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A Fuzzy Regression Discontinuity Approach

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Abstract

We examine the impact of the unconditional cash transfer AMEN Social program on children's schooling, using a fuzzy regression discontinuity approach. The data comes from the 2021 National Survey on Household Budget, Consumption and Standard of Living, which provides a solid foundation of information on household living conditions, education and health. The results of the analysis show a significant improvement in school attendance among children from households close to the eligibility threshold, thus confirming the positive effect of the AMEN Social program on schooling. However, these effects are observed in a context where targeting errors persist, in particular cases of inclusion of ineligible households and exclusion of households considered to be potential beneficiaries. This work is part of a process of evaluation of social public policies, with the ambition of contributing to the design of more equitable and effective programs in terms of human capital development.

Keywords : Unconditional Cash Transfers; School Attendance; Fuzzy Regression Discontinuity; Social protection; AMEN Social.

JEL codes : J13; H5; I38; C52

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1. Introduction

Cash transfers are now at the heart of social policies in many developing countries, serving as effective tools for poverty reduction and the promotion of human capital (Todd and Wolpin, 2006; skoufias and Maro, 2008; Caldès et al., 2006). Whether conditional or unconditional, these programs aim not only to alleviate the economic precariousness of households, but also to encourage investment in key areas such as health and education (Chong and Lau, 2025; Fiszbein and Schady, 2009; Schubert and Slater, 2006; Baird et al., 2011; Baird et al., 2014). At the international level, numerous impact evaluations have demonstrated the positive – sometimes differentiated – effects of these measures on children's schooling (Millán et al. 2020, Churchill et al. 2021, Premand and Barry 2022, Macours et al. 2012, Evans et al. 2023).

In Tunisia, the Amen Social program is part of this logic. It provides a Permanent Cash Transfer (PCT) to vulnerable households, combined with social support, aiming to help cover basic needs and strengthen access to social rights. However, despite a growing political commitment to reduce poverty and promote school enrollment among children in vulnerable households, empirical evidence on the effectiveness of such interventions remains limited. In the context of post-revolution economic fragility and constrained public resources, it is crucial to assess whether these cash transfers truly promote educational inclusion—or merely serve as temporary relief. This lack of evidence is particularly concerning given that the socio-economic context remains marked by structural challenges: imperfect targeting, potential exclusions, relatively low amounts paid in the face of inflation, and lack of systematic monitoring of long-term effects. Driven by a desire to understand the real effectiveness of these transfers, and inspired by the numerous studies conducted in other contexts, this work proposes to evaluate the impact of the Amen Social program on the schooling of children from beneficiary households. In particular, it is a question of examining whether, in a context of persistent precariousness, the monetary aid paid by the Tunisian State is effectively managing to support school attendance and reduce the risk of dropping out.

Launched in 2019 with technical and financial support from the World Bank, the AMEN Social program has become the cornerstone of Tunisia's social protection strategy. Implemented by the Ministry of Social Affairs, the program aims to support the country's most vulnerable populations through a combination of direct cash transfers, free or subsidized healthcare services, and economic empowerment measures. The program follows a dual approach: addressing the immediate needs of the poorest households while building their long-term self-sufficiency. As of December 2023, over 333,000 poor households—representing around 10% of the Tunisian population—were receiving regular monthly transfers. At the same time, 620,000 low-income households had access to healthcare coverage through AMG1 and AMG2 cards. Approximately 160,000 children from 103,000 households registered in the Social Registry also received targeted early childhood allowances. In its first year of implementation, the program mobilized a budget of 687.9 million Tunisian dinars—equivalent to nearly 0.7% of the country's GDP. This level of investment places Tunisia among the MENA region's top spenders in terms of the share of national wealth allocated to social transfers (World Bank, 2024).

Since December 2020, families have received a monthly allowance of 30 dinars per child aged 0 to 5. This support targets early childhood development, including nutrition, health, and cognitive stimulation. In July 2022, the program expanded to include children aged 6 to 18, providing the same 30 dinars per month per child. Tunisia has been grappling for several years with a troubling rise in school dropout rates, particularly affecting poor households and rural or inland regions. The numbers are stark: during the 2021/2022 school year, around 91,200 students dropped out—nearly 4% of the total student population across all levels. This figure rose to 109,000 in 2022/2023, driven by the lingering economic impacts of the Covid-19 pandemic and growing poverty (UNICEF, 2023). Beneath this crisis lie deep social and regional inequalities. While primary school enrollment is high—with a completion rate of about 95%—the situation worsens significantly in post-primary education. In rural areas, upper secondary school completion drops to 30%, compared to 57% in urban zones. Boys are more likely to drop out than girls, especially during lower secondary school, where dropout rates are highest. Key factors behind school abandonment include the cost of education, long distances to schools, economic insecurity, and a lack of future job prospects (UNICEF, 2023).

This study aims to contribute to the ongoing policy debate by evaluating the causal effect of the Amen Social Program on school attendance among poor children aged between 6 and 18 years. To do this, we use a Fuzzy Regression Discontinuity Design (FRD) based on the national Proxy Means Test (PMT) threshold and the last available data from the 2021 National Survey on Household Budget, Consumption and Living Conditions (EBCNV). This methodological choice allows us to assess whether households just below the eligibility threshold—who are more likely to receive the transfer—exhibit better educational outcomes than those just above it. By focusing on households located near the eligibility cutoff, the analysis isolates the program's impact on the school attendance of children aged 6 to 18. Specifically, the study has two main objectives. First, it evaluates the causal effect of unconditional PCT on the school attendance of children aged 6–18 within beneficiary households. Second, it contributes to the broader academic and policy debate on the efficiency of targeting systems and conditional or unconditional cash transfers in middle-income countries.

The rest of the paper is structured as follows: Section 2 discuses child poverty in Tunisia, their education, including enrolment, dropout and completion rates, and presents the program description. Section 3 outlines the data and identification strategy. Section 4 reports and discusses the results, and Section 5 concludes.

2. Background

2.1. Child poverty in Tunisia

In Tunisia, children are among the first victims of poverty, both because of their economic vulnerability, their total dependence on adults, and their marginal position in the hierarchy of family budget priorities. Their already fragile situation has deteriorated significantly in recent years, under the combined effect of recurrent economic crises, the rising cost of living, the Covid-19 pandemic, and a gradual weakening of social safety nets. This reality is particularly worrying in inland regions, isolated rural areas, and informal peri-urban areas, where children are exposed to multidimensional precariousness: material deprivation, inadequate housing, food insecurity, but also limited access to quality public services, particularly in the field of education (Kokas et al., 2021; El-Kogali and Krafft, 2015; UNICEF, 2023).

Between 2020 and 2023, child poverty in Tunisia worsened as a result of several successive economic shocks, including the Covid-19 pandemic, inflation, and droughts. According to UNICEF (2024), 26% of Tunisian children were living below the national poverty line in 2021, compared to 16.6% for the population as a whole. In total, about 826,000 children live in poverty in Tunisia, roughly one in four of the country's 3.2 million children under the age of 18. Among them, 162,000 are in extreme poverty, representing 5.1% of all children. Child poverty far exceeds that of adults, making it a major social issue for the country's future. Regional inequalities are marked: in the Centre-West, a particularly disadvantaged region, one in two children lives below the poverty line, highlighting the depth of territorial disparities (UNICEF, 2024). Before the pandemic, the child poverty rate in Tunisia was estimated at around 19% in 2018 (AfDB, 2023). The Covid-19 crisis lead to a sharp increase. By 2020, the rate has risen to 29%, affecting more than one million children (AfDB, 2023). Thanks to a partial economic recovery and emergency support measures, it declined slightly to 26% in 2021 (UNICEF, 2024).

Persistent economic challenges, including high inflation, slow economic growth, and a prolonged drought, have exacerbated poverty levels. In 2023, child poverty climbed to 28.4%. Extreme child poverty has also increased, from 5.1% to 5.8% over the same period. In comparison, the national poverty rate rose from 16.6% in 2021 to 18.4% in 2023, confirming that poverty hits children harder than the rest of the population. Beyond income deprivation, child poverty in Tunisia also encompasses various forms of multidimensional deprivation. According to UNICEF, one in two Tunisian children suffers from multiple deprivations: limited access to education, health care, adequate food, drinking water and decent housing (UNICEF, 2024). In other words, 50% of children experience at least one severe form of deprivation, which reveals a multidimensional poverty that is much more widespread than financial indicators alone suggest.

Table 1: Evolution of poverty in Tunisia (2018-2023): children vs. total population

Year	Child poverty rate (%)	Poverty rate (total population) (%)
2018 (before the Covid-19 crisis)	19	15
2020 (Covid-19)	29	21
2021	26	16.6
2023	28.4	18.4

Source : (INS, 2023); UNICEF & CRES (2024); UNICEF (2020, 2024).

2.2. Education in Tunisia: Enrolment, Drop-out and Completion Rates

Education is a central issue for human development in Tunisia, with a historically high rate of primary school enrolment, a symbol of the efforts made since independence to guarantee universal access to basic education. However, despite these initial advances, the Tunisian education system is now facing growing challenges, including a gradual decline in enrolment rates and a worrying drop-out rate, particularly at the secondary level. These developments reflect not only structural difficulties within the education system, but also the cumulative effects of social, territorial and economic inequalities that weigh on the educational trajectories of children and adolescents.

The primary school enrolment rate in Tunisia has been gradually declining over the past ten years. According to a national Multiple Indicator Cluster Survey (MICS-2023), this rate decreased from 98% in 2012 to 96.9% in 2018, to reach 92.2% in 2023 (INS and UNICEF, 2023). This decrease can be explained by a variety of factors, including socio-economic inequalities, lack of adequate infrastructure in rural areas, and regional disparities in access to education services. In 2022-2023, the number of students enrolled in public primary schools was estimated at 1.22 million, while about 121,579 students were enrolled in private schools, reflecting a clear dominance of the public sector with 91% of the enrolment (INS, 2025a).

Despite free and compulsory schooling up to the age of 16, the drop-out rate remains a concern, particularly at the secondary level. According to 2024 census data, 100,000 students aged 6 to 16 left school in 2024, representing 3.5% of all students (INS, 2025b). The phenomenon is more pronounced in the governorates of Kairouan, Mahdia, and Kasserine, where the dropout rate exceeds 6%.

The completion rate of education varies greatly between levels of education. While 95% of pupils complete primary school, reflecting strong academic continuity at this level, this rate falls to 74% in lower secondary education (middle school), suggesting a gradual disengagement as students' progress. The sharp decline to 49% in upper secondary school, which reveals a high dropout rate before obtaining the baccalaureate (INS, 2021). This trend highlights the difficulties faced by many students in continuing their education after basic education. UNICEF's 2024 annual report likewise attests that while Tunisia has achieved near-universal primary education and high preschool enrollment (89.3% for five-year-olds), yet significant challenges – particularly socio-economic disparities, dropout rates, governance issues, and weak learning outcomes. Although 9 in 10 children complete primary school, only 7 out of 10 complete junior high school, and only 46.6% of children from the poorest households (UNICEF, 2025).

According to Kokas et al., (2021), children living in the poorest households were less likely to attend school. This kind of deprivation decreases human capital accumulation among the youngest individuals and reduces the ability of poor households to seize future economic opportunities. Kokas et al., (2021) showed that children in Tunisia are expected to complete 10.2 years of schooling by age 18, but once adjusted for learning quality, this amounts to only 6.3 effective years – leaving a learning gap of 3.9 years. The ESCWA's report on multidimensional poverty in Tunisia showed that by shifting from a definition based on completing primary school to one based on completing secondary school, educational deprivation increases sharply, revealing a substantial gap in secondary education in Tunisia. Similarly, when considering all children aged 6 to 18, the rate of non-attendance or school delay rises to 18.7%, indicating that many adolescents are either not enrolled or are at least two years behind their expected grade level (ESCWA, 2017).

2.3. Program description

Social protection policy in Tunisia has undergone a gradual transformation over the decades, shifting from a model of universal assistance, based on national solidarity, to a more targeted and modernized approach focused on efficiency and equity. This transition has occurred in a context of socio-economic change, characterized by increasing urbanization, diversification of social needs and growing budgetary pressures on the State. These dynamics reflect ongoing efforts by public authorities to rationalize social interventions, strengthen mechanisms for targeting vulnerable populations, and enhance the impact of transfer programs. They also demonstrate a commitment to addressing persistent challenges of poverty, precariousness and social exclusion in a more appropriate and sustainable manner, relying on modern management tools such as integrated information systems and score-based targeting models.

Created in 1986 as a monthly unconditional cash transfer, the *Programme National d'Aide aux Familles Nécessiteuses* (PNAFN)[4] is Tunisia's main social protection program targeting individuals unable to work due to old age, disability, or chronic illness, as well as those without family support (Nasri et al., 2022).[5] Since the 2011 revolution, the PNAFN has expanded its coverage by 92%, reaching approximately 260,000 families in 2020 – about 8.4% of the total population. This marks a considerable extension of cover compared to its launch in 1986 when it covered only 74,000 families, and even compared to the pre-revolution estimates of 2009, when it covered only 115,000 families.

Concurrently, the average monthly transfer increased from TND 56.7 in 2010 to TND 180 in 2020 (around USD 67 per month). The non-contributory social protection program also provides access to public healthcare, either at reduced fees (*Assistance Médicale à tarif Réduit* – AMG II) or entirely free of charge (*Assistance Médicale Gratuite* AMG I). As of 2015, AMG I covered all households benefiting from the PNAFN. In 2023, about 263,000 households benefited from AMG I, and around 620,000 households from AMG II. The *Programme d'Allocations Scolaires*, an additional monthly cash transfer for PNAFN households with school-age children, was introduced in 2007 and aims to support children's access to education. By the end of 2013 almost 80,000 received the school allowance.

Despite its importance, the PNAFN cash transfer program has several structural limitations that hinder its effectiveness (Ben Cheikh et al., 2017; ILO 2011; Nasri et al., 2024). It is still based on a set of ad hoc legislative texts (circulars and decrees), which undermines its consistency and updating. The targeting criteria are essentially qualitative, difficult to verify, and non-objective (such as the criterion of "lack of income", which remains complex to monitor) leading to significant errors of inclusion and exclusion. The quota system by administrative area (governorate) also limits the fairness of targeting. In addition, the lack of a reliable information system complicates the traceability, monitoring, and use of data. The operational management of the program also suffers from delays, particularly in the processing of applications, the planning of field surveys, and decision-making. Additionally, several studies show low coverage of the poorest households (CRES and World Bank, 2022; Nasri et al., 2024). According to 2013 World Bank study, 42% of Tunisia's poorest quintile do not receive any form of assistance, either from PNAFN or from AMG II (World Bank, 2013, CRES and World Bank, 2022). At the same time, the exclusion error was particularly high. A joint study by the CRES and the AfDB revealed that 87% of poor households and 85% of very poor households did

[4] The National Program for Needy Families (PNAFN) was introduced by Circular No. 5 of the Ministry of Social Affairs (MoSA) on 16 May 1986. Subsequently, Decree No. 98-1812 of 21 September 1998 and Decree No. 98-409 of 18 February 1998 established two programs providing access to public medical services, either free of charge (Free Medical Assistance – AMG I) or at a reduced rate (Reduced-Tariff Medical Assistance – AMG II).
[5] Eligibility criteria are listed in Circular No. 5 of the MAS of 16 May 1998.

not benefit from the AMG card, even though it is dedicated to free healthcare for the poorest (CRES and AfDB, 2017). Moreover, in the absence of recertification mechanisms and updated information on beneficiaries, roughly 30% of PNAFN beneficiaries have been in the program for more than 20 years (Ben Cheikh et al. 2017). These limitations reveal the need for a thorough review of eligibility criteria and the targeting model in order to improve the program's performance.

Facing this situation, in 2013, the government embarked on a social protection reform to make national systems more integrated, financially sustainable, and better targeted (World Bank, 2022). To this end, in January 2019, the Tunisian Parliament legally established a new program called the AMEN social, which replace the PNAFN and AMG, based on a new targeting approach to identify the poor and vulnerable populations. AMEN social program is an extension of social protection in Tunisia that follows already existing programs in several developing countries, such as the Tayssir program in Morocco (Benhassine et al., 2015), Progresa-Oportunidades-Prospera (POP) in Mexico (Skoufias et al., 2001; Masino et al., 2020; Villa and Niño-Zarazúa, 2019), *Takaful and Karama cash transfer program in Egypt* (Breisinger et al., 2018; ElDidi et al., 2018), and Bolsa Familia in Brazil (Neves et al., 2022; Chioda et al., 2016).

Under the impetus of the Ministry of Social Affairs (MoSA), and with the technical and financial support of the World Bank, several initiatives have been launched. One of the most important was the creation of a centralized database of socio-economic information on vulnerable families. This database was built from the AMEN national survey, conducted in 2013, which collected data on about 900,000 households, forming the first National Social Registry in Tunisia (CRES and World Bank, 2022). This register was designed to provide an objective basis for a standardized assessment of living conditions, based on data on income, household composition, type of housing, and property held. At the same time, Tunisia has formally adopted the Proxy Means Test (PMT) as a targeting method. This approach was institutionalized by the Organic Law No. 2019-10 known as "Amen Social", promulgated in January 2019, which now provides a framework for social assistance on the basis of transparent and objective criteria (CRES and World Bank, 2022).

Thus, the identification of beneficiary households is currently based on the PMT socio-economic scoring model. PMT model is the most suitable targeting method to predict income and poverty status of households in developing countries for many raisons (Banerjee et al., 2020; Brown et al., 2018; Fiszbein and Schady, 2009). First, like many middle-income countries, the informal sector plays a central role in Tunisia's economy, accounting for nearly half of all jobs.[6] The high informality limits

[6] In 2014, the national informal employment rate in Tunisia was estimated at 25.8%; 31.7% of which was for men and 10.7% for women (Ben Cheikh and Moisseron, 2020). In 2019, the estimated rate rose to 43.9%,

the possibility of accurately assessing individuals' incomes through traditional administrative data (CRES and World Bank, 2022). Second, the implementation of more sophisticated methods, such as the Means Test, relies on the availability of comprehensive and reliable administrative databases on individuals' incomes. However, in Tunisia, this information is partial and incomplete, unlike in countries where the formal sector is more developed. Although several administrative files allow for partial estimates of the incomes of workers in the formal sector, essential data for other targeting models, such as the Hybrid Means Test (HMT) model, remain inaccessible.

The adoption of the PMT model is based on a standard of living index calculated from a set of observable household characteristics (such as geographic location, demographic and socioeconomic characteristics of household members, housing, ownership of durable goods, and access to basic services), in accordance with the specifications of the Amen Act (Article 8 of the Law of the Amen Social program). To ensure the relevance of the PMT model, the variables used must be strongly correlated with the standard of living of households (income or consumption) and must comply with strict identification criteria (Coady et al., 2004). Better targeting can ensure lower subsidy costs and reduced inclusion and exclusion errors. Grosh (1994) compared numerous social programs in Latin America and concluded that PMT model produced the best targeting outcomes, measured in terms of reducing inclusion errors, whereby a non-poor person is counted as poor (Brown et al., 2018).

3. Data and identification strategy

3.1. Data and descriptive statistics

This study uses microdata from the 2021 National Survey on Budget, Consumption, and Living Standards (EBCNV), conducted by the National Institute of Statistics. Originally planned for 2020, the survey was postponed due to the Covid-19 pandemic and ultimately carried out between March 2021 and March 2022. The EBCNV is Tunisia's principal household survey starting in 1968, then in 1974, and from 1980 one has been completed every five years (Betti et al., 2023; INS, 2023). The EBCNV 2021 survey was based initially on a random sample of 21,600 households representing 0.68% of total households in the country (68 surveyed household for every 10,000 household). It is a national representative sample distributed across the 24 governorates, for both urban and rural areas. The 21,600 households were drawn using a two stages stratified random sampling in each governorate. In the first stage a sample of primary units (district) is drawn with probability proportional to their size (PPS) in number of households. The district was defined by the General

indicating an increase compared to 2014, although it remained lower than the levels observed in Morocco (77.3%) and Egypt (62.5%) (Lopez-Acevedo et al., 2023).

Census of Population 2014 as a geographic area that contains on average 70 households. In the second stage of selection, 12 households are selected per primary district (sampled district). A second sample of 12 households is selected to be used as a substitutive sample if the interviewer failed to get contact with the originally selected household. During the 2021 survey, 17,394 out of 21,600 households were successfully interviewed, yielding a response rate of 80.53%.

The main purpose of the EBCNV 2021 survey is to provide information on households' acquisition of goods and services for consumption. The information collected from direct observation of household expenditure enables us to assess the situation and evolution of the standard of living and lifestyle of households and the Tunisian population. More specifically, the survey collects information related to household composition; housing and access to basic services; consumption and food security; education attendance; health conditions, chronic diseases and disabilities; cash transfers and financial aid; access to digital technologies, etc. (INS, 2023). The EBCNV 2021 also allows identification of the poor population and the drawing up of a profile of them. Poverty is measured using the cost-of-basic-needs (CBN) method, the approach adopted by INS in line with the World Bank's methodology (see Ravallion (2016) for more details).[7] An individual or a household is considered as poor if his/her per capita expenditure (or income) falls below a minimum level poverty line. The poverty rate stands at 16.6% in 2021 (12.7% in urban area vs. 24.8% in rural area), compared to 15.2% in 2015, and 20.5% in 2010 (INS, 2013). The poverty rate classified as "severe or extreme" stands at 2.9% in 2021, compared to 2.9% in 2015, 6% in 2010, and 7.4% in 2005. The extreme or severe poverty rate remains unchanged from 2015 at around 2.9%, and drown by 51% compared to 2010 (6%) – Table (2).

Table 2: Poverty rate and extreme poverty rate, 2005-2021 (%)

	Extreme poverty (%)				Overall poverty (%)			
Poverty measures	2005	2010	2015	2021	2005	2010	2015	2021
Urban	3	2.1	1.2	1.7	14.8	12.6	10.1	12.7
Rural	15.5	13.6	6.6	5.3	38.8	36	26	24.8
National	7.4	6	2.9	2.9	23.1	20.5	15.2	16.6

Note : Poverty rates at urban and rural areas take into account the population's consumption patterns and the cost of living in the different residential areas. Source : INS (2023).

The analysis focuses on the target population of the Amen cash transfer program, specifically households interviewed in the 2021 EBCNV that include at least one child aged 6 to 18. The target population is further characterized by program eligibility requirements, which typically include holding an AMG I (White card). Beneficiaries of the AMG I are almost systematically eligible for the

[7] "...The most important basic need is clearly the food expenditure necessary to attain the food-energy intake required to support normal activity levels. This is then augmented by an allowance for non-food goods" (Ravallion, 2016, p. 194).

monthly cash transfer, making this a crucial inclusion criterion. Other requirements include not being affiliated with a social security fund, and generally being located in the second decile of the PMT score (identified as the priority area of eligibility).To ensure consistency with the identification strategy, the sample is restricted to households for which the PMT score is available and falls within a window around the eligibility cutoff. All of this ensures a coherent and analytically relevant sample for estimating the program's effects.

The empirical analysis, based on a Fuzzy Regression Discontinuity (FRD) design, draws on a set of key variables from the 2021 EBCNV survey. Each variable plays a distinct role in targeting Poor beneficiaries households or in assessing the causal impact of the AMEN cash transfer program. Income is almost exclusively used to measure the well-being of the household (Deaton, 1997). An extensive literature examines the effects of low income on child outcomes such as test scores, behavior problems, and health (Mayer, 1997; Mayer, 2003; Deaton, 1997). In most developed countries, analyses of material living standards have generally used household income data, or components of income such as earnings (Balestra and Oehler, 2023). However, in most developing countries, where informality remains high, it is still difficult to obtain credible information on household income, whether from administrative sources or household surveys (Deaton and Grosh, 2000; Ravallion, 2003).[8] Tunisia is no exception to this overall patten, as reliable measures of household income remain particularly difficult to collect. It should, however, be noted that Tunisia, with the support of the World Bank, has recently launched the first survey of its kind to test the possibility of integrating an income module into the national consumption survey in the future. This initiative provides an estimate of household income based on wages and various income-generating activities, such as agriculture and ownership of durable goods.

Logarithm of annual per capita expenditure : The logarithm of annual per capita expenditure is the core welfare metric used to build the PMT model in our case study. It is the dependent variable in the initial multiple linear regression used to estimate the PMT score. The annual per capita expenditure covers all goods and services acquired for consumption purposes (purchased, self-produced, etc.), including the estimated rent that owner-occupied households or those living rent-free would pay if they were renting (INS, 2023). The average annual household consumption expenditure, derived from the 2021 EBCNV, is estimated at the national level at TND 20,328 (TND 22,152 in urban areas and TND 16,065 in rural areas). In current dinars, average annual expenditure per capita stands at TND 5,468 in 2021, compared to TND 3,871 in 2015, representing a nominal increase of 41.3% over

[8] See Deaton, (1997) for an informative discussion of income and consumption measurement issues in developing countries.

the period 2015-2021. This increase corresponds to an average annual growth rate of 5.9% (Table 3). At constant prices, expenditure remained almost stagnant over the period 2015-2021.

Table 3: Household and per capita expenditures, 2015-2021

Category	2015 EBCNV	2021 EBCNV	Average annual growth (%)
Urban area			
Average household expenditure per year	17365	22152	4.1
Average per capita expenditure per year	4465	6141	5.5
Urban population	7649278	7991848	0.73
Rural area			
Average household expenditure per year	11204	16065	6.2
Average per capita expenditure per year	2585	4041	7.7
Rural population	3531343	3767241	1.08
National average			
Average household expenditure per year	15561	20328	4,6
Average per capita expenditure per year	3871	5468	5,9
Total population	11180621	11759090	0,84
Average per capita expenditure by quintile			
Quintile 1	1392	2014	6,3
Quintile 2	2228	3258	6,5
Quintile 3	3014	4382	6,4
Quintile 4	4176	5921	6
Quintile 5	8548	11767	5,5

Notes : Authors' calculations based on the 2015 and 2021 survey data.

The PMT score is the central forcing variable (or running variable) of the Fuzzy RDD design. It provides a synthetic estimate of the household's standard of living and determines their theoretical eligibility for the AMEN cash transfer program. The score is constructed using a multiple linear regression model, using the log of expenditure as dependent variable and a set of covariables covering socio-demographic, economic, educational, and health to predict a household's welfare level. The analysis then examines the causal effect of the Unconditional Cash Transfer by exploiting the discontinuity around the empirical eligibility cutoff of this score. Below is a brief description of these covariables.

Education outcome : This is the main outcome variable of interest (dependent variable) in the second stage of the FRD analysis, used to measure the Unconditional Cash Transfer program's impact. It is a binary variable defined at the household level, taking the value 1 if at least one child aged 6 to 18 is in school. This age range (6 to 18) corresponds to the compulsory age of schooling in Tunisia, covering the formal cycles: primary, upper basic cycle, and secondary. The FRD analysis estimates the Local Average Treatment Effect (LATE) of the cash transfer on this schooling outcome, specifically for households near the PMT eligibility cutoff.

Household characteristics : This group includes a set of variables from the EBCNV 2021 survey at the household level, including the educational attainment of the head of household, housing conditions, the geographical area of residence, etc. These characteristics are also included as covariates in the final FRD model to test the robustness of the causal impact estimate, ensuring that the estimated effect is not due to other socio-economic differences between households on either side of the cutoff.

3.2. Methodology

This section outlines the methodology used to estimate the causal effect of the Amen permanent Cash Transfer program on children's schooling, grounded in the structure of the program's eligibility mechanism. The approach is a Fuzzy Regression Discontinuity (FRD) design.

3.2.1. The Proxy Means Test Model (PMT)

The PMT is an econometric model used by social protection programs to estimate a household's welfare level in the absence of reliable income data. As noted before, empirical studies on performance in targeting incidence suggest that the PMT model works well for developing countries, where a large proportion of households are self-employed or informally employed (Grosh, 1994). The results found, using the PMT model, are very encouraging. For example, in Chile and Mexico, approximately 90% of social assistance reached the bottom 40% of the population when a PMT model was adopted (Sebastian et al., 2018). In the case of Tunisia, due to the absence of reliable and available data on household incomes and the presence of a relatively high rate of informality, the PMT can be used as an appropriate targeting model for non-contributory social assistance programs currently revolve around the Amen Social scheme (PNAFN and AMG II).

The PMT model is officially endorsed by the MoSA to identify the categories eligible for the Amen social program and to classify them into poor and low-income groups, in accordance with Art. 2 of Organic Law N° 2019-10 of 30 January 2019 establishing the Amen Social program. The criteria for beneficiary selection and eligibility are established by the order of the MoSA of 19 May 2020. This order covers the definition of a scoring model that adopts the proxy means test based on multidimensional deprivation approach and using observable characteristics including :

- Demographic characteristics (age, gender, marital status, family size);
- Geographical characteristics (governorate, environment),
- Education (level of education);
- Health (disability);
- Professional and economic situation (professional status, nature of work, economic characteristics of the family);
- Housing characteristics (housing status, type of housing, housing characteristics, facilities);
- Access to basic public services (primary school, secondary school, health center).

The first PMT model was developed by CRES and World Bank (2022), combining data from the EBCNV 2015 and the Amen Social program social survey.

The PMT score is constructed by predicting a measure of welfare—specifically the logarithm of annual per capita consumption, using observable household characteristics. The final PMT model allows 77% to accurately identify the poorest 40% of the population. The PMT score decision was compared to that of the social worker regarding the eligibility of the poorest 40% for social benefits, and the compliance rate was around 82% (MoSA, 2022).

In this work, we try to identify from the EBCNV 2021, the same variables used by the MoSA in order to estimate an updated version of the PMT model. A consolidated household-level database was constructed by merging four complementary datasets covering economic characteristics and poverty, living conditions, health, and education. Using a unique common identifier, this integration produced a multidimensional dataset that captures poverty, housing conditions, schooling and literacy outcomes, and access to healthcare—providing a robust foundation for both the PMT model and the impact evaluation of the Cash Transfer under program Amen. As mentioned below, the PMT construction follows the methodological framework developed by CRES and the World Bank, grounded in empirical evidence from the 2015 National Survey of Budget, Consumption and Living Standards and aligned with national social assistance regulations. All potentially relevant variables were incorporated with household sampling weights, and the model was specified as a log-linear regression of per capita consumption on a set of socio-demographic, housing, and asset-related characteristics. More formally, we estimate the following equation :

$$y_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ik} + \varepsilon_i \quad \text{(eq. 1)}$$

Where y_i is the natural logarithm of the annual per capita consumption of household i, used as a proxy for well-being. X_{ik} is a vector of covariates, including socio-demographic characteristics, employment status, housing conditions, access to facilities, and other relevant factors.

The PMT score is then based on :

$$\hat{y}_i = \hat{\beta}_0 + \sum_{k=1}^{K} \hat{\beta}_k X_{ik} \text{ (eq. 2)}$$

The most common method in practice for estimating $\hat{\beta}_0$ and $\hat{\beta}_k$ $(k = 1, \dots, K)$ is Ordinary Least Squares (OLS) using log consumption per capita as the dependent variable.

3.2.2. The Fuzzy Regression Discontinuity Design (RDD)

The PMT score of (eq.2) serves as the running variable (or forcing variable) in the Regression Discontinuity Design (RDD design). The RDD is a quasi-experimental method used to estimate causal effects when treatment assignment is based on a cutoff (or threshold) in a continuous variable (PMT score in our case). This cutoff introduces a discrete change in treatment probability based on the continuous PMT score. This is the central insight behind the RDD: when households just above and just below the threshold are otherwise similar, comparing their outcomes allows us to identify local average treatment effects. Two essential assumptions should be met to provide a valid estimate of the local causal effect :

- Continuity assumption: The distribution of the ranking variable must be continuous around the threshold. In other words, there must be no strategic manipulation on the part of the participants to influence their position relative to the cutoff (Hahn et al., 2001; Imbens and Lemieux, 2008; Lee and Lemieux, 2010). This hypothesis can be tested empirically using the McCrary density test, which checks for no discontinuity in the distribution of the variable at this level (McCrary, 2008; Villamizar-Villegas et al., 2018).
- Local comparability assumption: Units close to the threshold must be similar, on average, in all their observable and unobservable characteristics (except treatment). This hypothesis is generally verified by analyzing the continuity of covariates on either side of the threshold (Imbens and Lemieux, 2008; Lee and Lemieux, 2010).

However, in practice, some households on either side of the threshold receive or do not receive the transfer, contrary to what the rule would stipulate (i.e., the cutoff does perfectly determine treatment status). In order to overcome this problem of imperfect assignment (noncompliance problem), we use the Fuzzy Regression Discontinuity Design method (FRD). This approach exploits not a discontinuity in the treatment itself, but a discontinuity in the probability of receiving the treatment at the threshold level, thus allowing us to identify a Local Average Treatment Effect (LATE) even in the presence of partial non-compliance with the assignment rule. The FRD uses the eligibility status as an instrumental variable for the actual program participation, allowing us to estimate the LATE.

In the context of our impact assessment, the use of a fuzzy discontinuity regression is a natural choice, given the specificities of the device studied. Indeed, although eligibility for the PCT is based on a quantitative criterion defined by a threshold, the actual allocation of the treatment does not operate in a totally rigid way: some eligible units do not benefit from the intervention, while others, which are not eligible, nevertheless access it. This partial non-compliance with the allocation rule justifies the adoption of a fuzzy RDD design, which allows for the exploitation of discontinuity in the probability of processing around the threshold, rather than in the processing itself (Imbens and Lemieux, 2008; Cattaneo et al., 2020).

In a FRD, identification is based on observations very close to the eligibility threshold, where assignment to treatment can be considered quasi-random (Hahn et al., 2001; Lee and Lemieux, 2010). By focusing on a narrow window around the cutoff, we ensure that households just above and just below the threshold are comparable on all observed and unobserved dimensions, except for their probability of receiving the treatment. The estimation is therefore carried out within a restricted bandwidth around the threshold, in which the assumption of continuity of potential outcomes is most credible (Imbens and Lemieux, 2008). To achieve a rigorous compromise between bias and variance, we adopt the nonparametric procedures for optimal bandwidth selection proposed by Imbens and Kalyanaraman (2012), which are considered the gold standard in the empirical literature.

The empirical design relies on three variables derived directly from the PMT score: Indicator for being below the PMT cutoff (Z_i); running variable (S_i); and interaction term ($Z_i \times S_i$) to capture a possible change in slope at the discontinuity. Z_i is a dummy variable equals 1 when the household's PMT score is less than or equal to the cutoff, and 0 otherwise. The running variable captures the centered running variable defined as :

$$S_i = \text{PMT score}_i - \text{cutoff} \quad \text{(eq. 3)}$$

The interaction term between the dummy indicator and the running variable is included to allow the slope of the regression function to vary on each side of the threshold. Our analysis is restricted to[9] : (i) households that have an AMG I card (While Card); (ii) households who are not affiliated to a social security fund; and (iii) households who are located in the second decile of the PMT score, identified as the priority area of eligibility.

The reduced-form relationship is estimated using the following specification :

$$Y_i = \beta_0 + \tau_{\text{jump}} Z_i + \beta_1 S_i + \beta_2 (Z_i \times S_i) + u_i \quad \text{(eq. 4)}$$

The variation in slope, or "kink," provides evidence of the LATE of the Permanent Cash Transfer for the complier population — that is, households whose probability of receiving the transfer is influenced by the eligibility threshold (Dong, 2018; Imbens and Angrist, 1994). The presence of a

[9] Those criteria are defined by the MoSA. The threshold used in our analysis corresponds to the maximum score observed within this subpopulation.

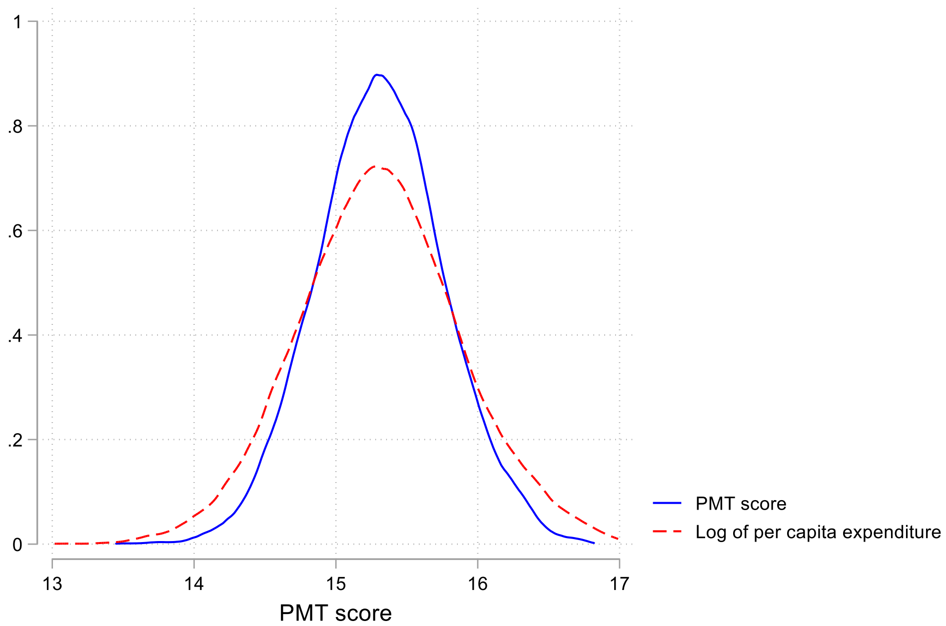
statistically significant kink, even without a discrete jump at the cutoff, suffices to identify a LATE in this econometric framework.

4. Results and Discussion

4.1. PMT scoring

Table (4) presents a summary of the final PMT regression model. It is estimated on a sample of 17,391 households using a stepwise regression[10] procedure to select the most relevant predictors. Figure (1) compares the distribution of the PMT score with that of the logarithm of per capita expenditure. The two curves are very close and follow similar trends, showing that the PMT closely reflects variations in actual household expenditure. The absence of visible discontinuity in these distributions supports the continuity assumption required in an RDD approach.

The PMT has an adjusted R-Squared just above 0.58, which is in the range of 0.4 to 0.65 commonly reported in other PMT studies (Brown et al., 2018; Sebastian et al., 2018). This indicates that the retained predictors capture a substantial share of the determinants of welfare, providing a solid basic for the targeting mechanism. In addition, the performance of our model is not far from that of the model adopted by the ministry of Social Affairs to implement the PMT approach using the Amen Social survey data (MoSA-PMT), whose explanatory power was estimated at 0.62.



[10] The stepwise regression procedure starts with all variables and then automatically eliminates those that do not contribute statistically significantly (p-value > 10%). This process, widely used in PMT models, simplifies the structure of the model without sacrificing its predictive capacity.

Figure 1 : Distribution of PMT Score and Log Per Capita Expenditure

A second central performance criterion is the ability of the PMT model to simultaneously minimize exclusion and inclusion errors (Coady et al., 2004). Our PMT model shows that, although effective in identifying a majority of poor households, it still faces a non-negligible exclusion error (34.8%). The inclusion error (12.5%) remains within acceptable thresholds, helping to limit cases of over-targeting. These results are consistent with levels observed in other PMT applications in middle-income countries, including those reported by the World Bank (2015) and the CRES and World Bank (2022) for Tunisia.[11] According to the CRES and Word Bank (2022), the exclusion errors range between 30% and 40%.

The two graphs of Figure (2) compare the distributions of per capita expenditure (in log) and PMT scores for three groups: non-beneficiary households, PNAFN/AMG I, and AMG II. In terms of per capita expenditure, PNAFN/AMG I beneficiaries appear poorer on average, with a density shifted to the left compared to non-beneficiaries, while AMG II households are in an intermediate position. The same hierarchy is found for the PMT score: the distribution of PNAFN/AMG I beneficiaries is more concentrated around lower values, consistent with a more vulnerable profile. The similarity of the rankings between the two variables suggests that the PMT score accurately reflects the economic well-being gradients observed in expenditure.

[11] In the MENA region, the following countries employ the PMT method in their main social safety net (SSN) programs: Morocco, Algeria, Jordan, Egypt, Kingdom of Saudi Arabia, Palestine, Tunisia, Yemen and Lebanon. Globally, close to 40 countries use the PMT method (World Bank, 2020).

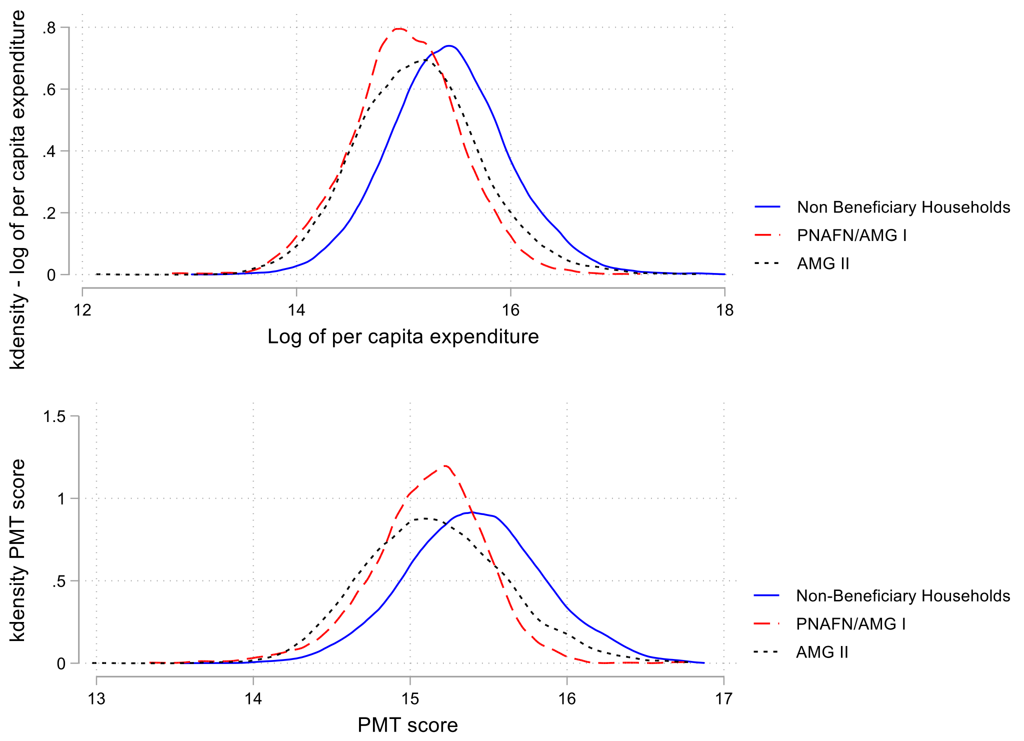


Figure 2: Distribution of Per Capita Expenditure and PMT Score by Program Eligibility Status

Table (4) highlights key demographic, educational, housing, and regional variables. Positive coefficients indicate factors associated with higher predicted consumption, while negative coefficients show reductions in predicted consumption. Notably, household size has a strong negative effect on consumption: each additional person reduces per capita consumption by approximately 16.4%. The results also highlight a significant premium for the level of education of the head of the household. Compared to no education head, primary education increases consumption by around 2.8%, secondary education by 6.3%, and higher education by 12.6%, confirming the key role of human capital. Housing conditions and the ownership of durable assets are also strongly and positively correlated with consumption. The presence of a living room, a solid building, and the ownership of equipment such as a refrigerator, washing machine, computer, or air conditioner are associated with higher levels of consumption, with effects ranging from 6.8% to 10.7%, suggesting their ability to capture the material well-being of households. Finally, a marked spatial gradient emerges: all regions, relative to the Great Tunis (reference region), have significantly lower levels of consumption. The decline ranges from 14% in the Northeast to more than 24% in the Center-West, indicating persistent territorial disparities.

Table 4: Key Predictors of Log Consumption per Capita (PMT Model), stepwise regression

Variable	Coefficient	Standard Error	Significance
Demographics			
Age of household head	3.65e-05	(2.52e-06)	***
Single	0.128	(0.016)	***
Widower	0.102	(0.010)	***
Household Size	-0.164	(0.002)	***
Rural	-0.015	(0.008)	*
Education (No education as reference)			
Primary	0.028	(0.009)	***
Secondary	0.063	(0.011)	***
Higher Education	0.126	(0.015)	***
Housing / Assets (Yes/No)			
Living Room	0.068	(0.008)	***
Construction: building	0.077	(0.014)	***
Refrigerator	0.080	(0.018)	***
Washing machine	0.091	(0.009)	***
Computer	0.087	(0.008)	***
Air Conditioner	0.107	(0.008)	***
Region (Great Tunis as reference)			
Northeast	-0.141	(0.011)	***
Northwest	-0.157	(0.012)	***
Central West	-0.244	(0.013)	***
Southeast	-0.150	(0.014)	***
South-West	-0.184	(0.016)	***
Constant	15.51	(0.034)	***
Observations	17,391		
Adjusted R-square	0.581		
F-statistic	377.57***		

Notes: Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. Although the full PMT model includes 71 predictor variables, only the most theoretically and empirically relevant variables are presented in this table for clarity. Reference categories are: married (for marital status), no education (for education), rudimentary housing (for construction), urban (for rural), and Greater Tunis (for region).

4.2. FRD results

The FRD analysis of the cash transfer program shows no significant discontinuity at the dummy indicator (Table 5), consistent with a fuzzy design where eligibility does not guarantee treatment (Imbens and Lemieux, 2008). Although no clear discontinuity was observed at the threshold, the significant negative interaction term indicates a change in the slope of schooling for compliers, reflecting a local causal effect of the cash transfer (−0.103, p = 0.002). Additionally, the positive coefficient (S_i) suggests that the probability of schooling rises as households approach the threshold, consistent with expected progressive effects under partial compliance. This dynamic indicates a more marked increase in schooling among eligible households, reflecting a slope effect, typical in contexts of imperfectly applied treatment, thus confirming a progressive and robust local causal effect in the vicinity of the eligibility threshold.

These results align with previous studies employing fuzzy or kink designs, which find gradual changes near thresholds rather than sharp jumps (Dong, 2018). Restricting the analysis to a ±1.5 bandwidth around the threshold ensures comparison among locally similar units, thereby strengthening the identification of the local causal effect, or Local Average Treatment Effect (LATE). Chib and Jacobi (2016) estimated the returns to compulsory schooling in the United Kingdom using a Bayesian FRD, highlighting a gradual change in earnings close to the threshold, without a clear discontinuity. Similarly, Zhang (2020) observes the absence of a net jump in wages around education reform in Taiwan, explaining this result by the incomplete implementation of education policy. Deiana and Mazzarella (2018), studying the retirement age in Italy, show that a significant change in slope, even in the absence of jumping, can be interpreted as a local causal effect for compliers, by combining the "kink" and "fuzzy" approaches in a coherent econometric framework (for further details on the Regression Kink Design, see Card et al., 2015, Nielsen et al., 2010, and Simonsen et al., 2016).

Table 5: Impact of Cash Transfers on School Enrolment (FRD Estimates)

Variable	Coefficient	Standard Error
Running Variable (S_i)	0.047***	(0.013)
Cutoff_i (Z_i)	0.0135	(0.016)
Interaction Term ($Z_i \times S_i$)	–0.103***	(0.029)
Constant	0.909***	(0.007)
Observations	5,974	

Notes: Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10. The interaction term $Z_i \times S_i$ captures the kink in the regression function.

Figure (3) visually reflects the main findings of the FRD model. Although there is no sharp vertical jump at the PMT threshold—consistent with the non-significant Cutoff_i the dummy indicator , the slopes of the lines before and after the cutoff differ noticeably. this change in slope corresponds to the significant and negative interaction term , indicating that households experience a different trajectory of schooling probability as their PMT score moves away from the threshold. The positive and significant coefficient for the Running Variable (S_i) is also reflected in the graph: the probability of schooling increases as households get closer to the cutoff point. This pattern is typical in fuzzy settings, where treatment is not perfectly implemented, leading to a progressive rather than abrupt change in outcomes around the cutoff. Overall, the figure illustrates a slope change rather than a discontinuous jump, which is theoretically consistent with a fuzzy design. The observed "kink" visually represents the local causal effect for compliers, aligning with the behavior expected in contexts of partial compliance.

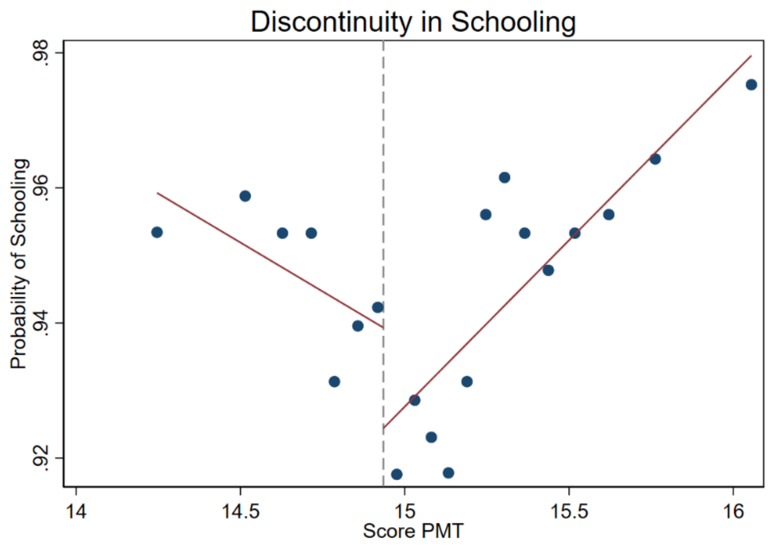


Figure 3 : Effect of cash transfer on schooling: discontinuity at the PMT threshold

4.3. Robustness Check

Table (6) presents the results of the Fuzzy RDD model incorporating socio-demographic covariates to assess the effect of the PCT on children's schooling. The enriched model confirms the robustness of the local effect of the cash transfer for households in the second decile of the PMT score.

Table 6 : Impact of Cash Transfers on School Enrolment, controlling for covariables

VARIABLES	Coefficient	std-error	
Running Variable (S_i)	0.033	(0.015)	**
Cutoff_i (Z_i)	0.005	(0.010)	
Interaction Term ($Z_i \times S_i$)	-0.092	(0.030)	***
Region (Great Tunis as reference)			
Northeast	-0.018	(0.011)	
Northwest	0.010	(0.011)	
Central East	-0.032	(0.010)	***
Central West	-0.035	(0.012)	***
Southeast	-0.005	(0.011)	
South-West	-0.032	(0.013)	**
Household size (= 2 as reference)			
Household Size = 3	0.076	(0.025)	***
Household Size = 4	0.109	(0.025)	***
Household Size = 5	0.141	(0.025)	***
Household Size = 6	0.144	(0.027)	***
Household Size = 7	0.161	(0.029)	***
Household Size = 8	0.141	(0.036)	***
Household Size = 9	0.148	(0.053)	***
Household Size = 10	0.154	(0.078)	**
Household Size = 11	0.158	(0.116)	
Household Size = 12	0.111	(0.163)	
Gender (Male = 1)	0.013	(0.011)	
Education (No education as reference)			
Primary	0.065	(0.010)	***
Secondary	0.109	(0.011)	***

Higher Education	0.112	(0.014)	***
Constant	0.730	(0.026)	***
R-squared	0.047		
Observations	5,977		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The inclusion of covariates such as household size, the education level of the household head (or leader), and regional indicators significantly enhances the rigor of the causal model by accounting for potential confounding variables and reducing unexplained variance. Empirical studies consistently show that adding such controls improves model precision and strengthens causal inference , For example Bloom et al., (2007) provide evidence that incorporating covariates in impact evaluations not only enhances the precision of estimated effects but also adjusts for non-random assignment—or "sorting"—into treatment and control groups, thereby reducing potential bias. So the main effect of the cash transfer interaction remains stable, which testifies to the robustness of the result.

The McCrary density test evaluates whether the running variable—in this case, the PMT score—shows any discontinuity in its distribution at the eligibility cutoff. Such discontinuities would signal possible manipulation or sorting by households to gain program eligibility. Following McCrary's (2008) approach, the test was implemented to verify the integrity of the assignment mechanism. As the p-value is well above 0.05, we do not reject the null hypothesis of the absence of manipulation around the threshold. This reinforces the validity of the FRD strategy used. The McCrary test (p = 0.311) does not detect any significant discontinuity in the density of the running variable (PMT score), which supports the hypothesis of no strategic manipulation around the threshold, a key condition for the validity of the FRD design (see Figure (4) for the manipulation test plot).

Table 7 : Density Manipulation Test (McCrary) around the PMT threshold

Element	Value
Total number of observations	5,974
Observations to the left/right of the threshold	1,915 / 4,059
N. effective used (left/right)	1,093 / 1,340
Core method	Triangular
Polynomial order of estimation (p)	2
Order of bias (q)	3
Estimated CV Method	Jackknife
Estimated Bandwidth (h) (Left/Right)	0.262 / 0.236
Robust statistic	-1.014
p-value (Robust)	0.311

Notes :

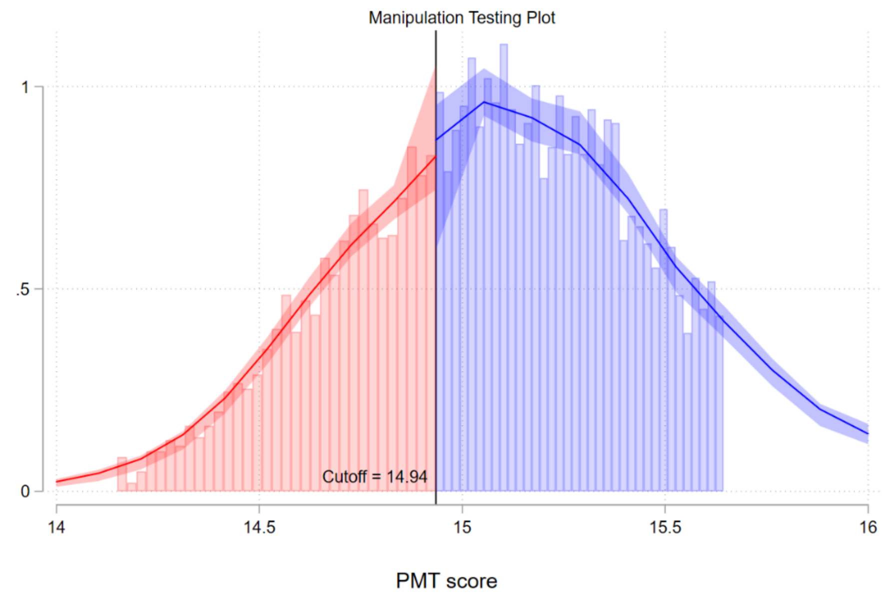


Figure 4 : Manipulation test plot.

Notes : The confidence intervals overlap and the p-value for the overlap size is 0.311, which is bigger than .05. So we can say there is no manipulation.

5. Conclusion

This study evaluated the causal impact of the AMEN Social unconditional cash transfer program on the school attendance of children aged 6–18 in Tunisia. Using data from the 2021 National Survey on Household Budget, Consumption, and Living Conditions (EBCNV), we employed a Fuzzy Regression Discontinuity (FRD) design to isolate the effect of the program on households located near the eligibility threshold of the Proxy Means Test (PMT) score. Our empirical results provide robust evidence that the AMEN Social program significantly increases the probability of school attendance for children in beneficiary households near the cut-off. Although the analysis did not reveal a sharp discontinuity (jump) in schooling rates at the threshold—consistent with the "fuzzy" implementation of the program—we observed a significant "kink" or change in the slope of the schooling probability. This finding indicates a positive Local Average Treatment Effect (LATE), suggesting that for "complier" households at the margin of eligibility, the cash transfer acts as a critical financial buffer that encourages investment in human capital and reduces the opportunity cost of schooling. However, the efficacy of the program is tempered by challenges in targeting accuracy. Our analysis of the PMT model highlights a persistence of targeting errors, with a considerable exclusion error that leaves many of the poorest households outside the program's reach. At the same time, we observed that a notable share of cash transfer beneficiaries are not poor, reflecting an inclusion error that undermines both the equity and efficiency of the system. The "fuzzy" nature of the discontinuity further corroborates discrepancies between theoretical eligibility and actual benefit receipt.

In terms of policy implications, these findings validate the use of unconditional cash transfers as a tool for educational inclusion in Tunisia's post-revolution context. but they also highlight the urgent need for structural adjustments. Crucially, we recommend a re-evaluation of the transfer amount**.** The current monthly allowance is increasingly insufficient given the severe inflationary pressures facing Tunisian households. In an economic environment where the cost of living—and specifically the cost of schooling—is rising, a static transfer value diminishes the program's ability to prevent school dropouts effectively.This is particularly salient given Tunisia's historical identity as a nation that places education at the core of its development model. The recent rise in dropout rates represents a troubling reversal of this legacy. Cash transfers should be viewed as a strategic investment in restoring Tunisia’s human capital. To honor the country's long-standing valuation of education, the government must ensure that the financial support provided is substantial enough to shield children's schooling from economic shocks. Also, persistent targeting lapses—seen in the inclusion of non-poor households and the exclusion of eligible ones—continue to undermine the equity and effectiveness of the Amen social .

Future research should focus on the long-term impacts of these transfers on educational attainment and labor market outcomes, as well as the potential benefits of combining cash transfers with supply-side interventions to improve the quality of education available to vulnerable populations.

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Appendix

Table A.1 : Descriptive Statistics of PMT Model Variables

Variable	Description	Mean	SD
Head and household characteristics			
	Age of Head Squared	3399.264	1617.140
Marital status (Y/N)			
	Single	0.039	0.193
	Widowed	0.146	0.353
	Divorced	0.023	0.151
Education (Y/N)			
	Primary	0.409	0.492
	Secondary	0.283	0.451
	Higher	0.111	0.314
Job (Y/N)			
	Senior Executive	0.078	0.268
	Middle Mgmt	0.026	0.159
	Other Employee	0.128	0.334
	Industry Boss	0.014	0.118
	Artisan	0.037	0.190
	Farmer	0.060	0.238
	Unemployed	0.025	0.156
	Retired	0.218	0.413
Contract (Y/N)			
	Fixed Term	0.260	0.439
	Permanent	0.514	0.500
	None	0.487	0.500
Household Size		3.717	1.531
Household Durable Goods and Dwelling			
Household Asset Ownership (Y/N)			
	Living Room	0.605	0.489
	Cooker (No Oven)	0.438	0.496
	TV (Normal)	0.637	0.481
	DVD Player	0.060	0.238
	Computer	0.264	0.441
	Dining Room	0.263	0.441
	Fridge	0.961	0.193
	Washing Machine	0.811	0.391
	Cooker (w/ Oven)	0.530	0.499
	Microwave	0.236	0.425
	Freezer	0.091	0.287
	Electric Oven	0.482	0.500
	Satellite Dish	0.952	0.214
	Heater	0.383	0.486
	Salon	0.582	0.493
	Dishwasher	0.046	0.209
	Smart TV	0.412	0.492
	Camera	0.047	0.211
	Dryer	0.515	0.500
	Video Games	0.029	0.168
	Iron	0.468	0.499
	Vacuum	0.122	0.328
Dwelling Characteristics (Y/N)			
	Apartment	0.060	0.237
	Collective	0.192	0.394
	Grid (No Bill)	0.047	0.212
	Gas Bottle	0.305	0.460
	Electric	0.068	0.252
	Charcoal	0.268	0.443
	Wood	0.060	0.238
	Animal Waste	0.001	0.025

	Heat: None	0.187	0.390
	Water - Private Cistern	0.009	0.095
	Water - Public Cistern	0.003	0.055
	Water - NGO Fountain	0.048	0.213
Region and Area of residence			
Region (Y/N)			
	North East	0.150	0.358
	North West	0.104	0.305
	Center East	0.229	0.420
	Center West	0.121	0.326
	South East	0.084	0.277
	South West	0.049	0.217
Area of residence (Y/N)			
	Rural	0.300	0.458

Notes : Authors' calculations based on 2021 survey data.

Table A.2: Descriptive statistics for beneficiary and non-beneficiary households.

Variable	Description	Beneficiary households according to PMT cutoff		Non Beneficiary households according to PMT cutoff	
		Mean	SD	Mean	SD
Head and household characteristics					
	Age of Head Squared	2763.7	1288.4	3524.5	1645.7
Marital status (Y/N)					
	Single	0.010	0.101	0.044	0.206
	Widowed	0.052	0.222	0.164	0.371
	Divorced	0.009	0.096	0.026	0.159
Education (Y/N)					
	Primary	0.545	0.498	0.383	0.486
	Secondary	0.185	0.389	0.302	0.459
	Higher	0.012	0.108	0.131	0.337
Job (Y/N)					
	Senior Executive	0.015	0.121	0.090	0.287
	Middle Mgmt	0.007	0.082	0.030	0.170
	Other Employee	0.104	0.305	0.132	0.339
	Industry Boss	0.004	0.067	0.016	0.125
	Artisan	0.024	0.155	0.040	0.196
	Farmer	0.105	0.306	0.052	0.222
	Unemployed	0.078	0.269	0.014	0.119
	Retired	0.053	0.224	0.251	0.434
Contract (Y/N)					
	Fixed Term	0.288	0.453	0.255	0.436
	Permanent	0.296	0.456	0.558	0.497
	None	0.636	0.481	0.458	0.498
Household Size		5.354	1.395	3.395	1.338
Household Durable Goods and Dwelling					
Household Asset Ownership (Y/N)					
	Living Room	0.554	0.497	0.616	0.486
	Cooker (No Oven)	0.439	0.496	0.438	0.496
	TV (Normal)	0.776	0.417	0.610	0.488
	DVD Player	0.015	0.122	0.069	0.253
	Computer	0.050	0.218	0.306	0.461
	Dining Room	0.078	0.269	0.300	0.458
	Fridge	0.939	0.240	0.966	0.182
	Washing Machine	0.582	0.493	0.856	0.351
	Cooker (w/ Oven)	0.502	0.500	0.535	0.499
	Microwave	0.034	0.182	0.276	0.447
	Freezer	0.027	0.161	0.103	0.304
	Electric Oven	0.287	0.452	0.520	0.500
	Satellite Dish	0.934	0.248	0.955	0.206
	Heater	0.128	0.334	0.433	0.495
	Salon	0.321	0.467	0.633	0.482

Dishwasher	0.016	0.124	0.052	0.221
Smart TV	0.218	0.413	0.451	0.498
Camera	0.015	0.121	0.053	0.224
Dryer	0.258	0.438	0.566	0.496
Video Games	0.004	0.060	0.034	0.181
Iron	0.120	0.325	0.536	0.499
Vacuum	0.004	0.065	0.146	0.353
Dwelling Characteristics (Y/N)				
Apartment	0.007	0.083	0.070	0.255
Collective	0.065	0.246	0.217	0.412
Grid (No Bill)	0.081	0.273	0.041	0.198
Gas Bottle	0.181	0.385	0.330	0.470
Electric	0.024	0.152	0.077	0.266
Charcoal	0.428	0.495	0.237	0.425
Wood	0.205	0.404	0.031	0.174
Animal Waste	0.003	0.053	0.000	0.013
Heat: None	0.147	0.354	0.195	0.396
Water - Private Cistern	0.021	0.144	0.007	0.082
Water - Public Cistern	0.009	0.092	0.002	0.044
Water - NGO Fountain	0.141	0.348	0.029	0.168
Region and Area of residence				
Region (Y/N)				
North East	0.136	0.342	0.153	0.360
North West	0.170	0.376	0.091	0.287
Center East	0.157	0.364	0.244	0.429
Center West	0.327	0.469	0.080	0.272
South East	0.108	0.311	0.079	0.270
South West	0.060	0.237	0.047	0.212
Area of residence (Y/N)				
Rural	0.657	0.475	0.229	0.420

Notes : Authors’ calculations based on 2021 survey data.