); Schady et al. (2008) for analyses of this targeting strategy and applications in Chile and Ecuador).

BBJ, on the other hand, follows two different targeting strategies based on the education level in which children are enrolled. The program considers one strategy for students enrolled in basic education (first to ninth grade, children aged 6 to 15 years) and a different one for those in high school (tenth to twelfth grade, children aged 15 to 18 years). In both education levels, the program makes a distinction between two types of schools: (i) priority and (ii) susceptible. However, the definition of what is considered a priority/susceptible school is different in each education level.

The classification of priority/susceptible schools in basic education is geographical; it is based on

[13]Before 2004 the targeting process followed a two-step process. First, the locality was defined as eligible based on a poverty index. Second, a Census gathered household information in eligible localities—which were mostly rural. See Aguilar et al. (2023) for further details. After 2004, the program extended to urban localities as well, relaxing the first step of the process.

a poverty index that is defined at the locality level using pre-existing information from the Mexican Census (Hanna and Karlan 2017a). Priority schools are defined as those found in a locality with a *very high* or *high* poverty degree, whereas susceptible schools are located in the rest of the localities.[14] After the schools' classification is defined, the central government sends them an official notification with their classification and the process required for families to apply for being program recipients.

All families in priority schools are eligible and to enroll they only need to complete a sign-up form with basic demographic characteristics and present their identity documents. Families in susceptible schools need to fill up an application form in which they self-report their demographic information and asset ownership, which are the inputs for the PMT. The algorithm for computing the index is quite similar to the one used in PROGRESA. If there is available budget after considering all the applicants from priority schools, applicants from susceptible schools are ordered according to their needs-based index. Selected families in susceptible schools are notified about their eligibility and must complete the documentation to enroll into the program.

In the case of high schools, the BBJ program also classifies schools in: (i) priority and (ii) susceptible, although the definition of those classifications differs from the one in basic education. Priority schools are public high schools and the rules indicate that within priority schools, those in localities with *very high* and *high* poverty levels are selected first, leaving TV-broadcast schools, and schools in localities with *middle*, *low* and *very low* poverty degrees afterwards. Susceptible schools are private high schools and within private high schools, those in localities with *very high* and *high* poverty degrees are prioritized. The program's administration requests each high school to provide its full enrollment data at the beginning of the academic year. Scholarships are then assigned following the previously described allocation ranking until the program's budget is exhausted. Consistent with BBJ's goal of being semi-universal among students in high school, students are *not* requested to apply or fill up any form, they automatically receive notice of being program recipients through their high school if it has been selected for the program.

2.2 Conditionalities and cash delivery

PROGRESA's design was innovative since it included giving incentives to promote desirable decisions. Cash transfers were delivered if the household members complied with specific conditions: (i) children had to enroll in and attend school regularly, (ii) all household members had to attend to health checkups

[14] More detail about the schools' classification and how the poverty levels are calculated can be found in the BBJ's rules of operation which can be found in the program's website.

regularly,[15] and (iii) the household head had to attend regular talks or events on different topics. In addition to receiving cash transfers, the households received food benefits for babies and infants, as well as supplements for pregnant women and mothers. Complementary cash transfers were also delivered for school supplies at the start of the school year and another one upon high school completion. Transfers were received by the female household head (if available in the household) every two months through direct deposits to a bank account or in cash if banking infrastructure was not available nearby. The transfer amounts increased with school grade and were larger for females from 7th grade onwards. In 2018, by the end of the program, the monthly transfers per child ranged between US$9.10 in 1st grade to US$34.34 in 9th. Total monthly transfers for a given household were capped at US$153.23.[16]

BBJ removed all the conditionalities, except the schooling condition since the program requires students to be *enrolled* in school. Regular attendance, however, is not verified. Differently from PROGRESA, the basic and high school components are not integrated, meaning that the benefits and transfer limits are considered separately for these school levels. The cash transfers for those attending basic education is delivered to either parent (or grandparent if the parents are not available). Female household members are no longer promoted to be the main recipients. The cash amounts per family are fixed at US$47.20 per month—about 17% of one minimum wage—, regardless of the number, grade or sex of children. In the case of high school, BBJ considers that students, rather than families, are the recipients. The amount of students per household that can receive the benefits is not capped and the cash amounts per student are also fixed at US$47.20 per month, independent of the grade and sex of the student.

The resources are delivered every two months, for up to ten months per year (matching the school term length, excluding payments in July and August). Similar to PROGRESA, the transfers are deposited in a bank account or given in cash if banking infrastructure is not available nearby.

3 Data sources

We gathered information from a rich set of data sources. We obtained information from many data requests through the Mexican government's transparency unit, and we complement these data with information from official Mexican surveys and administrative data from schools and both PROGRESA and BBJ's administrations.

[15] The frequency of the health checkups was at least once a year. Children under five and pregnant women were required to attend more frequently.

[16] Official figures in Mexican pesos. An exchange rate of MXN$19.22 per US dollar was used for the calculations.

National Survey of Household Income and Expenditure (ENIGH). This survey is the source employed nationally to update Mexico's income inequality and expenditure official figures. It is collected every two years by the National Institute for Statistics and Geography (INEGI). Importantly for us, it gathers information about government transfers at the program level for the most relevant government programs, which includes PROGRESA up to 2018 and BBJ starting in 2020. In our analysis we use the surveys for years 2016, 2018, 2020 and 2022. By design, ENIGH is representative at the national level. Therefore, we employ the official income and expenditure figures to assess how the benefits are delivered throughout the income and expenditure distributions. Since ENIGH indicates if the household receives resources from each program, we also use the self-reported information about assets and demographic structure to estimate inclusion and exclusion errors in the beneficiary population. While the public version of ENIGH only reports state and municipality as respondents' locations, we were granted access to work at INEGI's Microdata Lab, where we were able to add locality-level poverty indices to observations in the data.

Census and Poverty Index. The Census is also collected by INEGI every ten years with an Intercensus collected five years after each Census. These data sources are used by the National Population Council (CONAPO) to calculate the localities' poverty index, which is referenced by BBJ in its rules of operation.

Government data. We did several data requests to the government concerning the program operation and the delivery of resources. The most relevant administrative information received includes:

1. *PROGRESA and BBJ execution*. For each year at the locality level, we observe the total amount of households receiving benefits and the total cash amount distributed. This information is merged with Census data. We employ this to describe how the resources are distributed.

2. *BBJ applications*. For those households with students enrolled in *susceptible* schools, we obtained most of the information from the applications submitted along with an indicator if they were selected as eligible for being program recipients. We also obtained the algorithm that the government employs to compute the needs-based index and discriminate applicants. The government declared that the full dataset of applications could not be delivered to protect confidentiality, but just 3 out of 32 variables used to select recipients were reserved.

3. *BBJ school classification*. We obtained the official classification of every Mexican elementary, middle and high school: *priority*, *susceptible* or *non-susceptible*. We use such classification for two purposes: first, merging this information with the Census, we were able to assess if the program's operation

was following the protocols established in the rules; and second, we employ this classification as part of our difference-in-differences and regression discontinuity identification strategies.

Schools' administrative data. The F911 is the dataset that the Ministry of Education gathers yearly at the national level from schools. Every school from basic and middle education (up to high school) is mandated to fill this information. This is the dataset used by the government to report educational official figures, such as enrollment, dropout, and transition between grades. It also has information about school infrastructure and personnel. We use information from this dataset to construct our main outcomes. Importantly, the information is collected at the beginning and at the end of the academic year. This data was obtained from several information requests.[17]

National Survey of Occupation and Employment (ENOE). This survey is the source employed at the national level to report official employment figures. It is collected by INEGI on a quarterly frequency and is a rotating panel in which households participate for five quarters. All household members 15 years old and older are surveyed face to face or indirectly—i.e., asking other family members to provide proxy responses if a household member is not present at the moment of the interview. It is representative at the national level. The specific location of the households is reserved and only reported at the municipality level. We were also granted access to work with these data at INEGI's Microdata Lab, where we were able to add locality-level poverty indices to observations across ENOE waves.

4 Distribution of benefits

Short after PROGRESA started, Skoufias et al. (2001) evaluated its potential to reduce poverty using ENIGH. They estimated that PROGRESA's targeted implementation outperformed universal and geographical targeting methods even after considering the implementation cost. This has been more extensively discussed in the recent literature (Coady et al. 2004; Niehaus and Suri forthcoming; Hanna and Olken 2018a). In section 2.1, we described how both, PROGRESA and BBJ, involve targeting strategies that seek to identify the poor. The case of BBJ is particularly telling since the new administration very strongly advocated towards redistribution. However, BBJ was also designed to be more universal, aiming to reach a broader share of the population. By design, one might expect a more universal distribution of resources to be less progressive, unless taxation compensates (Hanna

[17]Some of the information is now publicly available through Sistema de Información y Gestión Educativa's website.

and Karlan 2017b) or misreporting causes important targeting errors (Martinelli and Parker 2009).[18] Also, the expansion of the recipient base, the reduction in the program's transfers, and the increased importance of geographical targeting in basic education make it difficult, *a priori*, to hypothesize how the programs compare.

We begin by looking at how the budget is distributed across households in different parts of the income distribution. Using data for household-level expenditures and localities' (geographic) poverty categorization, we see that the budget was more progressively distributed under PROGRESA (Figure 2). The lines in the graph show how the total budget is split by groups. When we look at geographical poverty classification, the positive slope suggests that as localities are classified as richer they receive a higher share of the transfers, being this concentration in the richest group highest under BBJ (Marquez-Padilla et al. 2025). When looking at household level information, we find a negative slope, meaning that as the expenditure quintile increases, households tend to receive less. Nonetheless, BBJ displays a flatter pattern, consistent with a more universal approach.

Also, in the same figure, the bars display the likelihood of being a program recipient, conditional on being in a given group. Here, we see a negative slope in both cases. Moreover, under PROGRESA, households in the highest quintile and in localities with the highest income level have a less than 10% probability of receiving the program. When we look at BBJ, the likelihood increase is proportionately higher for the richest groups in both graphs. Also, the strong reduction in the likelihood for households in localities at the two richest classifications reflects the geographical targeting implemented at the basic education level.

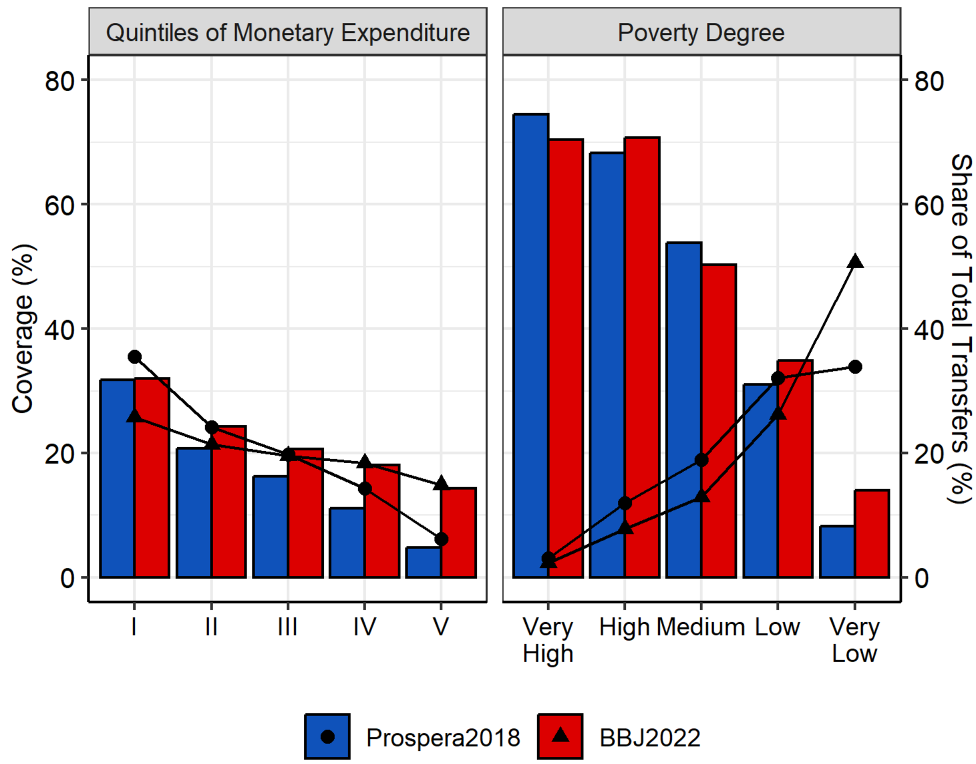
Using administrative information, we show how PROGRESA and BBJ's coverage at the basic education level is quite similar. However, in high schools, there seems to be a partial redistribution from the poorest areas to those with a very low poverty degree (Figure OA-1, Figure OA-2). All this evidence points to a more regressive distribution in BBJ.

To further assess the distribution of transfers, Figure 3 shows the average amount received by households as a percentage of their total expenditure. Regardless of whether we focus on quintiles of monetary expenditure or poverty degrees, it is clear that transfer amounts under BBJ were reduced. Such decrease affected households in the bottom quintile (and in the poorest localities) in the highest proportion.[19] For instance, those households in the lowest expenditure quintile suffered a reduction of about 20 percentage points of transfers as a proportion of expenditures, which is equivalent to a more

[18] In a recent paper, Aguilar and López (2025) estimate that misreporting could cause a misstargeting estimated up to 47% of the recipient base whenever the recipients are aware of the targeting strategy.

[19] We estimate income distribution using expenditures, but Figure OA-4 shows that the result is consistent if we had employed income.

Figure 2. Number of Beneficiary Households and Transfer Amounts



Note: This figure shows, by quintile of monetary expenditure and degree of poverty, (i) the percentage of households receiving a scholarship among those with at least one member attending basic or high school (bars), and (ii) the share of the total amount of scholarship funds received by each group (lines), for both programs.
Source: National Survey of Household Income and Expenditure (ENIGH) 2018, 2022, and CONAPO poverty index 2020.

than 50% cut with respect to PROGRESA levels.[20]

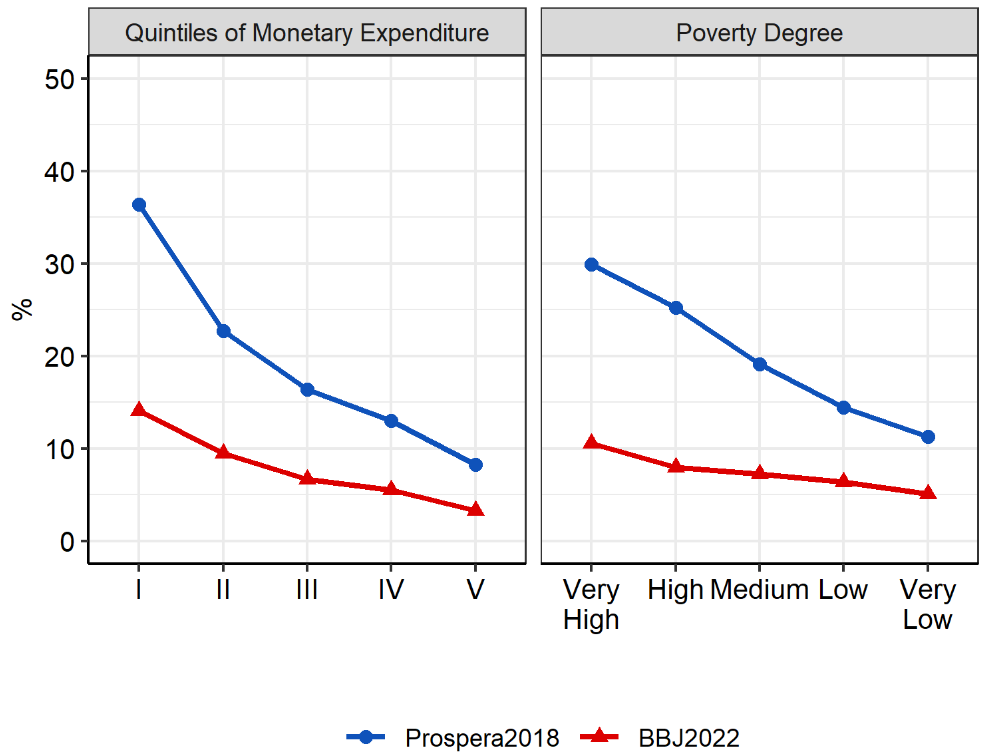
A similar picture results from looking only at transfers (Figure OA-3). Under PROGRESA, the average amount allocated to a household in the first quintile is approximately six times larger than the amount allocated to a household in the fifth quintile. For BBJ, this ratio decreases to less than two. The same pattern is observed at the localities' poverty degree level. Under PROGRESA, the average amount for households in the poorest areas is more than eight times higher than for those in the least poor areas, whereas for BBJ, this ratio is less than four.

5 Identification Strategy

As described in the introduction, this paper does not estimate the effect of the social policy transition between PROGRESA and BBJ. Rather, it focuses on one element, key to the design of redistributive

[20]In a separate study Hurtado (2025) shows how BBJ might have affected household expenditures.

Figure 3. Scholarship Transfer as a Percentage of Household Monetary Expenditure



Note: This figure shows the average amount received by households enrolled in the scholarship program as a percentage of their monetary expenditure, broken down by quintiles of monetary expenditure and poverty degree. The poverty degrees are defined using the CONAPO poverty index.
Source: National Survey of Household Income and Expenditure (ENIGH) 2018, 2022, and CONAPO poverty index 2020.

programs: the targeting strategy. In that regard, *treatment* should be understood as the semi-universal targeting,[21] which is compared to the proxy-means strategy.

In this paper we focus on basic education (elementary and middle schools). We employ two identification strategies and, consequently, we estimate two different treatment effects. First, we employ a DiD strategy to estimate an ATT for the targeting strategy. Second, we employ the rules of operation in an RDD setting to estimate a local ITT for those schools in the margin of being eligible for the *semi-universal* targeting.

Difference-in-Differences. We compare the evolution of dropout rates in *priority* and *susceptible* schools following the definition in the BBJ program. In Section 2, we describe how the school definition is based on their geography. Importantly, *susceptible* schools follow a targeting strategy very

[21] We refer to this strategy as *semi-universal* since not every single student in Mexican schools receive resources, which adds to an uncertainty related to the classification of the students' school. Also, once the school is selected, students or their families must sign-up to the program.

similar to that of PROGRESA whereas *priority* schools implement a semi-universal offer of resources. If valid, the parallel trends assumption allows us to isolate the targeting difference from time-specific differences, which include the political transition of the program, as well as elements shared between *priority* and *susceptible* schools. The no anticipation assumption in our setting implies that students did not change their dropout patterns prior to the implementation of BBJ. We think this assumption is likely to hold since PROGRESA was cancelled abruptly and there was no public information about how BBJ was going to be implemented. For the assumption to be violated, students would have had to be able to infer how BBJ was going to be implemented and then change their decision to stay in school or drop out based on whether they expected their locality to be classified as priority, susceptible or non-susceptible.

Employing the F911 data for educational outcomes, we estimate the average treatment on the treated (ATT) effect using a two-way fixed effects model as well as an event study design. Importantly, the adoption of BBJ occurred nationally within a single school year, thus, our analyses are not subject to usual concerns in staggered-adoption designs.[22] We use OLS to estimate the parameters in the following specification:

$$Y_{st} = \theta_s + \gamma_t + \sum_{r \neq 2017} \tau_r \, \texttt{Priority}_s \times \mathbb{1}\{t = r\} + U_{st} \tag{1}$$

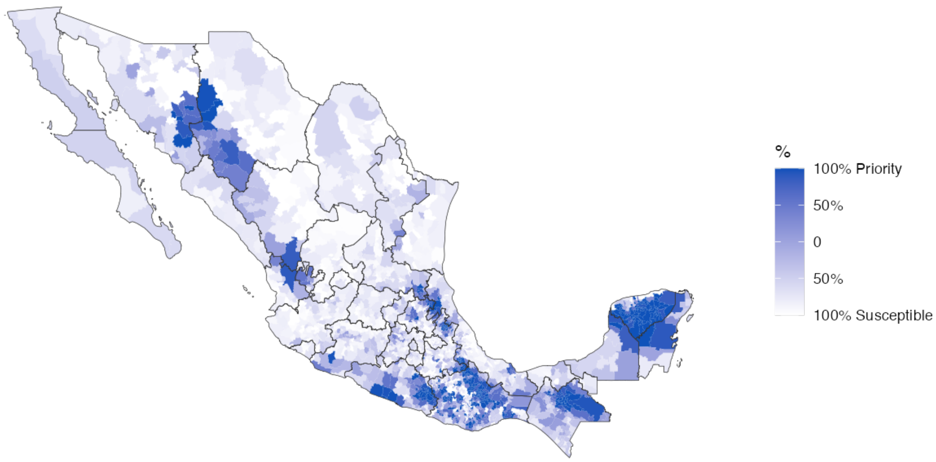
where Y_{st} is an outcome of interest, θ_s are school fixed effects, γ_t are academic year fixed effects, $\texttt{Priority}_s$ is an indicator equal to 1 if school s is defined as a priority school (rather than as a susceptible school), τ_r are our parameters of interest which measure the differential trend in dropout relative to that of susceptible schools, and U_{st} is a mean-zero stochastic error term affecting the outcome. We use 2017–2018 as the reference academic-year since it was the last year fully covered by PROGRESA. We cluster standard errors at the locality level to account for serial autocorrelation of outcomes within localities. Figure 4 shows the cross-sectional variation in treatment assignment.

Regression Discontinuity. We leverage the fact that *susceptible* and *priority* schools are defined based on their locality's poverty index. As described in Section 2, priority schools are in localities with *very high* or *high* poverty levels, whereas susceptible schools are in non-priority localities. Nonetheless, our design is a fuzzy one since there are some exceptions in the program's design in which localities can be classified as *priority* even if their poverty index is below the cutoff value.[23] These categories are defined

[22]Nonetheless, we are currently working on estimating treatment effects using estimators robust to heterogeneous effects across panel units.

[23]Exceptions include, e.g., being an indigenous locality, being considered as "Prioritary Attention Zone" by the Secretaría del Bienestar (Ministry of Welfare), or being a locality with less than 50 inhabitants but based on contextual characteristics, it

Figure 4. Geographic Variation of School Classification



Notes: This figure shows the difference of the share of schools classified as Priority and the share of schools classified as Susceptible across municipalities. Darker blue implies a larger share of Priority schools within the municipality, whereas lighter blue implies larger shares of Susceptible schools.

based on a continuous poverty index. Using the index as the running variable and the index level between *High* poverty degree and *Medium* poverty degree as the cutoff value, we employ a regression discontinuity identification strategy to estimate a local treatment effect. The main specification is:

$$\begin{aligned} Y_l &= \alpha_R + f_R(\texttt{Poverty Index}_l - c) + U_l \\ Y_l &= \alpha_L + f_L(\texttt{Poverty Index}_l - c) + U_l \qquad (2) \\ \tau_{RDD} &= \alpha_R - \alpha_L \end{aligned}$$

where Y_l is the outcome in locality l; $f_R(.)$ and $f_L(.)$ are local linear regression functions which are allowed to vary—in functional form but not on the polynomial degree—at either side of the cutoff; $\texttt{Poverty Index}_l$ is the running variable, the locality-level poverty index; c is the cutoff value. Our main parameter of interest, τ_{RDD} captures the local intent-to-treat (ITT) effect that results from the comparison between susceptible and priority schools at the cutoff point $\texttt{Poverty Index}_l = c$. This variation captures the targeting difference insofar as potential confounders' functions are continuous at the cutoff. Any differential time variation between susceptible and priority schools that could threaten

is the program's priority to bring coverage to it.

the parallel trends assumption in our DiD identification would not be a concern here. Nonetheless, our estimate would lack the DiD generality. In that sense, our DiD and RDD results are complementary: while our DiD strategy yields estimates that are generalizable to a larger subset of the population, our RDD estimates' internal validity requires weaker assumptions.

6 Main Results

6.1 Main outcome

We now turn to estimating treatment effects on educational outcomes. Since its original design, PROGRESA had the objective to *"[...] elevate living standards through improvements in the opportunities for education [...],"* an objective still present in BBJ's design which aims *"[...] to grant scholarships that contribute to school permanence [...]."* We thus focus on dropout rates as our main outcome of interest. We use the official Ministry of Education's definition of dropout, which tracks the total students enrolled in a given school across academic years:

$$D_{st} = 100 \cdot \frac{(E^e_{st} - E^b_{s(t+1)}) - (G^e_{st} - NF^b_{s(t+1)})}{E^b_{st}}$$

where D_{st} denotes the dropout rate of school s from academic year t, E^e_{st} denotes the number of students enrolled in school s at the e̲nd of academic year t, $E^b_{s(t+1)}$ denotes the number of students enrolled in school s at the beginning of academic year $t+1$, G^e_{st} denotes the number of students who graduate from school s in academic year t and $NF^b_{s(t+1)}$ denotes the number of new students enrolled in first grade in school s in the b̲eginning of academic year $t+1$. Intuitively, this definition captures the difference in the number of students from the beginning of an academic year relative to the end of the previous academic year, net of students who graduate and those who are being enrolled in school for the initial school grade.

Other studies concerning school dropout (enrollment) typically rely on individual level self-reported survey measures. We, on the other hand, use the administrative data that is employed for Mexican official figures to measure dropout rates. We consider our measure to be an improvement over self-reported survey measures which are subject to social desirability bias. Particularly in our setting, where the cash transfer is conditional on children's enrollment, parents have a larger incentive to over-report their children's enrollment if they think they will be penalized for not enrolling *all* of their children. Our administrative measure, however, comes at the expense of being unable to track *the same student's* evolution across school grades. For our RDD identification strategy we sum enrollment figures across schools within localities and compute dropout rates at this level in order to be able to estimate dropout particularly for the transition between basic and middle education (i.e., from 6th to 7th grade).[24] By performing the estimation at the locality level we are allowing for students to migrate *across schools* so long as schools are located within the *same locality*.

6.2 Difference-in-Differences: The Targeting Effect on Basic Education

Figure 5 shows raw dropout rate means over time for priority and susceptible localities as well as the event study estimates for elementary and middle schools. In Figure 5a and Figure 5b we show the means and event-study estimates for elementary education. The pre-BBJ estimates provide evidence in favor of our design's validity for analyzing basic education. We cannot reject the null hypothesis that dropout rates in priority and susceptible localities were on similar trends prior to the implementation of BBJ. After the implementation of BBJ, we observe an average treatment effect that denotes a reduction of about 0.76 percentage points in droput rates. Notably, the effect is tiny in the first 2 years of the program (-0.018pp (p-value = 0.94) and -0.46pp (p-value = 0.03), respectively), and it then increases (in absolute value) during the 3rd and 4th years after the program's implementation to -1.67pp (p-value < 0.01) and -0.92pp (p-value < 0.01), respectively.

Regarding students in middle education, we find an increase in dropout rates of about 0.3pp in the four years after BBJ was implemented. However, in this case we are not able to rule out the existence of differential pre-trends across schools located in priority and susceptible schools (see Figure 5c and Figure 5d).

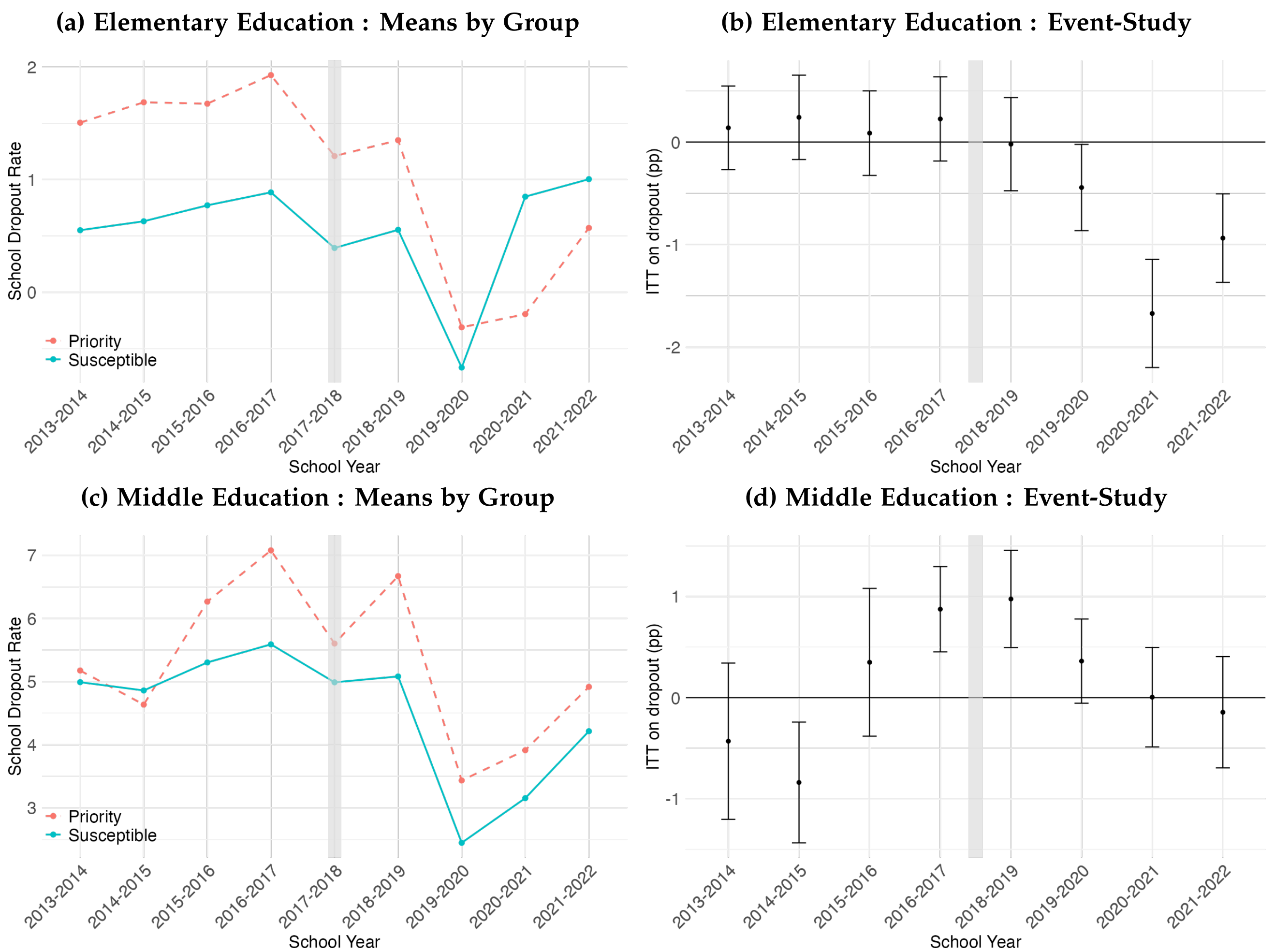
6.3 Regression Discontinuity: The Effect on the Marginally Eligible

First Stage. Before presenting our RDD estimates we provide evidence that the probability of a locality being categorized as priority in fact shifts discontinuously at the cutoff. Using Government data with school classifications and CONAPO's poverty index data, Figure OA-5 shows that this probability sharply increases by about 55pp from 45% to 100% at the cutoff between localities with a *Medium* poverty degree and those with a *High* poverty degree. Robust local polynomial estimates show a first stage of 55pp, with an F-statistic of over 370.

Monotonicity Given that the design is fuzzy, we also require a monotonicity assumption in order to interpret our results as a local average treatment effect (Imbens and Angrist 1994; Heckman et al. 2006). In our context, the monotonicity assumption implies that there are no *defier* schools, which would be

[24]We require this aggregation since not all schools who serve elementary education also serve middle school and viceversa.

Figure 5. Intent-to-Treat on Dropout Rates



those that if the cutoff had fallen to the right (left) of their poverty index they would be defined as priority (susceptible) schools.

No Manipulation Assumption Additionally, the validity of our design relies on schools being unable to manipulate their location based on the localities' poverty index so as to lie on a particular side of the cutoff. We present evidence in favor of this assumption in Appendix OA-C. In summary, we cannot reject the hypothesis that the poverty index's density is continuous at the cutoff (p-value=0.13).

For ease of presentation we show our RDD estimates in figures but we present more detail for these estimates in Table OA-3. Figure 6a shows dropout for primary education, pooling together dropout from school grades 1–5. Figure 6b shows dropout for secondary education, pooling together the two school grades for which we are able to compute dropout: 7th and 8th. Finally, Figure 6c shows the dropout rate from sixth to seventh grade—a grade we refer to as "the transition grade"—which marks the transition from elementary to middle education.[25]

We estimate that dropout rates in elementary education increase, insignificantly, by 1.1*pp*. In the case of dropout in middle education, we estimate a bigger increase of 1.7*pp* (p-value=0.22). Somewhat surprisingly, we estimate a *decrease* of 1.8*pp* (p-value=0.82) in dropout for students transitioning from elementary to middle education. It is worth highlighting the fact that even the conventional RD estimate—as opposed to the bias-corrected—results in a negative, if noisy, point estimate.

7 Conclusion

In 2019, PROGRESA—the internationally recognized Mexican conditional cash transfer program—was replaced by the Becas Benito Juárez (BBJ) program under a new government that promoted an anti-poverty narrative. While PROGRESA was structured around means-testing, BBJ adopted a mixed strategy to target recipients, while it implemented a more universal approach in specific locations (and for high school students), it also kept a means-test structure in other locations. In this paper, we exploit this structure to assess the impact of the targeting strategies.

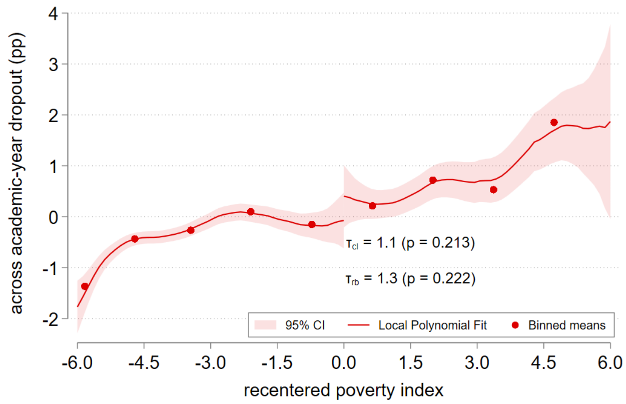
While our paper does not provide direct evidence of the impact that the change in social policy had on educational outcomes, it builds on the PROGRESA literature that has shown positive impacts on schooling outcomes. The main tradeoff evident in the change between PROGRESA and BBJ is an important increase in the beneficiary base at the expense of decreased transfer amounts. Theoretically, one could expect a positive effect resulting in the beneficiary base increase and a negative in the reduction of transfers. We contribute in this discussion by providing a rigorous estimate of the base increase resulting from a more universal approach in targeting.

Looking at the particular case of PROGRESA's end rather than being a limitation for being a particular case is very informative for the universal versus targeted discussion since many countries followed the conditional cash transfer design established by PROGRESA as a result of the rigorous evidence presented while evaluating its effects. Still, we refrain from making any welfare judgement resulting from this social policy transition. Presently, our work focuses on expanding the impacts of this targeting comparison by looking at the labor and expenditure impacts on households.

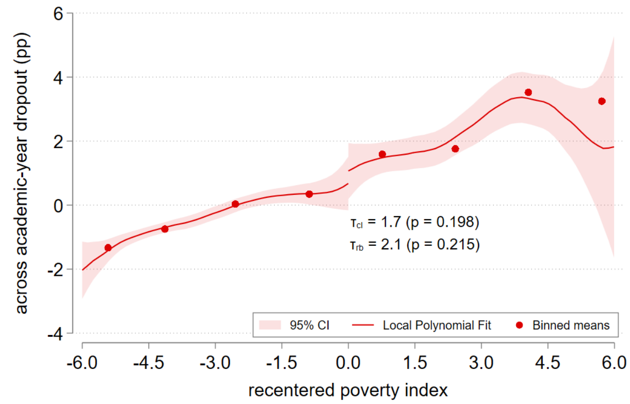
[25]We analyze differently the transition, since it usually involves a change in school.

Figure 6. RD Estimates on Dropout

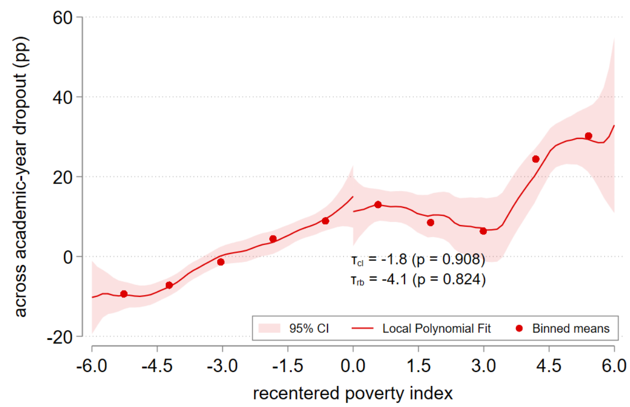
(a) Elementary - Grades 1–5



(b) Middle School - Grades 7–8



(c) Transition grade from Elementary to Middle School



Notes: This figure shows dropout rates as a function of the (recentered) poverty index. In Panel (a) we show the dropout rate for children enrolled in school grades 1–5, corresponding to elementary education. Panel (b) shows the dropout rate for children enrolled in school grades 7 and 8, corresponding to middle school education. Panel (c) shows dropout for children enrolled in sixth grade, which corresponds to the transition grade between elementary and middle school education. We partial out dropout on fixed effects for academic years 2018, 2019 and 2020. τ_{cl} denotes de conventional RD estimate while τ_{rb} denotes the robust estimate. We use a data-driven bandwidth and a triangular kernel as recommended by Calonico et al. (2014).

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From Means-Tested to Universal Antipoverty Programs: Distributional Consequences and Effects on Dropout

Appendix – For Online Publication

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OA-A Differences between PROGRESA and BBJ

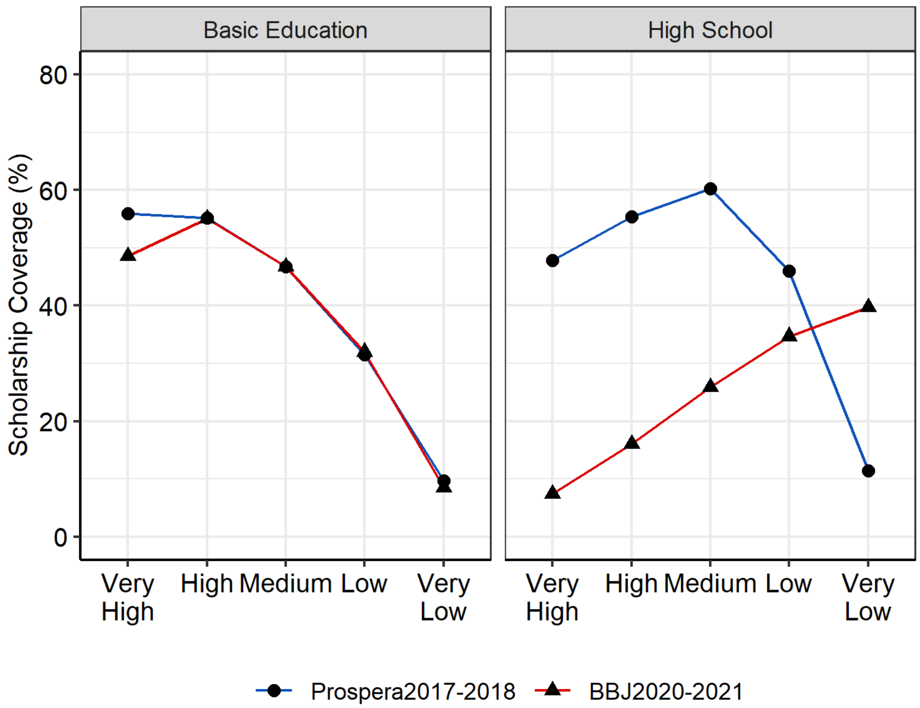
Table OA-1. PROGRESA and BBJ Design

	Prospera	BBJ	
		Primary and Secondary	Tertiary
Objective	Promote enrollment, regular school attendance, and completion to selected households members and reduce the prevalence of child labor	Promote students' retention and completion	
Targeted Population	Households with an estimated per capita income lower than LBMa	Children and youth enrolled in priority schools	All students
Conditionality	School enrollment and attendance	School enrollment	
Targeting level	Locality + HH	School + HH	Universal
Targeted School	—	Priority / Susceptible	Public schools
Amounts (MXN)	Depends on school year and sex of the beneficiary. The maximum amount per household on Primary and Secondary education is $1,350 and for Tertiary $2,470	$920 per HH	$920 per student
Extra Cash	Completion and Utilities Bonus	No	
Adj for urban or rural localities	Yes	No	
Number of Beneficiaries	6.5 M	11 M	
Education budget	$29,448 M	$ 89,078 M	
Total Budget (MXN)	$81,537 M	$102,799 M	

Notes: This table shows the characteristics of both the PROGRESA and BBJ programs' design.

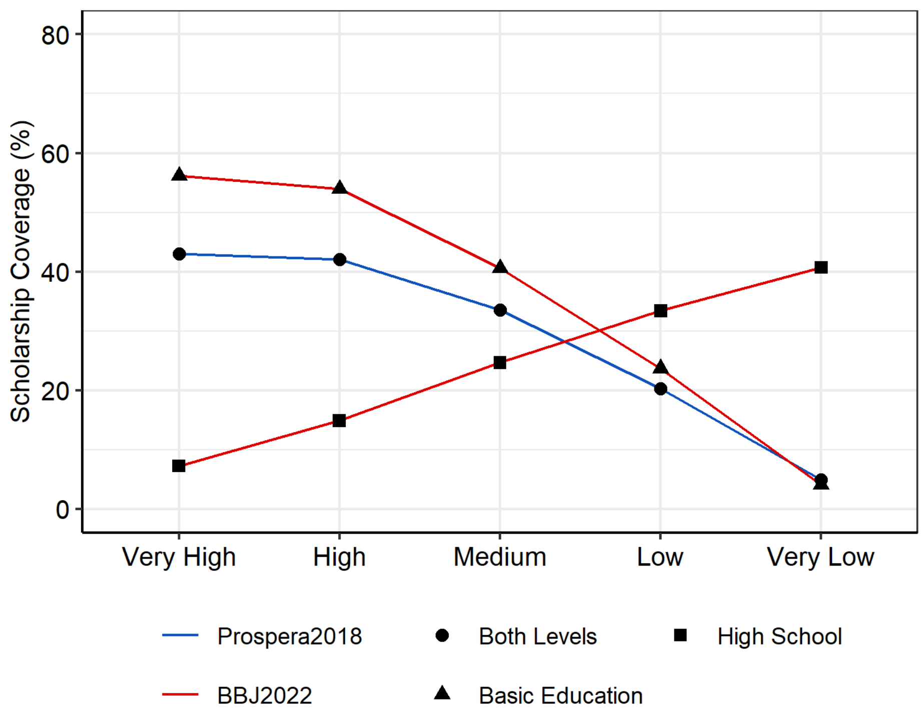
OA-B Distribution of Benefits

Figure OA-1. Program Coverage Using F911 Dataset



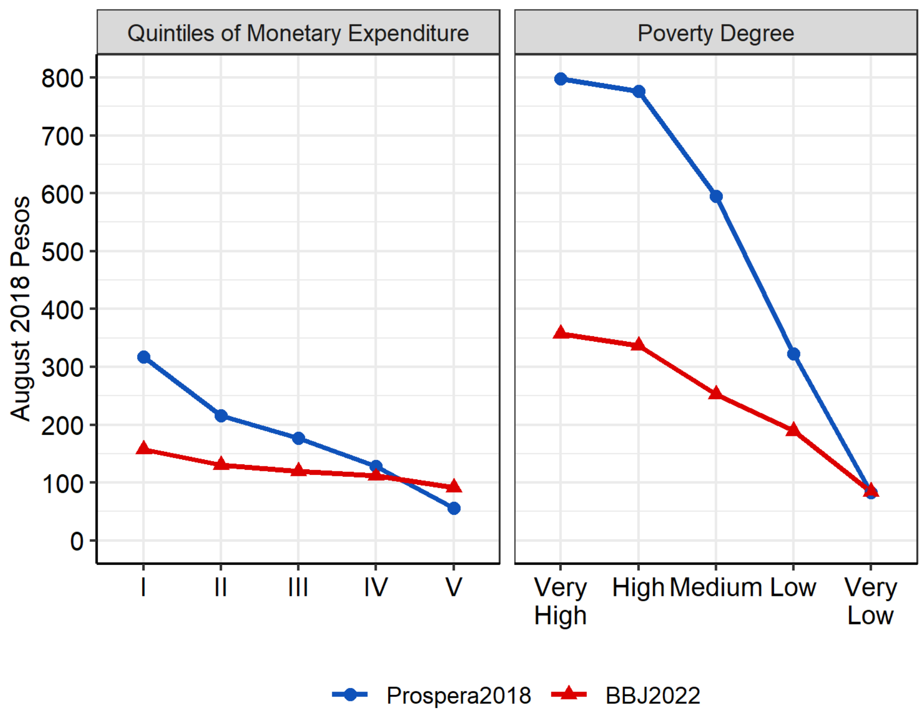
Note: This figure shows the total number of scholarship recipients as a percentage of the population aged 0–14 for basic education and 15–19 for the high school level, disaggregated by degree of poverty. We use data from the Prospera and BBJ programs for the 2017–2018 and 2020–2021 cycles, respectively.
Source: Scholarship administrative data (F911 dataset), available upon request; Census 2020; and CONAPO Poverty Index 2020.

Figure OA-2. Program Coverage Using Publicly Available Administrative Data



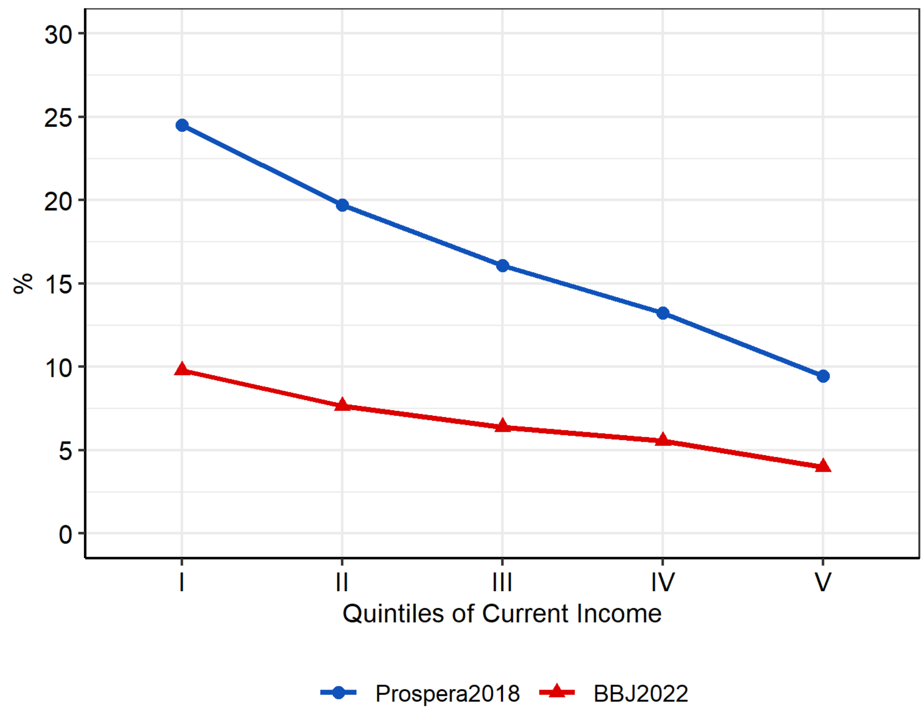
Notes: This figure shows the total number of scholarship recipients as a percentage of households for PROSPERA and BBJ at the basic education level, and as a percentage of the population aged 15–19 for BBJ at the high school level, disaggregated by degree of poverty. For PROSPERA, the available data do not allow us to distinguish between basic and high school education levels. In both cases, we include only recipients who received a positive cash transfer during the reference period. The data for PROSPERA correspond to the last bimester of 2017—the most recent and complete information available—while the data for BBJ refer to the first quarter of 2022.
Source: Publicly available scholarship administrative data for both programs: Prospera and Becas Benito Juárez. When not available, the data can be shared upon request. Census 2020, and CONAPO Poverty Index 2020.

Figure OA-3. Average Monthly Scholarship Transfer per Household



Note: This figure shows the average monthly amount assigned to households with at least one member attending basic or high school, broken down by quintiles of monetary expenditure and poverty degrees. The poverty degrees are defined using the CONAPO poverty index.
Source: National Survey of Household Income and Expenditure (ENIGH) 2018, 2022, and CONAPO poverty index 2020.

Figure OA-4. Scholarship Transfer as a Percentage of Household Monetary Expenditure, by Quintiles of Current Income



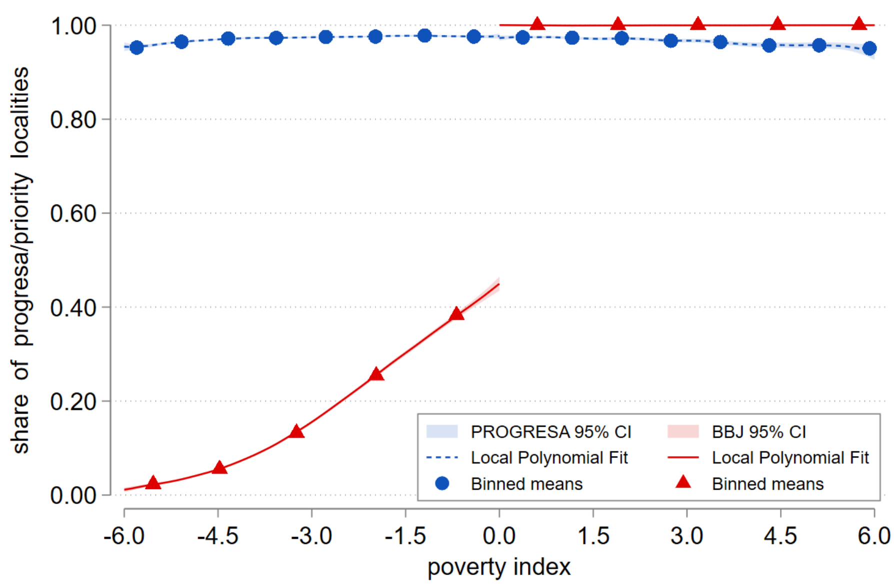
Note: This figure shows the average amount received by households enrolled in the scholarship program as a percentage of their monetary expenditure, broken down by quintiles of current income.
Source: National Survey of Household Income and Expenditure (ENIGH) 2018, 2022, and CONAPO poverty index 2020.

OA-C Validity of Regression Discontinuity Design

C.1 First Stage of BBJ Program

In this section we present evidence in favor of the relevance condition required for our fuzzy regression discontinuity design to be interpreted as causal. We observe a discontinuous increase of over 50*pp* on the probability of a locality being considered as priority according to its poverty index value at the cutoff.

Figure OA-5. First Stage



Notes: This figure shows, in red, the probability of a locality being classified as Priority as a function of its poverty index. In blue we show the probability of having PROGRESA beneficiaries for localities with a given poverty index.

C.2 McCrary No Manipulation Test

We present the McCrary No Manipulation Test on our running variable. The null hypothesis is that the distribution of localities around the cutoff is continuous and the alternative is that it is not continuous. We present the test pooling the observations from our data across all years. However, we can also conduct the test year-by-year and the results show even more evidence in favor of the null.

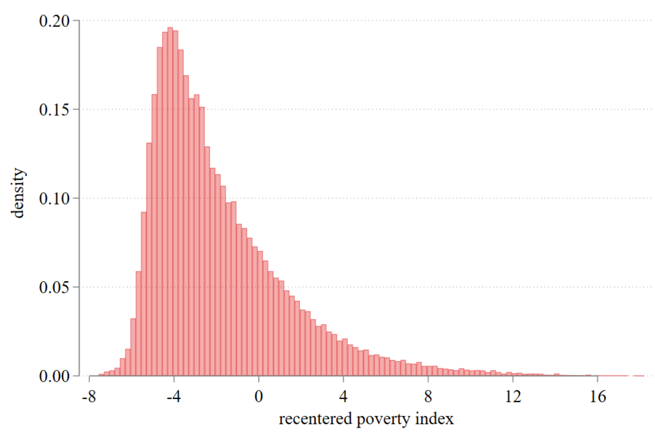
Table OA-2. McCrary Test Statistics

	Statistic	p-value
Poverty Index	1.52	0.13

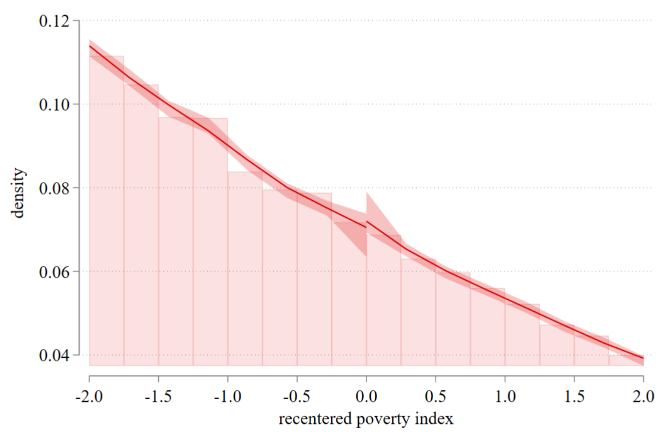
Notes: This table shows the test statistic and p-value associated to the McCrary No Manipulation Test on our running variable. An observation is a locality-year.

Figure OA-6. No Manipulation McCrary test on running variable

(a) Distribution of poverty index



(b) Distribution in a neighborhood of the cutoff



Notes: This figure shows the distribution of the running variable. In Panel (a) we show the histogram depicting the distribution of all localities. In Panel (b) we zoom into a neighborhood around the cutoff and show local polynomial fits of the density along with their corresponding 95% confidence intervals. An observation is a locality-year.

OA-D Regression Discontinuity Tables

Table OA-3. RD Estimates on Dropout

	(1) Pooled Grades 1–5	(2) Pooled Grades 7–8	(3) Grade 6
Panel A: ITT			
Priority	-0.56***	-0.27	-12.04***
	(0.19)	(0.28)	(2.88)
Observations	738606	148800	75173
Panel B: LATE			
Priority	1.11	1.71	-1.76
	(0.89)	(1.33)	(15.31)
Effective observations (left)	161748	39976	13179
Effective observations (right)	86685	15656	6837
Robust p-value of LATE estimate	0.222	0.215	0.824
F-statistic (First Stage)	1172	520	374
Academic Year FE	✓	✓	✓

Notes: This table shows treatment effect estimates of the targeting strategy of BBJ on dropout rates. Panel A shows intent-to-treat estimates and Panel B shows LATE estimates. Column (1) pools dropout across the five grades in primary education in Mexico, column (2) pools dropout across the first two years of secondary education in Mexico, and column (3) shows estimates for sixth grade on its own. We use a triangular kernel and a data-driven bandwidth as recommended by Calonico et al. (2014). Clustered standard errors at the locality level are shown in parentheses. In Panel A we estimate $\texttt{Dropout}_{lgt} = \alpha_t + \beta\ \texttt{Priority}_l + \delta_1\ \texttt{Poverty Index}_l + \delta_2\ \texttt{Priority}_l \times \texttt{Poverty Index}_l + u_{lgt}$. An observation is a locality-school grade-year. Significance levels: * p<0.1, ** p<0.05 and *** p<0.001.