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Harnessing Administrative Data for Impact: The Case of Jordan's Unified Cash Transfer Programme

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Abstract

Over the past decade and a half, Jordan has grappled with persistent economic challenges, including slow growth and deep-rooted structural issues. In 2018, poverty stood at 15. 7%, which is likely to increase further due to recent economic shocks. In response, Jordan has scaled up its social protection system, particularly through the National Aid Fund (NAF), which administers key social assistance programmes. NAF's Unified Cash Transfer (UCT) programme, launched in 2022, aims to alleviate poverty by providing targeted financial support to vulnerable households. This paper evaluates the short-term impact of Jordan's UCT programme on economic outcomes, living standards, and school attendance, using administrative data from the National Unified Registry (NUR). Using a combination of rigorous methodologies—regression discontinuity design and propensity score matching with difference-in-differences, the study examines whether the UCT alleviates vulnerability and prevents poverty traps. Although there are positive effects on children's school enrolment, the programme shows limited success in increasing household income and asset ownership. The study also assesses the programme's targeting mechanism and data management processes to offer recommendations for future impact evaluations that facilitate improving the effectiveness of the programme in addressing households' socio-economic risks.

JEL Classification: I38, H53, O15

Keywords: Social assistance, cash transfer, targeting, impact evaluation, Jordan

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1 Introduction

The innovative use of data can significantly improve social and economic outcomes—especially for the poor—by generating insights that improve well-being (World Bank, 2021). One such data source is administrative data, typically generated through interactions of individuals or households with public services like schools or tax systems, which can inform policies. Population-level administrative data such as civil registries can inform a wide range of government policies, including social protection policies (Barca, Hebbar, Knox-Vydmanov, & Brzezinska, 2023). These data are less expensive and burdensome to gather, allow tracking over time, and can capture information that is difficult to collect accurately in surveys, which helps minimise errors or biases like social desirability or recall bias (Cole, Dhaliwal, Sautmann, & Vilhuber, 2022). However, challenges persist, including data quality issues, lack of standardisation, and limited access, particularly in low- and middle-income (LMIC) countries. Furthermore, while routine analysis based on descriptive statistics is common, using administrative data for 'rapid analytics' or evaluation of social protection programmes is still rare, with a few exceptions from, *inter alia,* Lesotho, the Philippines, and Mongolia (ADB, 2014; Orbeta, Melad, & Araos, 2021; Pace, Daidone, Bhalla, & Prifti, 2021).

Over the past decades, social protection systems, consisting of policies and programmes aimed at reducing and preventing poverty and vulnerability, have been scaled up globally. Social assistance schemes—particularly cash transfer programmes—gained momentum in LMICs to reduce socio-economic vulnerability and break the intergenerational transmission of poverty (Brooks, 2015; Kawar, Nimeh, & Kool, 2022; Niño-Zarazúa, 2019). A large body of evidence testifies to their positive impacts across many dimensions, such as increased consumption or expenditures (Bastagli et al., 2019; Habimana, Haughton, Nkurunziza, & Haughton, 2021), productive investment (Daidone, Davis, Handa, & Winters, 2019) and in some cases labour outcomes, (Baird, McKenzie, & Özler, 2018; Kabeer & Waddington, 2015) or schooling (Gaentzsch, 2020; Kilburn, Handa, Angeles, Mvula, & Tsoka, 2017), to name a few. While cash transfers can be effective tools for poverty alleviation, their design, implementation, contextual factors and recipient behaviour, play significant roles in determining outcomes (Della Guardia, Lake, & Schnitzer, 2022; Filmer, Friedman, Kandpal, & Onishi, 2018; Kotsadam & Villanger, 2022).

The Hashemite Kingdom of Jordan, a country in the Middle East, has a long tradition of social assistance programmes and subsidies aimed at helping citizens meet their basic needs and reduce poverty-related risks. In this paper, we conduct an impact evaluation of Jordan's Unified Cash Transfer (UCT) programme, relying on Jordan as a useful case study due to its historical reliance on social assistance and recent advancements in its social protection system, as well as the availability of large-scale administrative data. Since the late 1980s, targeted efforts to reduce poverty have been made with the establishment of the National Aid Fund (NAF), an institution designed to provide protection and support to vulnerable households in Jordan. Since then, the country has expanded and strengthened its social protection system. Today, NAF implements various social assistance programmes and initiatives next to its flagship programme, the Unified Cash Transfer, which was launched in February 2022. The UCT's aim is to reduce monetary poverty in Jordan, and in 2023 the programme reached more than 170,000 beneficiary households per month through a Proxy-Means Test (PMT) targeting mechanism.

The study has two main contributions. First, we evaluate the extent to which the UCT programme succeeds in reducing vulnerability and preventing poverty traps among beneficiary households in the period from February 2022 to February 2024. Using administrative data from Jordan's National Unified Registry (NUR) and employing a regression discontinuity design as well as a combination of propensity score matching (PSM) and difference-in-differences (DiD), we study the short-term impact of monthly cash transfers on poverty, economic outcomes, living standards and school attendance. This analysis is based on the notion that the poor tend to be the highly exposed to idiosyncratic and covariate risks, but have few tools to deal with these risks such as formal insurance mechanisms (Holzmann, Sherburne-Benz, & Tesliuc, 2003). As individuals and households try to navigate these risks, social protection programmes and policies can enter as protective or preventive measures that provide immediate relief, or mitigate risks and avert deprivation, respectively, but also promote households' income-generating capacities or transform social norms (Sabates-Wheeler & Devereux, 2007). In the context of Jordan, its social assistance landscape predominantly features reactive and shock-responsive programmes that are protective or preventive in nature (Kawar et al., 2022). Evaluating the impact of the UCT thus becomes essential to gauge its effectiveness with regards to enabling households to manage risks, and to create the evidence base that can support strengthening the technical foundation of social protection efforts in the country.

Second, through a thorough analysis of the UCT's design and data management processes, this study aims to enhance the effectiveness of the programme and sets out to be a foundation for further impact evaluations of Jordan's cash programmes, leveraging the potential of Jordan's National Unified Registry administrative data. Thereby, we aim to foster a productive research-policy partnership by promoting close collaboration between researchers and the Government of Jordan in utilising its administrative data, leading to innovative, policy-relevant studies (Cole et al., 2022).

Our findings are inconclusive. Contrary to the UCT's main objective of poverty reduction in the Kingdom, we find a negative impact on income and assets, that seems to be partly driven by improvements in well-being among non-beneficiary households, and partly by a deterioration among beneficiaries. While household heads are able to improve labour outcomes in some scenarios, these do not necessarily translate into improvements in income, and a possible substitution effect may be at play. The most positive effects are observed regarding children's schooling outcomes, which suggest that children in beneficiary households are more likely to be enrolled in school, and less likely to drop out. Besides this, the process analysis reveals several key areas where data management, process, storage as well as the targeting design can be improved. We identify several key policy recommendations to strengthen the effectiveness and efficiency of Jordan's Unified Cash Transfer programme as well as its data management that can build on this paper as a foundation for future impact evaluations.

The remainder of this paper is structured as follows. Section 2 provides an in-depth background on the context of social assistance and the Unified Cash Transfer programme in Jordan. Data and methods are presented in Sections 3 and 4, and Section 5 provides the results. In Section 6, we discuss the findings, and conclude with policy recommendations in Section 7.

2 Background

Over the past decade and a half, Jordan has been facing challenges with respect to slow economic growth and structural issues that can be attributed, in part, to various external shocks, including regional conflicts. As the population in Jordan has more than doubled from about 5 million in 2000 to more than 11 million in 2022 (World Bank, n.d.-b), pressure on limited public and natural resources has intensified. On top of that, Jordan was affected by price and supply shocks of key imported commodities such as oil and wheat, associated with the Russian war on Ukraine. Despite these global challenges, Jordan has most recently experienced better-than-anticipated growth (2.7% in the first half of 2023), fuelled by a recovery in international tourism, the reopening of the economy after the COVID-19 pandemic, and enhanced export performance (World Bank, 2023a). Moreover, enhanced economic activity had a slight impact on labour market indicators, with unemployment rates decreasing gradually, even though labour force participation remains low, especially among women and youth. While inflation had reached a high of 5.4 percent in September 2022, annual inflation continued to decelerate to 1.4 percent in October 2023, driven by lower fuel and transportation prices (World Bank, 2023a).

Nonetheless, employment shocks, inflation and price increases are disproportionately affecting the poorest households in Jordan. An increase in the poverty rate from 15.7% in 2018[1] to 24.1% in 2022 testifies to their struggles during the past years and highlights a need for continued investment in poverty reduction efforts in the Kingdom (The Jordan Times, 2022).

Social Assistance in Jordan

Social protection has become a cornerstone for combating socio-economic issues and promoting sustainable development in Jordan. Formalised in the National Social Protection Strategy (NSPS) 2019-2025, social protection in Jordan is based on the three pillars *opportunity*, *empowerment* and *dignity*, which focus on decent labour market conditions and social security, universal services like education and health care, and social assistance, respectively (Hashemite Kingdom of Jordan, 2019). The remainder of this study will focus on the *dignity* pillar, that encompasses government-provided targeted, and temporary social assistance to citizens. Jordan has a long history of programmes and initiatives designed to support its citizens in meeting their basic needs and reduce poverty-related risks, through a variety of mechanisms including commodity subsidies, in-kind provision of food and housing, and cash transfers (Hashemite Kingdom of Jordan, 2019). Significant progress has been made in shifting social assistance resources away from subsidies, for instance the infamous 'bread subsidy', towards poverty-targeted programmes (FAO, 2018). In 2019, together with international donors, the Government of Jordan (GoJ) had allocated a budget of 100 million Jordanian Dinars (JOD) to its National Aid Fund (NAF) which administers social assistance in the Kingdom, which rose to JOD 240 million or 0.7% of GDP in 2023 (World Bank, n.d.-a). Covering more than 220,000 households in 2023, Jordan's cash transfer programmes are now the largest in terms of coverage of the poor in the Middle East and North Africa (MENA) region (World Bank, n.d.-a).

The National Aid Fund

Established in 1986, the National Aid Fund (NAF) stands as an administratively and financially independent institution dedicated to providing protection and support to vulnerable households in Jordan. Its multifaceted mission includes raising the living standards of Jordanian households, and ultimately empowering them to secure a continuous source of income by transforming their members into productive and engaged contributors to society (NAF, 2023). With the aim to reduce poverty rates and alleviate the severity of poverty, NAF implements several programme lines, including regular and one-time cash assistance, economic empowerment programmes and cash plus services that empower households economically and break the

[1] The national poverty line in Jordan was 99.9 Jordanian Dinars (JOD) per capita per month in 2018, an equivalent of 322.3 USD in 2017 Purchasing Power Parity (PPP) prices (UNICEF, 2020b).

inter-generational transmission of poverty[2].

The Unified Cash Transfer programme

Over the past years, a key strategic objective of the National Social Protection Strategy has been to consolidate cash assistance implemented by the National Aid Fund and expand coverage, while improving targeting accuracy of social assistance programmes. Since the beginning of 2022, NAF's flagship social protection programme is the Unified Cash Transfer (UCT) programme, that combines the previous *Monthly Financial Aid* programme (cash assistance to poor households whose head is unable to work, amongst others due to being elderly, sick, or having a disability), and the former *Takaful* programme. In 2019, NAF had launched the *Takaful* programme, designed to provide monetary support to poor households, seeking to reduce the poverty rate from 15.7% in 2018 to 13.1% by the year 2021 (UNICEF, 2020b). In early 2022 these two programmes were merged and transformed into the Unified Cash Transfer (UCT) programme, which is now NAF's flagship programme for cash transfers to poor households. The UCT programme improves upon previous programmes like *Takaful* and the *Monthly Financial Aid* programme in that it addresses the compartmentalisation of Jordan's social assistance landscape, by providing assistance under one common name to a larger share of households. Furthermore, through a new poverty-based targeting system implemented in early 2022, the UCT aims to reach the most vulnerable households in the country.

In 2023, the UCT reached more than 170,000 beneficiary households per month (approximately 120,000 from the original UCT caseload plus an additional 50,000 households from the *Monthly Financial Aid* programme who are gradually being migrated), and more than 866,000 individuals, 52% of which are children up to the age of 18 (NAF, 2023). The UCT has fully adopted a digital payment mechanism to deliver cash assistance to beneficiaries through bank accounts, electronic wallets, and prepaid cards. Monthly transfers range between 40 and 100 JOD (148 to 370 USD based on 2017 PPPs in April 2024 (IMF, 2024)), depending on household size[3]. Geographically, beneficiary households are distributed across all governorates in the Kingdom, with the majority of households, about 29%, living in the capital city Amman, followed by Irbid (22%) and Zarqa (16%).

[2]These programmes are: 1) Main cash transfer programmes (*Monthly Financial Aid* programme, Unified Cash Transfer programme), 2) Targeted aid programmes (Emergency Aid programme, Physical Rehabilitation programme, Additional Aid programme, Winter Aid programme), 3) Economic empowerment programmes (training, qualification and employment programmes), and 4) Additional services (Takaful+, consisting of a health insurance programme, renewable energy programme, Makani project as well as food parcels and purchasing vouchers).

[3]The base transfer amount is 40 JOD (148 USD 2017 PPP) for one person, and an additional 15 JOD (55.5 USD 2017 PPP) is added for every additional household member, up to a maximum of 100 JOD (370 USD 2017 PPP).

To achieve the most just and equitable distribution of funds in the UCT programme, NAF uses a digital poverty-based targeting mechanism based on a Proxy-Means Test (PMT) to assess households for eligibility for the UCT. This PMT was developed in cooperation with The World Bank and Jordan's Department of Statistics (DoS), and is based on the Household Income and Expenditure Survey (HIES) of 2017/18. The PMT includes indicators that collectively measure demographics, geographic factors, educational status, health, and material well-being, amongst others. The full model is displayed in Table A.1. After this model had been established, the weights that result from coefficients in the PMT model are used to 'impute' income, or to predict household income based on the selected correlates. The running variable that determines eligibility into the UCT is then established based on the function

$$X_i = \frac{\max(income_{imputed},\ income_{reported})}{household\ size}, \tag{1}$$

where X_i is the running variable expressed as per capita income, which can be based either on a household's imputed income from the PMT model, or reported income, whichever is higher. Households are assessed at the time of their application, where their imputed income is estimated, and their eligibility based on their rank in the variable X_i is determined[4]. In addition to this ranking, a total of eleven filters are applied with the aim of minimising inclusion errors (Table A.2), based on which households are automatically deemed ineligible.

3 Data

The National Unified Registry for Social Protection

We use administrative data on 205,665 households from Jordan's National Unified Registry (NUR). The NUR was launched in 2013 to improve the targeting and efficiency of social protection programmes and to develop a case management system for the provision of services to poor and vulnerable households (World Bank, 2023b). Historically based on the Income and Sales Tax Department database, the NUR links databases from 30 different government agencies and accesses 38 different registries. Its aim is to unify and verify household information, to enable collaboration between different ministries and user agencies, and to provide a single registry of social assistance beneficiaries. Moreover, the NUR is an integral part of Jordan's National Social Protection Strategy 2019-2025, which has prioritised a further development of the registry for targeting potential social assistance beneficiaries. Different components of the NUR like the

[4]Households are technically re-assessed on a monthly basis in line with regular data pull for monitoring purposes as described later. However, until summer 2024, households had not been excluded from the programme even in case they achieved a substantial improvement in well-being.

education data base EMIS have been used for research and evaluation in the past, for instance towards a study on out-of-school children (UNICEF, 2020a). However, to our knowledge, the NUR has not been leveraged as the sole data base for other (research) studies.

As of December 2022, the NUR consists of a back-end data aggregator housed by the Minister of Digital Economy and Entrepreneurship (MoDEE), which unifies citizen data based on the national ID, and a front-end management of information system (MIS) hosted by the National Aid Fund. This MIS system allows NAF to register beneficiaries through the application form, apply the targeting formula, update beneficiary data, manage payment, and serves for grievance redress mechanisms and monitoring and evaluation purposes. Once a beneficiary applies to a NAF cash transfer programme, the NUR automatically pulls data from the different databases and pre-fills about 70% of the household's application sheet. With the help of the NUR as well as home visits by social workers, self-reported application data is verified and updated in case of discrepancies between the application and NUR data. Eventually, the data provided serves as input for the proxy-means test that identifies the poorest households to be included in the UCT programme.

Data Cleaning

The National Aid Fund cooperates with an external company for data management and storage, which pulls data from the National Unified Registry for registration of beneficiaries and monitoring activities on a monthly basis. The data we use in this study come from five of those data pulls, namely from February 2022 when households first applied and were freshly assessed—which serves as the baseline for our study—as well as four follow-up rounds from September 2022, November 2022, June 2023, and finally February 2024, two years after the start of the UCT programme. We obtain household-level data with information on household demographics, economic activity of the household head, household-level reported and imputed income (the result of the proxy-means test) as well as some individual-level demographic data. In addition to that, we have access to a variety of indicators on household well-being that stem from the previous *Takaful* programme's targeting methodology, which are still part of the regular data pull. These indicators are mostly categorical variables on various measures of living standard (some of which overlap with the UCT PMT model), based on which we construct further outcome variables.

Using the five rounds of raw NUR data, we perform various steps of data cleaning in order to obtain our final sample and variables of interest (Table A.3). Our raw data base contains information on 519,109 households. Attrition in our sample is limited. For example, 1.3%[5] of beneficiary households and only 0.3% of non-beneficiary households are not retained between rounds 1 and 2. Further, attrition only amounts to 0.04% and 0.07% of beneficiary and non-beneficiary households between rounds 2 and 3, 0.4% and 1.1% between rounds 3 and 4, and 0.8% and 0.7% between rounds 4 and 5, respectively. We conclude that attrition is reasonably small—an additional benefit of administrative data over survey data—and therefore perform no further attrition-related adjustments (Card, Chetty, Feldstein, & Saez, 2010).

In terms of data cleaning, we first retain only a subset of UCT beneficiaries, namely those who newly applied to the UCT programme at its launch in early 2022. In other words, we exclude households from the former *Takaful* (N=82,331) and *Monthly Financial Aid* programmes[6], as these households had either been receiving cash previously, or were selected as part of a different target group and through a different targeting mechanism[7]. Eventually, 436,778 households are non-*Takaful* households, out of which we keep 389,648 households that have non-missing data across all five rounds for our main results.

After that, we employ a set of corrections pertaining to the running variable. While initially, households with a monthly per capita income of 123 JOD or less were supposed to be eligible for the UCT, a significant number of households below this cut-off did not receive any transfers. The cut-off eventually became 119.2 JOD for various reasons, amongst others funding constraints. Hence, we relabel households as non-beneficiaries if their running variable was between 119.2 JOD and 123 JOD per person and month, in case they have never become eligible in later data rounds and never received any transfer. Additionally, we drop household observations that were deemed eligible only in round 1 (but not in rounds 2 to 5), and have received between 1-6 monthly payments (N=10,895), meaning that transfers were terminated latest in September 2022. This has occurred in line with (income) data corrections performed between February and September 2022. Many of those households had per capita incomes just below the cut-off of 119.2 JOD, as shown in Figure B.2. We disregard information on those households as they would not be a good counterfactual and potentially contaminate the results, having received some, albeit few, payments. We drop a further set of households who are excluded from the

[5]However, 99.4% of beneficiary households are recuperated in later survey rounds, meaning that attrition between rounds 1 and 2 is likely due to data correction, and temporary issues in data processing, rather than non-random attrition. We still exclude them from our analysis due to the missing information in round 2, which is important for our analysis, as will be explained below.

[6]Those households were not part of our sample of 519,109 households.

[7]The *Monthly Financial Aid* programme is a cash transfer programme for households whose head is economically unable to produce an income, such as (single) female-headed households, or households whose head is disabled or unable to work due to other reasons. Hence, this additional categorical targeting element results in a narrower target population group than the former *Takaful* programme and current UCT programme (poverty targeting only), and thus makes a perfect comparison between the *Monthly Financial Aid* programme and the previous *Takaful* case load, now UCT case load, difficult.

programme in various ways, amongst others by eligibility filters, or because they have not been reachable by field staff (N=50,162). Within this group, we identify approximately 47% of households as excluded through filters as reflected in our data, while the rest may be excluded due to other case-specific reasons. Moreover, some households exhibit no reported or registered income[8] in the NUR. This mismatch between income and expenditures, and resulting income deficit, has already been flagged in the *Takaful* baseline report from 2020 (UNICEF, 2020b). As a remedy, those households are automatically assigned a 'reported' income of 220 JOD in the system, pertaining to exactly the Jordanian minimum wage. As this may not necessarily reflect the actual level of well-being within the household, we also exclude them from our analysis (N=1,729). Lastly, we exclude observations from households with extreme income outliers in the running variable[9] (N=68).

Moreover, we make some adjustments to household's beneficiary status based on the number of payments they have received over the course of the two years under analysis. We assume that households are fully treated if they received 21 payments or more[10]. In addition, we assume that households are non-beneficiaries when their number of payments is zero, even though they may have been deemed eligible in later survey rounds based on changes to their (imputed) income.

Eventually, for our main analysis, we only use households who were ranked based on imputed income (see Equation 1), or whose imputed income was higher than reported income. We believe that using both types of income could severely influence the comparability of households, and thus not satisfy the requirements for a regression discontinuity design, our preferred methodology as specified in Section 4. On the contrary, using a ranking solely based on imputed income will be more granular and comparable. Lastly, in our main model, we exclude households who are beneficiaries but received only 20 payments or less, as those households have not been fully treated (N=13,878). We later run robustness checks in which we re-integrate them into the sample. This leaves us with a final sample of 205,665 households for our main analysis, among them 42,001 beneficiary, and 163,664 non-beneficiary households.

[8]Our data collects different types of income, with the main variables being 'imputed' income—the result from the PMT model—and a form of reported income, that can be self-reported, or stem from the tax data base and reflect 'real income' of the household.

[9]We define an outlier as having a monthly per capita income of three standard deviations above the mean, for example equivalent to JOD 5,130 ($19,000 2017 PPP) and above in round 1.

[10]The maximum number of payments would be 24 for two years, but some households had received a quarterly payment at the beginning of the UCT programme, which used to be the payment modality in the old *Takaful* programme. Hence, at 21 payments, households would have received the cash transfer for the full two years.

3.1 Descriptives

Table 1 provides summary statistics for selected household characteristics and outcome variables within the final sample at baseline (February 2022), disaggregated by beneficiary status in the Unified Cash Transfer programme. Due to the fact that households are assessed for eligibility based on various demographic, economic and geographic indicators, those two groups are constructed to be systematically different, which is reflected in the significant differences across all variables of Table 1. Geographically, the large majority of applicants to the UCT is concentrated in urban areas, and especially the capital city of Amman, in line with the general population distribution in Jordan. Moreover, Table 1 shows that beneficiary households are on average slightly larger than non-beneficiary households and are less likely to have a female-head of household, which is due to the fact that most of these vulnerable households were absorbed by the *Monthly Financial Aid* programme, and cross-participation in multiple programmes has been very limited. Logically, beneficiaries exhibit lower levels of both imputed and reported income.

Table 1: Summary statistics at baseline (February 2022)

	Beneficiaries	Non-Beneficiaries	Difference
Geography			
Urban (%)	80.92	85.57	0.0465***
	(0.39)	(0.35)	(0.00)
Live in Amman (%)	37.90	41.91	0.0401***
	(0.49)	(0.49)	(0.00)
Demographics			
Household size	5.63	3.16	-2.47***
	(1.60)	(1.76)	(0.01)
Dependency ratio	133.89	43.03	-0.91***
	(0.78)	(0.54)	(0.00)
Female household head	3.74	26.88	0.23***
	(0.19)	(0.44)	(0.00)
Age of household head	41.32	45.37	4.05***
	(9.15)	(15.13)	(0.06)
Household income			
Monthly per capita income—reported (JOD)	52.79	115.61	62.82***
	(17.38)	(75.67)	(0.21)
Monthly per capita income—imputed (JOD)	88.88	238.10	149.22***
	(21.79)	(145.10)	(0.37)
Employment			
HH head works (any job)	68.19	49.37	-0.19***
	(0.47)	(0.50)	(0.00)
Head is in irregular employment	55.38	31.78	-0.24***
	(0.50)	(0.47)	(0.00)
Head is in regular employment	8.66	11.40	0.03***
	(0.28)	(0.32)	(0.00)
Head is a business owner	3.99	6.11	0.02***
	(0.20)	(0.24)	(0.00)
Nr. of regular income sources in HH	41.55	61.87	0.20***
	(0.61)	(0.75)	(0.00)
Household assets			
Household has any assets	30.06	48.78	0.19***
	(0.46)	(0.50)	(0.00)
Household owns land	14.94	24.14	0.09***
	(0.36)	(0.43)	(0.00)
Household cultivates land	14.49	23.49	0.09***
	(0.35)	(0.42)	(0.00)
Household owns a car	18.32	34.70	0.16***
	(0.39)	(0.48)	(0.00)
Household owns property	2.34	6.71	0.04***
	(0.15)	(0.25)	(0.00)
Children's schooling			
All school children are enrolled (%)	92.83	70.63	-0.22***
	(0.26)	(0.46)	(0.00)
Nr. non-enrolled children	0.18	0.55	0.38***
	(0.66)	(0.96)	(0.01)
Any child dropped out (%)	65.17	18.54	-0.47***
	(0.48)	(0.39)	(0.00)
Nr. children who dropped out	1.1	0.51	-0.58***
	(0.88)	(0.66)	(0.01)
Observations	42,001	163,664	205,665

Standard errors in parentheses

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

4 Methodology

4.1 Fuzzy regression discontinuity design

As described above, households are ranked based on their imputed income, and then assigned to treatment—in this case cash receipt—based on their rank. Due to this non-random assignment and the structure of the targeting mechanism, our preferred methodology for this impact evaluation is the quasi-experimental regression discontinuity design (RDD), which has been used in previous studies, for instance for an evaluation of a similar programme in Egypt (El Enbaby et al., 2022), or in Bergolo and Galván (2018), MacPherson and Sterck (2021), Altındağ and O'Connell (2023), or Mora, de Crombrugghe, and Gassmann (2022). We use a fuzzy RDD due to the imperfect assignment of treatment, meaning that some households around the eligibility cutoff may not receive the treatment—the UCT cash transfer—even if they are eligible, and vice versa. In other words, some households with $X_i \leq c$, i.e., where the ranking variable (imputed monthly per capita income) X_i is lower than the eligibility threshold c (119.2 JOD), may not have received the transfer for various reasons, while others with $X_i \geq c$ received the transfer even though they are not technically eligible. Indeed, we observe that approximately 2.5% of eligible households by ranking do not receive the UCT transfers, while approximately 1.3% of non-eligible households do. A fuzzy RDD design helps address non-compliance with original treatment assignment $T_i = f(X_i \leq c)$. As it is imperfect, the probability of receiving treatment no longer jumps from 0 to 1 exactly at the cutoff. Actual take-up of treatment is therefore expressed by the binary variable D_i, where for some households, $T_i \neq D_i$. The observed outcome in this fuzzy regression discontinuity is therefore $Y_i = T_i Y_i(1, D_i(1)) + (1 - T_i) Y_i(0, D_i(0))$.

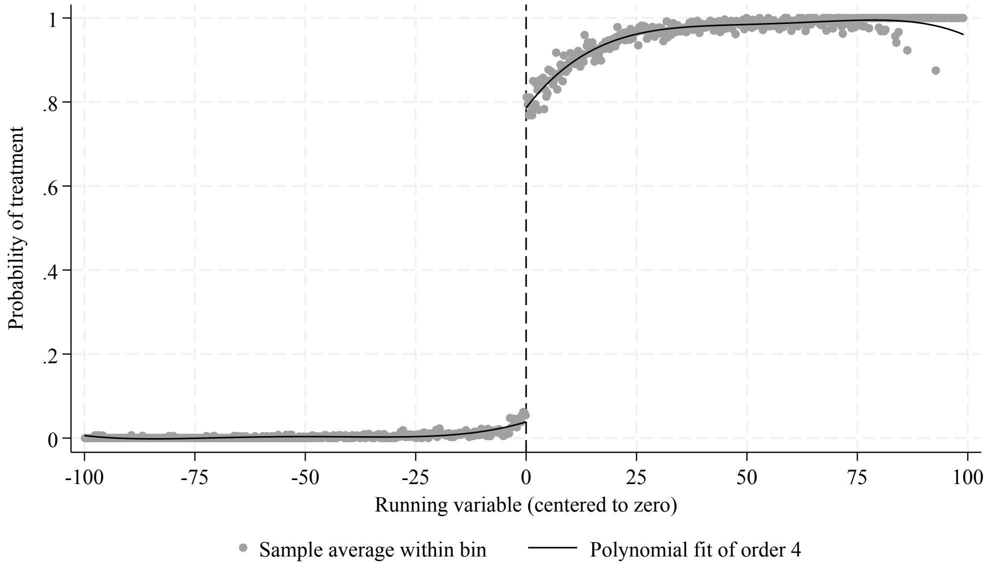
In a fuzzy RDD, eligibility for the programme defined as having a running variable lower or larger than the cut-off, is thus instrumented by actual, observed treatment, in our case cash receipt (Bertanha & Imbens, 2020). Essentially, fuzzy RDD measures the local average treatment effect (LATE) for complier households, instead of the general average treatment effect (ATE). The first-stage estimation equation is as follows:

$$D_i = \alpha_1 + \beta_1 T_i + f(X_i) + \epsilon_i, \tag{2}$$

where D_t and T_t are treatment assignment and take-up as defined above, and $f(X_i)$ is a flexible function in the running variable X_i. The second-stage regression is:

$$Y_{i,t+1} = \alpha_2 + \beta_2 \hat{D}_{i,t+1} + f(X_{i+1}) + \epsilon_{i,t+1}, \tag{3}$$

Figure 1: Regression discontinuity plot: treatment take-up



Note: We limit the range of the running variable to monthly per capita incomes of 100 or less (in absolute terms) as data become relatively sparse for larger incomes.

where $Y_{i,t+1}$ is our outcome variable of interest in the follow-up period $t+1$, such as imputed per capita income, reported per capita income, household head income type and employment, asset ownership, and children's schooling.

We first centre the running variable X_i to zero, based on the eligibility cut-off point of monthly per capita income of approximately JOD 119.2, and then inverse the running variable so that households with $X_i > 0$ are considered treated households, and vice versa. Figure 1 shows the regression discontinuity plot for treatment take-up D, $\mathbb{P}(D_i = 1|X_i = x)$, for our sample. This figure shows that treatment assignment is indeed fuzzy and there is two-sided non-compliance. Using the Stata command `rdrobust` to estimate the first-stage relationship between UCT eligibility and actual receipt of the cash transfer results in a coefficient of 0.73, consistent with the jump observed at the cut-off in Figure 1.

Yet, in line with the data cleaning described in Section 3, a non-significant number of households, many of them close to the cutoff c had to be excluded from the analysis. As a result, the manipulation test for verifying continuity of the running variable around the cutoff becomes invalid (Figure B.3 in Appendix B). However, given that households do not have full information regarding the elements in the PMT model and weights of different indicators, or the exact eligibility criteria of the UCT more generally, active manipulation by treatment or control units around the cutoff is practically impossible. We also test for discontinuities at the threshold for various covariates used to generate the running variable (Tables A.8 and A.9), which prove to be insignificant at conventional significance levels, in other words, there is no significant jump at the threshold for relevant household characteristics. Therefore, we consider the bias to be sufficiently small for a fuzzy RDD to still be valid and employ it as our main methodology. We proceed estimating the fuzzy regression discontinuity model using bandwidth selection procedures in the form of MSE-optimal bandwidth selector for the RD treatment effect estimator as our main analysis.

4.2 Propensity score matching and difference-in-difference estimator

Still, we acknowledge the potential drawbacks induced by non-discontinuity in the running variable, and perform a second type of analysis based on a combination of propensity score matching (PSM) and difference-in-difference (DiD) estimator, as a robustness test to our main analysis. Specifically, we estimate the propensity score and use inverse probability weighting (IPW) to identify causal effects, following Özler, Çelik, Cunningham, Cuevas, and Parisotto (2021). First, we assign a propensity score $\hat{p}$ to each household, representing the estimated probability that a household with specific baseline characteristics is selected for treatment–the UCT cash transfer. We then use IPW to estimate treatment effects by applying regression weights that are equal to $1/\hat{p}$ for beneficiaries, and $1/(1-\hat{p})$ for non-beneficiary households.

Given that our sample size is extremely large, containing more than 200,000 observations, we first draw a random sample of 10% of beneficiary and non-beneficiary households each, that allows for a more efficient analysis. We then estimate the propensity score $\hat{p}$ using a logit model that includes all available variables used in the PMT model (or the closest approximation thereof), which is presented in Table A.7. In line with Özler et al. (2021), we winsorize the propensity score and trim the original sample by dropping households whose propensity score is below 0.05 or above 0.95, as this may violate the condition that the probability of treatment is bounded away from zero and one which is required for matching or re-weighting (Nichols, 2008). This leaves us with a final sample of 3,086 beneficiary (treatment), and 4,585 non-beneficiary (control) households. Figure B.5 displays the kernel density plots for the treatment and control groups, both before and after applying inverse probability weights, and Tables A.8 and A.9 show the balance across covariates at baseline in February and September 2022, respectively, for the trimmed sub-samples. While the sample is highly unbalanced at baseline, with large and statistically significant differences between treatment and control households, we manage to eliminate those differences after matching based on inverse probability weights. As confirmation, a Hotelling's T-squared test for a set of zero means returns an F-statistic of 0.753 and a p-value of 0.832.

Eventually, we follow Song and Imai (2019) and Saldivar-Frausto, Unar-Munguía, Méndez-Gómez-Humarán, Rodríguez-Ramírez, and Shamah-Levy (2022) and apply the weights generated above in a DiD estimator to estimate treatment effects using the the same outcome variables as in 4.1, according to:

$$\text{DiD} = \left(\overline{Y}_{T,\text{post}} - \overline{Y}_{T,\text{pre}}\right) - \left(\overline{Y}_{C,\text{post}} - \overline{Y}_{C,\text{pre}}\right) \tag{4}$$

where $\overline{Y}_{T,\text{post}}$ is the average outcome for the treatment group at endline (after cash receipt), $\overline{Y}_{T,\text{pre}}$ is the average outcome for the treatment group at baseline (before receiving cash), $\overline{Y}_{C,\text{post}}$ is the average outcome for the control group at endline, and $\overline{Y}_{C,\text{pre}}$ is the average outcome for the control group at baseline.

5 Results

5.1 Main results: Impact of UCT programme

In this section, we analyse the impact of the Unified Cash Transfer programme on beneficiaries during the two-year period between 2022 and 2024. We mainly find that beneficiaries experience a relative decrease in their level of well-being, both in terms of monetary and multidimensional indicators such as asset ownership, although household head employment and children's schooling improves.

The short-term impacts of the UCT programme on income and employment obtained from the fuzzy regression discontinuity model on are displayed in Table 2. As income and employment can be cyclical across the year, we initially report outcomes for both the endline in February 2024 as well as June 2023 in order to ensure capturing structural, rather than temporary effects. Contrary to the programme's objective, the results show that household income, in the form of both imputed and reported income has decreased over time for beneficiary households in comparison to non-beneficiary households. Two years after implementation, beneficiary households' monthly imputed per capita income via the PMT model was approximately 11.4% lower, and reported per capita income 40% lower than that of non-beneficiaries (see Figure B.4 for regression discontinuity plots of reported and imputed income).

Despite the overall decrease in household income, household heads among beneficiaries show an increase in the likelihood to earn an income and be in employment. As Table 2 illustrates, the share of household without income decreases by 32.1 percentage points over two years, while more household heads earn income from irregular work (+25.7 percentage points), and to a lesser extent from regular work (+6.2 percentage points). Similarly, household head employ-

Table 2: Fuzzy RD: income and employment

	(1) June 2023	(2) February 2024
Household income		
Monthly reported household income (log)	-0.430***	-0.390***
	(0.0669)	(0.0742)
Monthly reported per capita income (log)	-0.419***	-0.396***
	(0.0550)	(0.0600)
Monthly imputed household income (log)	-0.044***	-0.072***
	(0.0183)	(0.0185)
Monthly imputed per capita income (log)	-0.086***	-0.114***
	(0.0109)	(0.0112)
Household head income		
Head earns no income	-0.288***	-0.321***
	(0.0258)	(0.0264)
Head earns income from irregular work	0.244***	0.257***
	(0.0268)	(0.0277)
Head earns income from regular work	0.042***	0.062***
	(0.0112)	(0.0170)
Employment		
Household head works	0.236***	0.271***
	(0.0270)	(0.0269)
Head is in irregular employment	0.199***	0.214***
	(0.0277)	(0.0276)
Head is in regular employment	0.001	0.000
	(0.0035)	(0.0032)
Head is a business owner	0.037***	0.061***
	(0.0105)	(0.0113)
Number of regular income sources within household	0.134***	0.127***
	(0.0379)	(0.0330)

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable. The results for household income are expressed as percentages, and all other results are expressed as percentage points, as the outcome variable is binary, except the number of regular income sources, which is expressed in absolute values.

ment amongst beneficiary households is increasing over time, by up to 27.2 percentage points, compared to non-beneficiary households. This seems to be driven by increases in the share of irregular employment (21.4 percentage points), as well as business ownership (6.1 percentage points), while there are no effects on regular employment, which is likely due to the small sample size of household heads in this category. Moreover, the number of regular income sources in the household, or the number of household members who have employment, also slightly increases for beneficiary households, by approximately 1.3 percentage points.

We also find significant and sustained, albeit negative impacts of the UCT programme on asset ownership (Table 3). Beneficiary households are more likely to have no assets (-5.6 percentage points) than non-beneficiary households, and less likely to have any assets, or to have experienced an increase in the number of assets (-9.4 percentage points) by February 2024.

Table 3: Fuzzy RD: assets and schooling

	(1) June 2023	(2) February 2024
Asset ownership		
Household has no assets	0.030	0.056***
	(0.0261)	(0.0264)
Household has any asset	-0.029	-0.055***
	(0.0263)	(0.0267)
Household experienced increase in number of assets	-0.076***	-0.094***
	(0.0138)	(0.0151)
Indicators in proxy-means test		
Household owns land	-0.037*	-0.036*
	(0.0208)	(0.0194)
Household cultivates land	-0.035*	-0.035*
	(0.0209)	(0.0192)
Household owns a car	-0.042*	-0.076***
	(0.0221)	(0.0227)
Household owns property	-0.007	-0.009
	(0.0117)	(0.0116)
PMT asset index[1]	-0.022*	-0.029**
	(0.0118)	(0.0118)
Children's school attendance		
All children are enrolled	0.359***	0.371***
	(0.0244)	(0.0255)
Number of non-enrolled children	-0.490***	-0.454***
	(0.0459)	(0.0467)
Any child dropped out of school	-0.037	-0.062
	(0.0371)	(0.0384)
Number of children who dropped out	-0.071	-0.049
	(0.0502)	(0.0474)

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable. The results for assets and indicators in the proxy-means test are expressed as percentage points, as the outcome variable is binary, except for the PMT asset index, whose coefficient is expressed in absolute values. The results for children's schooling are expressed in percentage points, except the number of non-enrolled children or children who dropped out, which are expressed in absolute values.
[1]This PMT asset index was constructed by the authors to analyse changes in only the structural, non-demographic aspects in the PMT model. We construct this index through principal-component factor analysis using the indicators on livestock ownership, land ownership, land cultivation, car ownership, property ownership and stock ownership.

This is also reflected in the asset-related indicators used for income imputation, the proxy-mans test model (Table 3). Our results show negative impacts on indicators like land ownership or cultivation (though only significant at the 10% level), or owning a car (-7.6 percentage points).

Finally, we analyse the effects of the UCT programme on children's school enrolment and drop-out. As Table 3 shows, children in beneficiary households are 37.1 percentage points more likely to all be enrolled in school by February than children in non-beneficiary households. In line with that, the number of children within households who are not enrolled in school drops by nearly 0.5.

Table 4: Fuzzy RD: income and employment (round 2 baseline)

	(1) June 2023	(2) February 2024
Household income		
Monthly reported household income (log)	-0.527***	-0.554***
	(0.1489)	(0.140)
Monthly reported per capita income (log)	-0.479***	-0.519***
	(0.1150)	(0.1060)
Monthly imputed household income (log)	-0.047	-0.066*
	(0.0338)	(0.0350)
Monthly imputed per capita income (log)	-0.065***	-0.090***
	(0.0163)	(0.0184)
Household head income		
Head earns no income	-0.287***	-0.359***
	(0.0452)	(0.0451)
Head earns income from irregular work	0.230***	0.302***
	(0.0486)	(0.0499)
Head earns income from regular work	0.063***	0.071***
	(0.0206)	(0.0200)
Employment		
Household head works	0.216***	0.295***
	(0.0487)	(0.0495)
Head is in irregular employment	0.176***	0.246***
	(0.0491)	(0.0490)
Head is in regular employment	-0.014**	-0.009
	(0.0067)	(0.0060)
Head is a business owner	0.052***	0.051***
	(0.0161)	(0.0153)
Number of regular income sources within household	0.120*	0.114*
	(0.0647)	(0.0611)

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable. The results for household income are expressed as percentages, and all other results are expressed as percentage points, as the outcome variable is binary, except the number of regular income sources, which is expressed in absolute values.

5.1.1 Fuzzy RDD: Round 2 as baseline

As mentioned in Section 3, data corrections were performed between the baseline round in February 2022 and September 2022 due to identified errors[11]. To verify our results, we thus replicate the analysis in 5.1 using the second round of data collection in September 2022 as baseline, and rank households based on the imputed per capita income at this moment in time. We keep the eligibility threshold of JOD 119.2 from the baseline constant. Figure B.6 in Appendix B shows the corresponding regression discontinuity plot which shows that treatment assignment is now even more fuzzy, with significant two-sided non-compliance, especially to the

[11] These errors refer to, amongst others, but not limited to, errors in the recording and verification of income data and other variables, as well as some retrospective changes to the targeting mechanism (an additional filter had been installed where households who have a reported or imputed income above a certain threshold would be deemed ineligible. This maximum threshold is the equivalent of 100 JOD per person for the first five household members, and 50 JOD per person for any household member after that).

Table 5: Fuzzy RD: assets and schooling (round 2 baseline)

	(1) June 2023	(2) February 2024
Asset ownership		
Household has no assets	0.024	0.078
	(0.0508)	(0.0505)
Household has any asset	-0.025	-0.764
	(0.0485)	(0.0479)
Household experienced increase in number of assets	-0.010	-0.053**
	(0.0175)	(0.0258)
Indicators in proxy-means test		
Household owns land	-0.034	-0.031
	(0.0383)	(0.0383)
Household cultivates land	-0.023	-0.023
	(0.0384)	(0.0383)
Household owns a car	0.012	-0.043
	(0.0447)	(0.0452)
Household owns property	-0.009	-0.008
	(0.0231)	(0.0239)
PMT asset index[1]	-0.015	-0.020
	(0.0222)	(0.0241)
Children's school attendance		
All children are enrolled	0.353**	0.461***
	(0.0572)	(0.0554)
Number of non-enrolled children	-0.428***	-0.634***
	(0.1030)	(0.1060)
Any child dropped out of school	-0.062	-0.186*
	(0.0915)	(0.0975)
Number of children who dropped out	-0.056	-0.221*
	(0.1120)	(0.1170)

Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable. The results for assets and indicators in the proxy-means test are expressed as percentage points, as the outcome variable is binary, except for the PMT asset index, whose coefficient is expressed in absolute values. The results for children's schooling are expressed in percentage points, except the number of non-enrolled children or children who dropped out, which are expressed in absolute values.
[1]This PMT asset index was constructed by the authors to analyse changes in only the structural, non-demographic aspects in the PMT model. We construct this index through principal-component factor analysis using the indicators on livestock ownership, land ownership, land cultivation, car ownership, property ownership and stock ownership.

right of the cut-off. The first-stage relationship between UCT eligibility and actual receipt of the cash transfer in this scenario is 0.36, while the manipulation test now finds no evidence for discontinuity around the cut-off (Figure B.7).

Considering data from September 2022 as baseline, the negative effects of UCT receipt on imputed and reported income persist, with decreases in reported per capita income of as much as 52% among beneficiary households compared to non-beneficiary households (Table 4). Monthly imputed per capita income is about 9% per person per month lower.

Similar trends are observable for income of the household head, which show a positive impact of 30.2 percentage points by February 2024 on income from irregular work, and 7.1 percentage points from regular employment, respectively. Similarly, there are positive effects on actual employment (+29.5 percentage points), mostly driven by irregular employment (+24.6 percentage points) and business ownership (+5.1 percentage points).

The results on asset ownership are partly sustained, with a lower likelihood for beneficiary households to experience an increase in assets between September 2022 and February 2024 (Table 5). However, we cease to observe significant effects on asset indicators used in the PMT model. On the other hand, effects on children's schooling are persistent, and even slightly stronger as in Table 3. Children in beneficiary households are 46 percentage points more likely to all enrol in school, and fewer of them are non-enrolled.

5.1.2 Fuzzy RDD: Heterogeneous effects

Next to these general results and to discern potential difference across population sub-groups, we perform some heterogeneity analyses based on household size and area of residence. We find that overall, income and schooling effects are mostly driven by large(r) households, while there are few geographic differences, though effects seem to be slightly stronger in Amman.

Tables A.4 and A.5 show the results for the February 2022 and September 2022 baselines, respectively, split into small (1-3 members), medium-sized (4-6 members), and large (7+ members) households, households living in urban versus rural areas, as well as households living in Amman versus other governorates. Overall, the negative impacts on income seem to become worse the larger the households. While there are no significant effects on small households, beneficiary households with seven members or more experience a decrease in reported per capita income of approximately 53%, and imputed per capita income of 10% relative to non-beneficiary households. Nevertheless—and notwithstanding slight differences in magnitude—household head income and employment seem to improve consistently across those three groups. Heads of small households are even more likely to be business owners (+13 percentage points), or have a regular source of income. Beneficiary children of medium-sized and large households are much more likely to be enrolled in school (+62 percentage points), and fewer children in these households are not enrolled (-0.92).

In terms of geographic differences, we observe similar effects on school enrolment on all children of beneficiary households, no matter where they live, although the effects on enrolment are slightly stronger in rural areas, as well as among children living in Amman. We also find similar negative effects on imputed per capita income across all areas, whereas beneficiary households in rural areas and in Amman are once again more strongly affected by decreases in reported income compared to non-beneficiaries. The strongest heterogeneity seems to be that for rural beneficiary households, economic opportunities are more scarce, and in contrast to urban counterparts, we find no significant effects of UCT receipt on indicators like regular income, business ownership or the number of income sources in the household in rural areas.

5.1.3 Fuzzy RDD: Robustness

We employ a set of robustness tests to demonstrate that our results above hold. First, we lift the restriction on the number of payments for beneficiary households imposed in Section 3, and include households who received only 20 payments or less, expanding the sample to 163,851 non-beneficiary, and 42,398 beneficiary households. These households may not have been 'fully treated' but did benefit from the programme in more or less intensive ways. The results in columns (1) and (2) of Table A.6 show that the outcomes at endline are largely consistent[12] with the main results in Section 5.1, both in terms of magnitude and significance. Second, we consider all household observations that are non-missing in rounds one, two and five (February 2022, September 2022, February 2024), and include observations with potential missing information during survey rounds three and four. Again keeping all households, irrespective of the number of payments, this further increases the total sample to 164,531 non-beneficiary, and 42,427 beneficiary households. Columns (3) and (4) in Table A.6 again show that the resulting point estimates are largely robust to this inclusion, and are in line with our main results in terms of magnitude and significance.

5.2 Difference-in-differences

The fuzzy RDD results from Section 5.1 local average treatment effects (LATE) at the eligibility threshold. Despite there being reasons to believe that manipulation is negligible, interpretation of these results requires caution due to the data issues described in Section 3. In order to verify these results and obtain more generalisable findings, we re-weight households based on their baseline characteristics using inverse probability weighting (IPW), and then apply a Difference-in-Difference (DiD) estimator, as detailed in Section 4. In contrast to the fuzzy RDD that uses household observations around the cut-off, we first draw a random sample of 10% of beneficiaries and non-beneficiaries households each, and then calculate the average treatment effect on the treated (ATT). The results of the DiD analysis are displayed in Tables 6 to 7 for the February 2022 baseline, and Tables A.10 and A.11 for the September 2022 baseline.

[12]The only exception occurs in terms of asset ownership when considering February 2022 as baseline, where coefficients cease to be significant.

Table 6: Difference-in-differences: income and employment

	Control		Treatment		DiD
	Baseline Mean	Difference Coef	Baseline Mean	Difference Coef	Coef
Income					
Household income reported (log)	6.328	-0.055	6.259	-0.228***	-0.187***
	(0.016)	(0.041)	(0.008)	(0.032)	(0.052)
Per capita income reported (log)	4.784	0.008	4.691	-0.171***	-0.193***
	(0.014)	(0.033)	(0.007)	(0.027)	(0.042)
Household income imputed (log)	7.181	0.029***	6.845	-0.023***	-0.053***
	(0.005)	(0.007)	(0.005)	(0.007)	(0.010)
Per capita income imputed (log)	5.614	0.032***	5.277	-0.024***	-0.058***
	(0.003)	(0.007)	(0.003)	(0.007)	(0.010)
Household head income					
No income	0.290	0.416***	0.082	0.136***	-0.267***
	(0.007)	(0.013)	(0.005)	(0.012)	(0.018)
Irregular income	0.384	-0.104***	0.721	-0.010	0.088***
	(0.007)	(0.013)	(0.008)	(0.016)	(0.020)
Regular income	0.326	-0.312***	0.197	-0.126***	0.178***
	(0.007)	(0.009)	(0.007)	(0.012)	(0.015)
Employment					
Household head works	0.469	-0.241***	0.654	-0.038**	0.199***
	(0.007)	(0.012)	(0.009)	(0.017)	(0.021)
Head is in irregular employment	0.287	-0.078***	0.544	0.004	0.080***
	(0.007)	(0.012)	(0.009)	(0.018)	(0.021)
Head is a business owner	0.017	-0.002	0.039	0.017**	0.018**
	(0.002)	(0.003)	(0.003)	(0.007)	(0.008)
Nr. regular income sources in HH	0.609	-0.333***	0.440	-0.011	0.308***
	(0.011)	(0.019)	(0.011)	(0.022)	(0.029)
Observations	4,585	9,170	3,086	6,172	15,342

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

Note: The results for household income are expressed as percentages, and all other results are expressed as percentage points, as the outcome variable is binary, except the number of regular income sources, which is expressed in absolute values.

In line with the fuzzy RDD, we observe a negative impact of UCT receipt on both imputed and reported income between February of 2022 and 2024. Although the direction of these estimates is consistent, they are much lower in magnitude (e.g., 19.3% for reported, and -5.8% for imputed monthly per capita income). However, the results on reported income are not sustained under the corrected baseline data in Table A.10, meaning that only imputed income has a robust and negative effect, both driven by an increase in imputed income among non-beneficiaries, and a decrease among beneficiary households.

Further, we do observe increasing economic activity of beneficiary household heads that confirm previous results, which however don't survive changing the baseline from February to

Table 7: Difference-in-differences: assets and schooling

	Control		Treatment		DiD
	Baseline Mean	Difference Coef	Baseline Mean	Difference Coef	Coef
Assets					
Household has no assets	0.576	-0.102***	0.595	-0.011	0.093***
	(0.007)	(0.013)	(0.009)	(0.016)	(0.021)
Household has assets with revenue	0.198	0.042***	0.205	0.012	-0.032*
	(0.006)	(0.011)	(0.007)	(0.015)	(0.019)
Household has any assets	0.424	0.102***	0.405	0.011	-0.093***
	(0.007)	(0.013)	(0.009)	(0.016)	(0.021)
Indicators in proxy-means test					
Household owns land	0.186	0.028***	0.194	0.015	-0.017
	(0.006)	(0.010)	(0.007)	(0.015)	(0.019)
Household cultivates land	0.181	0.027***	0.189	0.016	-0.015
	(0.006)	(0.010)	(0.007)	(0.015)	(0.018)
Household owns a car	0.296	0.119***	0.281	-0.011	-0.129***
	(0.007)	(0.013)	(0.008)	(0.015)	(0.019)
Household owns property	0.043	0.020***	0.048	0.008	-0.013
	(0.003)	(0.006)	(0.004)	(0.009)	(0.011)
PMT asset index	0.138	0.028***	0.141	0.009	-0.022**
	(0.004)	(0.006)	(0.004)	(0.009)	(0.011)
Children's school attendance					
All children are enrolled	0.703	-0.251***	0.948	-0.047***	0.185***
	(0.009)	(0.018)	(0.005)	(0.009)	(0.020)
Number of non-enrolled children	0.709	0.439***	0.139	0.186***	-0.149***
	(0.023)	(0.047)	(0.011)	(0.020)	(0.052)
Any child dropped out of school	0.328	0.232***	0.497	0.166***	-0.071**
	(0.013)	(0.026)	(0.013)	(0.020)	(0.033)
Number of children who dropped out	0.666	0.338***	0.886	0.269***	-0.081*
	(0.017)	(0.033)	(0.018)	(0.029)	(0.045)
Observations	4,585	9,170	3,086	6,172	15,342

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

Note: The results for assets and indicators in the proxy-means test are expressed as percentage points, as the outcome variable is binary, except for the PMT asset index, whose coefficient is expressed in absolute values. The results for children's schooling are expressed in percentage points, except the number of non-enrolled children or children who dropped out, which are expressed in absolute values.
[1]This PMT asset index was constructed by the authors to analyse changes in only the structural, non-demographic aspects in the PMT model. We construct this index through principal-component factor analysis using the indicators on livestock ownership, land ownership, land cultivation, car ownership, property ownership and stock ownership.

September 2022 (see Tables 6 and A.10). Hence, there seems to be some, but weaker evidence for positive effects of UCT receipt on the income and employment of household heads. If anything, our results suggest that both beneficiary and non-beneficiary households may have experienced a decrease in the number of income sources, or jobs, within their households. Regarding assets, we find that beneficiary households are less likely to have any assets, driven by both an increase in assets among non-beneficiaries (Table 7) and a decrease in assets among beneficiaries (Table A.11), and any negative impacts in terms of asset variables in the PMT model are largely driven by an increase in car ownership among non-beneficiary households.

Finally, our results show that, similar to the fuzzy RDD estimates, children in beneficiary households are more likely to be all enrolled in school, and less likely to have dropped out, although the coefficients are slightly lower in magnitude (Tables 7 and A.11). Yet, these favourable results hide that in both non-beneficiary and beneficiary households, schooling outcomes seem to have deteriorated over time, with children being less likely to be enrolled, and more likely to drop out, while UCT receipt seems to cushion some of these negative dynamics for recipient households.

6 Discussion

In this study, we have leveraged Jordan's National Unified Registry to conduct an impact evaluation of the Unified Cash Transfer programme administered by the National Aid Fund between February 2022 and February 2024. The objective of this study, as mentioned in the introduction is twofold. First, we put forward an estimate of the impact of the UCT programme on various economic and non-economic indicators, using various estimation methods to verify the robustness and accuracy of our results. Most notably, despite the programme's goal to reduce poverty in the Kingdom, its effects on household well-being are inconclusive. We find that UCT beneficiary households achieve lower levels of income in the short term, though some positive effects stand out, for instance with regards to the household head's economic activity, or children's schooling.

Income, employment and assets

Our main outcome of interest is household income, which is associated negatively with UCT receipt. This seems to occur simultaneously through a relative increase in income among non-beneficiaries, as well as a decline in beneficiary households' income, and is observed both for reported and imputed income. Taking our estimations at both baselines from February 2022 and September 2022 as lower- and upper bounds, we observe a local average treatment effect of the programme between -9% and -11% for imputed, and between -40% to -52% for reported monthly per capita income. The average treatment effect on the treated ranges from -5.8% -6% for monthly imputed per capita income[13]. Notably, the measures of income we use are net of

[13] Average treatment effects on the treated on reported income are insignificant in Table A.10, hence we are cautious about making claims about this outcome variable.

the UCT cash transfer, meaning that there may be a substitution effect at play, where cash received from the UCT programme represents a relatively stable and reliable income stream and thus substitutes other parts of household income. This substitution effect has been reported in different scenarios in previous studies (Asfaw, Davis, Dewbre, Handa, & Winters, 2014; Baird et al., 2018; Ribas & Soares, 2011). As non-beneficiaries must find other income sources to improve their level of well-being, hence the income increases among this group, beneficiaries can rely on the UCT transfer.

Nonetheless, negative effects on imputed or reported income do not allow us to make assumptions about the UCT's achievement in terms of poverty reduction among Jordanian households. Poverty in Jordan is estimated using monthly per capita consumption, not income, based on the Household Income and Expenditure (HIES) survey collected by the Department of Statistics (DoS), which is not part of NUR. We therefore cannot claim the programme to have, or rather not have, any impact on poverty reduction, although the negative effects on income may be correlated with a deterioration of monetary well-being, and eventually poverty among beneficiary households.

Moreover, we observe mixed effects on labour supply of the household head, in line with previous cash transfer research (Bastagli et al., 2019). Though there seem to be positive local average treatment effects on economic activity of the household head, average treatment effects on the treated depend on timing and underlying data, and are thus not robust. In the LATE estimations, beneficiary household heads are more likely to work, in line with previous research on the effect of cash transfer programmes on labour supply, particularly engaging in irregular work activities, and correspondingly, increasingly gaining an income from irregular employment. Those positive effects are also significant for business ownership among beneficiary households, albeit at a much lower magnitude. While those effects seemingly do not translate into higher household income overall, they could be early signs of the UCT programme having an encouraging effect on labour market outcomes, even though a strengthening of employment, especially in the formal sector, is constrained by Jordan's generally high unemployment rate (World Bank, 2023a). On top of that, this may provide further evidence for a substitution effect, where households shift employment away from laboured work to other forms of non- (or lower)-waged labour (Asfaw et al., 2014). However, doubts remain whether the UCT transfer value is sufficient to allow for altered labour decision on the intensive- or extensive margin, in line with previous research (Kabeer & Waddington, 2015), which we will discussed below.

Lastly, the results on asset ownership suggest that the UCT programme thus far has limited ability to structurally improve household well-being, or rather fails to cushion a divergence in asset endowments between non-beneficiary and beneficiary households. In both the LATE and ATT estimations, asset accumulation among non-beneficiary households leads to an overall negative effect of the UCT programme on beneficiary's asset endowments. Although we cannot specifically test this hypothesis, this may be a result of uncertainty among beneficiary households who take sub-optimal decisions that maximise their short-term utility—remaining eligible for cash transfer, as has been found in various previous settings (Mora et al., 2022). Non-beneficiary households, on the other hand, may be more under pressure or more ready to realise structural improvements in their living conditions without external financial support. As a result, they seem to incur higher income gains over time, which subsequently translate into asset accumulation. Beneficiary households may be reliant on the cash transfer, or face other barriers that render them vulnerable and unable to accumulate assets, especially in the short term (Barrett, Carter, & Chavas, 2017; Premand & Stoeffler, 2020).

Reducing risk

These findings highlight obstacles facing the programme in improving household income and structural assets, rendering it, at best, a protective, rather than promotive instrument that in some circumstances lessens the intensity of income shocks, but has limited capacity in promoting structural improvements in well-being (Kawar et al., 2022). This leads us to an assessment of whether in this case, poverty traps may be at play, and to what extent the UCT programme influences the ability of poor and vulnerable households to overcome such poverty traps. A poverty trap is a self-reinforcing mechanism that keeps households in poverty over time (Barrett, Carter, Chavas, & Carter, 2019). In these situations, poor households cannot—or are not willing to—accumulate enough assets or income to escape poverty.

In the context of the UCT, we observe that local average treatment effects, in comparison to average treatment effects on the treated are much stronger in magnitude, for instance on imputed and reported income. In other words, effects on households that are just eligible seem to be stronger than on the overall beneficiary population. Now, households have not been re-interviewed since their application in February 2022, no households have been 'forcibly graduated' out of the programme thus far, and they have not been informed of an official re-evaluation point. Yet, adverse incentive effects to either misreport the level of well-being or actively avoid an improvement in structural well-being in order to remain eligible for the UCT may be at play (Banerjee, Hanna, Olken, & Sumarto, 2020; Mora et al., 2022; Wolfe, 2002). We assume that while households are unaware of the precise PMT model, they know that eligibility into the programme is based on certain volatile or structural indicators of well-being, such as having a car. Apart from this behavioural component, the lack of beneficiary households to accumulate assets provides further suggestive evidence that poverty traps may be at play (Barrett et al., 2017, 2019). Of course, this could be due to the fact that asset accumulation takes time, and positive gains will not become evident over the course of only two years. However, it could also hint at the fact that beneficiary households are so structurally poor and vulnerable that they are practically unable to invest in productive assets (Kraay & McKenzie, 2014). Alternatively, the cash received through the UCT programme may not be invested in productive activities or assets, and thus may have limited impact in terms of helping households to move out of poverty eventually.

Nonetheless, an important consideration is the transfer accuracy, or the sufficiency of the cash transfer amount in allowing for such productive investments. In the UCT, transfer amounts vary between 40 JOD to 100 JOD per household per month, depending on household size. The large majority of households (76%) receive the full amount of 100 JOD, 18% receive 85 JOD and only about 6% receive 70 JOD or less. Yet, even 100 JOD per month—equivalent to the poverty line for one person—may not be sufficient to achieve structural improvements in well-being, especially within larger households. This is somewhat confirmed through our heterogeneity analyses, which show that the negative observed impacts intensify, the larger the household. While there are of course trade-offs between coverage and transfer adequacy, the cash transfers are on average only equivalent to 18% of the poverty line among Jordanian beneficiary households, and may thus be insufficient to cover the needs of all household members as well as productive investments simultaneously.

Schooling

Finally, we find that children of households who are beneficiaries of the Unified Cash Transfer programme are consistently more likely to (all) be enrolled in school, and fewer children within these households are not enrolled, similar to previous studies (Baird, Ferreira, Özler, & Woolcock, 2014; Bastagli et al., 2019; Kilburn et al., 2017). Beneficiary households are also less likely to have a child drop out of school. The increased school enrolment and reduced drop-out is important because education is a critical tool for breaking the inter-generational transmission of poverty, offering long-term benefits such as higher income potential (Moore, 2001). Additionally, higher enrolment rates suggest that the cash transfers help reduce immediate financial barriers to education, allowing households to prioritise schooling for their children. However, as schooling outcomes like school enrolment may vary considerably throughout the year due to the school cycle and school holidays, and the EMIS data base may not always be immediately updated, these results are to be interpreted with caution.

Limitations

Our study is not without limitations. First of all, the time frame during which the UCT programme has been implemented thus far is rather short. In other words, we can only detect short-term effects, but are unable to analyse to what extent the UCT programme enables households to sustainably improve their level of well-being, and for previously poor households, to ultimately move out of poverty. A follow-up evaluation of the programme is hence needed in order to continue monitoring the functioning of the programme and assess mid- to long-term effects, possibly including graduation effects. A second limitation concerns the data used in this impact evaluation, which. As explained in Section 3, the data for determining eligibility come from the NUR, Jordan's integrated government database, while they are managed by an independent data company contracted by NAF. There, applications are processed, and the data are transformed and stored. For monitoring and evaluation purposes, an analysis of the proxy-means test is currently complicated, as not all indicators within this PMT model are stored in the data that we used. Furthermore, especially among non-beneficiary households and households in the informal sector, some of the data, e.g., regarding employment or income, may naturally not be updated in the NUR system, and thus provide limited variation over time for conducting an impact evaluation. Another limitation in terms of data is that after application, eligible households are being visited and their information is verified, while non-eligible households—or at least those who are far from being eligible—are often not. Therefore, there may be a discrepancy in terms of the data quality across beneficiary and non-beneficiary observations. Our difference-in-difference model addresses this limitation, but more structural verification of non-beneficiary data would be helpful for future evaluations. On top of that, the complex targeting mechanism of the UCT programme led us to exclude households who were ranked based on their reported income (Section 3, Equation 1). As a consequence, the estimates in this study may not hold for the entire beneficiary population, but only for the subset who was ranked based on imputed income.

Concluding remarks and way forward for the UCT programme

The Unified Cash Transfer programme shows some positive developments, particularly in children's school enrolment, highlighting its effectiveness in addressing immediate non-monetary needs. These results are promising, as they suggest that the programme supports education as a tool to break the inter-generational transmission of poverty. However, persistent decreases in household income and asset ownership raise concerns about the programme's long-term effectiveness. Likely, the programme prioritises risk coping over risk prevention and mitigation, addressing immediate financial pressures but failing to prevent financial risks and provide sustainable pathways out of poverty. Asset accumulation among non-beneficiary households further emphasises this gap. While the UCT achieves its protective function by providing some immediate relief, its overall poverty-reducing potential remains limited.

Due to the short implementation time frame, this study primarily captures short-term effects, limiting our ability to assess how the programme supports long-term structural improvements in household well-being and poverty alleviation. If the programme seeks long-term impact, complementary measures like skills development or job creation programmes are necessary. At the time of writing, the National Aid Fund had already begun to develop additional, supplementary elements to the cash transfers, such as a link with UNICEF Jordan's *Makani* project, an intervention that integrates learning support, community-based child protection services, early childhood development (ECD), adolescent and youth participation and skills development (UNICEF, 2022). In addition, NAF administers skills training programmes with the aim to increase employment among beneficiaries to the fund, a further strengthening of which and linkage with the UCT could further improve employment and income-generation outcomes.

While our study provides a foundation for future impact evaluation and process improvements, we leave further assessments, which could enhance the robustness of our findings, to future research.

7 Policy recommendations for future impact evaluation

The second objective of this study is to conduct a process evaluation that focuses on how administrative data can be utilised for monitoring and evaluation of the UCT programme in Jordan. It also aims to assess how the programme's design and implementation feed into and enhance the evaluation process, ensuring that administrative data informs improvements in programme effectiveness and accountability over time. Based on the findings above as well as the insights we have gained into the UCT programme while conducting this impact evaluation on-site, the following design and evaluation policy recommendations have emerged.

Revision of targeting model

From a programme design perspective, the targeting model and process should be revised and structured. At the time of writing (summer 2024), there are ongoing efforts to revise the proxy-means test used to impute income for the UCT in line with updated household data availability and refined indicators to more accurately predict poverty in the Kingdom. This will help increase the targeting efficiency and ensure the most vulnerable households are reached. Furthermore, we recommend to reduce the complexity in eligibility decisions taken after the income imputation model. While we acknowledge that some control mechanisms are useful and needed to filter out households with very high levels of well-being, such as income caps, or property ownership caps, additional layers of exclusion or inclusion render the targeting mechanism less transparent. Above all, we recommend that targeting should be based on the PMT or income imputation model *only*, and households should not be ranked based on the formula in Equation 1. This will not only facilitate impact evaluations in the future, which may estimate local average treatment effects around the threshold in an RDD model, but also help ensuring fairness in the ranking exercise as well as minimising income reporting errors.

Data processing and storage

Moreover, we recommend to change the way data is processed and stored for easier use of the rich administrative data for monitoring and evaluation purposes. At first, key outcome variables that reflect the overall objectives of the UCT programme need to be defined. These can be, amongst others, but not limited to, (per capita) income, employment—potentially of all working-age household members—on the intensive and extensive margin (e.g., type of employment), different and specific asset indicators or school enrolment. Raw data on these key outcome variables should be stored separately in each data run, next to the 'outcome' of the PMT model, so that they can later be used more easily. In the current system, where mainly the output of the income imputation model as well as some other categorical variables from earlier targeting systems is stored, we had to proxy for some of these variables, so a storage of the underlying raw data will facilitate further evaluation activities. Furthermore, all of this data should be collected for relevant beneficiary and non-beneficiary households alike. Whenever data is pulled from the NUR, it should also be coded clearly whether this variable comes from the NUR data base, or was self-reported by the household, in order to ensure transparency and that all variables used for monitoring and evaluation accurately and objectively reflect households' levels of well-being.

Our goal has been to leverage the rich administrative data from the National Unified Registry, and outline future directions for the Unified Cash Transfer programme within the context of Jordan's social protection landscape. This analysis, while only capturing short-term outcomes, lays the groundwork for long-term evaluations. While having administrative data is critical, its quality is equally important. Notwithstanding the current data limitations, this study contributes to both policy design and evaluation, ensuring further improvements in the potential of leveraging the data for improving the UCT's effectiveness in addressing households' socio-economic risks.

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A Appendix

Table A.1: Expenditure model for income imputation

Variable	Value	Weight
Demographics		
Age household head	Age	-0.0171
Age household head squared	Age squared	0.0002
Gender household head	Head is female (reference: male head)	0.1245
Gender and marital status	Head is female, never married	-0.1049
Gender and marital status	Head is female, divorced	-0.0847
Gender and marital status	Head is female, widow	-0.0599
Disability household head	Head is disabled or chronically ill	-0.0059
Education household head	Can read or elementary education (reference: illiterate)	0.0655
Education household head	Preparatory, basic, secondary, vocational	0.1169
Education household head	Intermediate diploma, BA, post-BA	0.2517
Household members	Number of working age members (age 15-64)	0.0174
Disabled household members	Share of working age members who are disabled	-0.2135
Household members	Share of working age members who are males age 15-17	0.1909
Household members	Share of working age members who are males age 18-44	0.1428
Household members	Share of working age members who are males age 45-64	0.0111
Household size	Household size	-0.1573
Household size squared	Household size squared	0.0049
Dependency ratio	Dependency ratio	-0.1771
Ownership of assets		
Livestock	Household owns livestock	-0.4863
Livestock productivity	Imputed livestock productivity	0.0651
Land ownership	Household owns land	0.001
Land cultivation	Household cultivates land	0.0601
Car ownership	Household owns a car	0.4368
Number of cars	Number of private cars	0.27
Age of car	Age of newest car	-0.0307
Age of car squared	Age of newest car, squared	0.0004
Other vehicles	Number of cargo vehicles, taxis, buses	0.1829
Property ownership	Household owns residential or commercial property	0.016
Stock ownership	Household owns stocks	0.1136
Housing		
Type of house	HH lives in an apartment (vs. villa, house, shack/slum)	0.0692
House size	Area of the house per capita	0.0057
Utility costs	Value of water and electricity bills	0.1446
Geography		
Rural	Household lives in rural area	-0.0845
Governorate	Balqa (reference: Amman)	-0.1677
Governorate	Zarqa	0.0415
Governorate	Madaba	0.0041
Governorate	Irbid	-0.081
Governorate	Mafraw	-0.2212
Governorate	Jerash	-0.1123
Governorate	Ajloun	-0.1162
Governorate	Karak	-0.259
Governorate	Tafilah	-0.201
Governorate	Ma'an	-0.1006
Governorate	Aqaba	-0.1428

Table A.2: Filters for exclusion from UCT programme

Category	Exclusion Criteria
Ownership of assets or real estate	The household earns two or more (?)
Ownership of assets/buildings	The cash value is ≥69120 JOD
Ownership of assets or land	The monetary value is ≥74,880 JOD
Ownership of assets or agricultural units	The return is ≥10250 JOD
Ownership of assets or livestock	The estimated production is 352 JOD and more (based on per capita productivity of 40 JOD for cows, 15 JOD for camels, and 4 JOD for sheep and goats)
Ownership of assets or vehicles	2 or more
Vehicle model and age of vehicle in years	Five years or less
Financial assets (stocks, bonds)	The return is ≥10250 JOD
Having a maid	The household has a maid
Sole proprietorship and/or ownership of company	A sole proprietorship with a capital of 3,000 JOD or more, or a share in a company exceeding 3,000 JOD, or a family owns two establishments, regardless of capital.
Membership in professional unions	The head of household belongs to any professional union (doctors, dentists, engineers, lawyers, nurses, etc.).

Table A.3: Overview: Data cleaning

	Nr. of household observations
Raw data	**519,109**
— *Takaful* beneficiaries	82,331
— Missing data rounds	122,427
— Eligibility corrections	10,895
— Exclusion by filter	50,162
— Outliers	68
— Income corrections	1,729
— Reported income for ranking	31,954
— Small number of payments	13,878
Final sample	**205,665**
— Thereof beneficiary households	42,001

Table A.4: Heterogeneous results RDD

	(1) Small HH	(2) Medium HH	(3) Large HH	(4) Urban	(5) Rural	(6) Amman	(7) Other Gov.
Income							
HH income reported (log)	-0.263	-0.432***	-0.600***	-0.370***	-0.526**	-0.415***	-0.381***
	(0.2295)	(0.0884)	(0.1734)	(0.0798)	(0.187)	(0.117)	(0.0961)
PC income reported (log)	-0.242	-0.423***	-0.528***	-0.375***	-0.520***	-0.429***	-0.379***
	(0.1953)	(0.0743)	(0.1389)	(0.0644)	(0.1468)	(0.0965)	(0.0765)
HH income imputed (log)	-0.083	-0.100***	-0.148***	-0.085***	-0.052	-0.076**	-0.073**
	(0.0518)	(0.0147)	(0.0287)	(0.0168)	(0.0532)	(0.024)	(0.0245)
PC income imputed (log)	-0.102*	-0.116***	-0.103**	-0.115***	-0.112***	-0.121***	-0.108***
	(0.0476)	(0.0134)	(0.0322)	(0.0129)	(0.0321)	(0.0159)	(0.0157)
Household head income							
No income	-0.357***	-0.320***	-0.383***	-0.306***	-0.389***	-0.389***	-0.270***
	(0.0775)	(0.027)	(0.0642)	(0.0291)	(0.0692)	(0.0332)	(0.0348)
Regular income	0.190*	0.263***	0.324***	0.241***	0.360***	0.320***	0.215***
	(0.0845)	(0.0306)	(0.0623)	(0.0305)	(0.0709)	(0.0363)	(0.0359)
Irregular income	0.167***	0.051***	0.062*	0.065***	0.013	0.068***	0.053***
	(0.0483)	(0.0134)	(0.0265)	(0.0127)	(0.0253)	(0.0159)	(0.0149)
Employment							
Housheold head works	0.365***	0.265***	0.311***	0.252***	0.343***	0.320***	0.232***
	(0.0771)	(0.0333)	(0.056)	(0.0301)	(0.0613)	(0.0358)	(0.0346)
Head irregular employment	0.217**	0.218***	0.223***	0.187***	0.352***	0.259***	0.179***
	(0.0816)	(0.0317)	(0.0517)	(0.0294)	(0.0615)	(0.0358)	(0.0339)
Head regular employment	0.023	-0.002	0.011	0.000	0.003	0.008	-0.006
	(0.0155)	(0.0043)	(0.0097)	(0.0037)	(0.0094)	(0.0051)	(0.0043)
Head business owner	0.127**	0.049***	0.071**	0.066***	0.006	0.051***	0.053***
	(0.0439)	(0.0119)	(0.0241)	(0.0122)	(0.022)	(0.0137)	(0.0128)
Nr. income sources in HH	0.157*	0.081*	0.328**	0.127***	0.117	0.081*	0.143**
	(0.0819)	(0.0369)	(0.1062)	(0.0352)	(0.0811)	(0.0338)	(0.0442)
Assets							
HH has no assets	0.070	0.079*	0.057	0.048*	0.151*	0.108**	0.026
	(0.0702)	(0.032)	(0.0578)	(0.0287)	(0.0613)	(0.0369)	(0.0353)
HH has assets with revenue	-0.079	-0.039	-0.124*	-0.047*	-0.026	-0.081***	-0.022
	(0.0492)	(0.0244)	(0.0712)	(0.0208)	(0.0528)	(0.0232)	(0.0297)
HH has any assets	-0.070	-0.079*	-0.057	-0.048*	-0.148*	-0.106**	-0.025
	(0.0708)	(0.0326)	(0.0585)	(0.0288)	(0.0624)	(0.0375)	(0.0355)
Indicators in PMT							
HH owns land	-0.051	-0.038*	-0.094	-0.037*	-0.017	-0.073**	-0.010
	(0.0514)	(0.0226)	(0.0695)	(0.0213)	(0.0534)	(0.0231)	(0.0292)
HH cultivates land	-0.062	-0.036	-0.079	-0.035*	-0.015	-0.070**	-0.008
	(0.0489)	(0.0226)	(0.0699)	(0.0214)	(0.052)	(0.0233)	(0.0291)
HH owns car	-0.045	-0.101***	0.014	-0.074**	-0.128*	-0.056	-0.059*
	(0.0521)	(0.0276)	(0.0728)	(0.0238)	(0.0592)	(0.0375)	(0.0328)
HH owns property	0.000	0.003	-0.065	-0.010	-0.009	-0.016	-0.001
	(0.0251)	(0.0126)	(0.0475)	(0.0129)	(0.0231)	(0.018)	(0.0143)
PMT Asset index	-0.038	-0.031*	-0.057	-0.027*	-0.023	-0.055***	-0.012
	(0.0304)	(0.0142)	(0.0428)	(0.0138)	(0.0331)	(0.0141)	(0.0179)
Children's schooling							
All children enrolled	0.281**	0.344***	0.622***	0.374***	0.391***	0.419***	0.321***
	(0.0899)	(0.0277)	(0.0746)	(0.029)	(0.065)	(0.038)	(0.0336)
Nr. non-enrolled children	-0.074	-0.437***	-.926***	-0.457***	-0.506***	-0.509***	-0.417***
	(0.1456)	(0.0534)	(0.1675)	(0.0523)	(0.1312)	(0.0689)	(0.0652)
Any child dropped out	-0.103	-0.067	-0.167	-0.048	-0.175	-0.039	-0.107*
	(0.1684)	(0.0502)	(0.1072)	(0.0403)	(0.1357)	(0.0603)	(0.0587)
Nr. dropped out children	-0.032	-0.049	-0.217	-0.017	-0.113	0.006	-0.092
	(0.1343)	(0.0617)	(0.1522)	(0.0469)	(0.1391)	(0.0691)	(0.062)

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

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable.

Table A.5: Heterogeneous results RDD (round 2 baseline)

	(1) Small HH	(2) Medium HH	(3) Large HH	(4) Urban	(5) Rural	(6) Amman	(7) Other Gov.
Income							
HH income reported (log)	-0.254	-0.435***	-0.599***	-0.37***	-0.523**	-0.415***	-0.381***
	(0.2235)	(0.089)	(0.1736)	(0.0798)	(0.187)	(0.117)	(0.0961)
PC income reported (log)	-0.240	-0.423***	-0.525***	-0.375***	-0.518***	-0.429***	-0.380***
	(0.1911)	(0.0742)	(0.1391)	(0.0643)	(0.1467)	(0.0964)	(0.0765)
HH income imputed (log)	-0.082*	-0.101***	-0.148***	-0.085***	-0.052	-0.076**	-0.073**
	(0.0476)	(0.0148)	(0.029)	(0.0169)	(0.0532)	(0.024)	(0.0245)
PC income imputed (log)	-0.117*	-0.115***	-0.101**	-0.115***	-0.111***	-0.121***	-0.108***
	(0.0459)	(0.0134)	(0.0322)	(0.0129)	(0.0321)	(0.0159)	(0.0157)
Head income							
No income	-0.366***	-0.318***	-0.381***	-0.306***	-0.388***	-0.39***	-0.270***
	(0.0748)	(0.0275)	(0.0643)	(0.0291)	(0.0692)	(0.0332)	(0.0348)
Irregular income	0.200*	0.262***	0.322***	0.241***	0.359***	0.320***	0.215***
	(0.0812)	(0.0308)	(0.0624)	(0.0305)	(0.0708)	(0.0363)	(0.0359)
Regular income	0.166***	0.051***	0.063*	0.065***	0.013	0.068***	0.053***
	(0.0465)	(0.0134)	(0.0266)	(0.0128)	(0.0253)	(0.0159)	(0.0149)
Employment							
Household head works	0.369***	0.264***	0.309***	0.252***	0.342***	0.320***	0.232***
	(0.0759)	(0.0333)	(0.0559)	(0.0301)	(0.0611)	(0.0358)	(0.0346)
Head irregular empl.	0.221**	0.217***	0.221***	0.187***	0.351***	0.259***	0.179***
	(0.0785)	(0.0316)	(0.0517)	(0.0294)	(0.0614)	(0.0358)	(0.0339)
Head regular employment	0.019	-0.002	0.011	0.000	0.003	0.008	-0.006
	(0.0146)	(0.0043)	(0.0097)	(0.0037)	(0.0094)	(0.0051)	(0.0043)
Head business owner	0.125**	0.049***	0.071**	0.066***	0.005	0.051***	0.053***
	(0.0425)	(0.0119)	(0.0241)	(0.0122)	(0.022)	(0.0137)	(0.0128)
Nr. income sources in HH	0.165*	0.080*	0.328**	0.127***	0.117	0.081*	0.143**
	(0.0778)	(0.037)	(0.1064)	(0.0352)	(0.0811)	(0.0338)	(0.0442)
Assets							
HH has no assets	0.077	0.079*	0.056	0.048*	0.152*	0.108**	0.026
	(0.0668)	(0.032)	(0.0579)	(0.0287)	(0.0611)	(0.0369)	(0.0353)
HH assets with revenue	-0.069	-0.040	-0.125*	-0.047*	-0.027	-0.081***	-0.022
	(0.0447)	(0.0242)	(0.0714)	(0.0208)	(0.0528)	(0.0232)	(0.0297)
HH has any asset	-0.077	-0.079*	-0.055	-0.048*	-0.149*	-0.106**	-0.025
	(0.0665)	(0.0326)	(0.0587)	(0.0288)	(0.0622)	(0.0375)	(0.0355)
Indicators in PMT							
HH owns land	-0.045	-0.039*	-0.095	-0.037*	-0.017	-0.073**	-0.010
	(0.0471)	(0.0226)	(0.0697)	(0.0213)	(0.0534)	(0.0231)	(0.0292)
HH cultivates land	-0.055	-0.037	-0.080	-0.035*	-0.016	-0.07**	-0.008
	(0.0448)	(0.0226)	(0.0701)	(0.0214)	(0.052)	(0.0233)	(0.0291)
HH owns car	-0.043	-0.102***	0.016	-0.074**	-0.128*	-0.056	-0.059*
	(0.0492)	(0.0274)	(0.0729)	(0.0237)	(0.0591)	(0.0375)	(0.0328)
HH owns property	-0.005	0.003	-0.062	-0.010	-0.008	-0.016	-0.001
	(0.0239)	(0.0125)	(0.0474)	(0.0129)	(0.023)	(0.018)	(0.0143)
PMT asset index	-0.035	-0.031*	-0.057	-0.027*	-0.023	-0.055***	-0.012
	(0.0279)	(0.0141)	(0.0429)	(0.0138)	(0.0331)	(0.0141)	(0.0179)
Children's schooling							
All children enrolled	0.283**	0.344***	0.622***	0.375***	0.391***	0.419***	0.321***
	(0.0899)	(0.0277)	(0.0746)	(0.029)	(0.065)	(0.038)	(0.0336)
Nr. non-enrolled children	-0.079	-0.436***	-.925***	-0.457***	-0.506***	-0.509***	-0.417***
	(0.1457)	(0.0534)	(0.1674)	(0.0523)	(0.1312)	(0.0689)	(0.0652)
Any child dropped out	-0.101	-0.067	-0.166	-0.048	-0.175	-0.039	-0.107*
	(0.1673)	(0.0502)	(0.107)	(0.0403)	(0.1356)	(0.0603)	(0.0587)
Nr. children dropped out	-0.033	-0.049	-0.216	-0.017	-0.121	0.006	-0.092
	(0.1344)	(0.0616)	(0.152)	(0.0468)	(0.1403)	(0.0691)	(0.062)

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

Note: The number of observations is not reported, as it may vary across estimations due to the separate MSE-optimal bandwidth selection procedure for each outcome variable.

Table A.6: Fuzzy RDD robustness checks

	(1) All Payments Round 1 baseline	(2) All Payments Round 2 baseline	(3) Missing Values Round 1 baseline	(4) Missing Values Round 2 baseline
Income				
HH income reported (log)	-0.395***	-0.564***	-0.396***	-0.562***
	(0.0783)	(0.1434)	(0.0781)	(0.1429)
PC income reported (log)	-0.398***	-0.523***	-0.398***	-0.503***
	(0.0629)	(0.1023)	(0.0627)	(0.0973)
HH income imputed (log)	-0.064**	-0.065*	-0.064**	-0.065*
	(0.0201)	(0.0349)	(0.0201)	(0.0349)
PC income imputed (log)	-0.112***	-0.092***	-0.112***	-0.098***
	(0.0116)	(0.018)	(0.0117)	(0.0162)
Head income				
No income	-0.321***	-0.358***	-0.322***	-0.359***
	(0.0281)	(0.0454)	(0.028)	(0.0454)
Irregular income	0.258***	0.302***	0.258***	0.301***
	(0.0292)	(0.0498)	(0.0292)	(0.0497)
Regular income	0.063***	0.070***	0.064***	0.071***
	(0.0118)	(0.02)	(0.0119)	(0.0201)
Employment				
Household head works	0.274***	0.294***	0.274***	0.293***
	(0.0278)	(0.0503)	(0.0279)	(0.0501)
Head is in irregular employment	0.213***	0.243***	0.213***	0.242***
	(0.0277)	(0.0493)	(0.0277)	(0.0492)
Head is in regular employment	0.000	-0.010	0.00	-0.010
	(0.0031)	(0.0062)	(0.0032)	(0.0062)
Head is business owner	0.064***	0.052***	0.064***	0.052***
	(0.0115)	(0.0155)	(0.0115)	(0.0155)
Nr. of income sources in HH	0.131***	0.116*	0.132***	0.123*
	(0.0333)	(0.0609)	(0.0333)	(0.0611)
Assets				
HH has no assets	0.052*	0.074	0.052*	0.072
	(0.0274)	(0.0509)	(0.0273)	(0.0508)
HH has assets with revenue	-0.038*	-0.015	-0.037*	-0.011
	(0.0219)	(0.0397)	(0.0219)	(0.0399)
HH has any assets	-0.050*	-0.073	-0.050*	-0.071
	(0.0278)	(0.0483)	(0.0277)	(0.0482)
Indicators in PMT				
HH owns land	-0.034*	-0.031	-0.033	-0.027
	(0.0203)	(0.0385)	(0.0204)	(0.0386)
HH cultivates land	-0.034*	-0.023	-0.032	-0.02
	(0.0197)	(0.0385)	(0.02)	(0.0387)
HH owns a car	-0.073**	-0.041	-0.077***	-0.041
	(0.0234)	(0.046)	(0.0228)	(0.0459)
HH owns property	-0.008	-0.004	-0.008	0.000
	(0.0117)	(0.0237)	(0.0116)	(0.0235)
PMT asset index	-0.031**	-0.020	-0.029*	-0.017
	(0.0113)	(0.0243)	(0.012)	(0.0246)
Children's schooling				
All children are enrolled	0.370***	0.452***	0.37***	0.454***
	(0.0252)	(0.0553)	(0.0254)	(0.0555)
Number of non-enrolled children	-0.458***	-0.614***	-0.457***	-0.618***
	(0.0467)	(0.1053)	(0.0468)	(0.1058)
Any child dropped out	-0.062	-0.189*	-0.062	-0.189*
	(0.04)	(0.0983)	(0.04)	(0.0989)
Number of children who dropped out	-0.041	-0.219*	-0.042	-0.218*
	(0.0471)	(0.1177)	(0.0471)	(0.1182)

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

Table A.7: Regression results from estimation of the propensity score (round 1)

Dep. variable: Treatment take-up	(1) Round 1	(2) Round 2
Age of household head	-0.060***	-0.041**
	(0.019)	(0.019)
Age of household head squared	0.000	-0.000
	(0.000)	(0.000)
Household head is female (reference: male)	0.127	0.119
	(0.112)	(0.112)
Head is female, never married	-0.991***	-0.827***
	(0.283)	(0.278)
Head is female, divorced	-0.849***	-0.825***
	(0.293)	(0.277)
Head is female, widowed	-1.480*	-1.363*
	(0.759)	(0.768)
Head is female, disabled or chronically ill	0.285***	0.285***
	(0.099)	(0.095)
Household size	2.342***	2.373***
	(0.111)	(0.117)
Household size squared	-0.115***	-0.117***
	(0.010)	(0.010)
Dependency ratio	1.781***	1.803***
	(0.064)	(0.064)
Share of HH members of working age, disabled	1.975***	1.936***
	(0.294)	(0.271)
Share of male HH members, age 15-17	-0.214	0.253
	(0.416)	(0.406)
Share of male HH members, age 18-44	-1.703***	-1.919***
	(0.300)	(0.295)
Household owns land	-1.635***	-1.375***
	(0.386)	(0.417)
Household owns livestock	-1.593**	-1.463**
	(0.708)	(0.647)
Household cultivates land	0.596	0.534
	(0.391)	(0.420)
Household owns a car	-2.617***	-2.555***
	(0.072)	(0.070)
Household owns property	-1.509***	-1.450***
	(0.163)	(0.129)
Household owns stocks	-3.030***	-3.341***
	(0.648)	(0.632)
Household lives in an apartment	0.545***	0.579***
	(0.068)	(0.068)
Rural	0.489***	0.512***
	(0.125)	(0.124)
Governorate: Amman (reference: Ajloun)	0.079	0.187
	(0.315)	(0.294)
Governorate: Aqaba	1.332***	1.411***
	(0.396)	(0.384)
Governorate: Balqa	1.823***	1.862***
	(0.333)	(0.313)
Governorate: Irbid	0.766**	0.789***
	(0.315)	(0.295)
Governorate: Jerash	0.978***	0.961***
	(0.358)	(0.342)
Governorate: Karak	1.435***	1.413***
	(0.391)	(0.374)
Governorate: Ma'an	1.015*	1.018**
	(0.519)	(0.474)
Governorate: Madaba	0.809**	0.813**
	(0.374)	(0.357)
Governorate: Mafraq	1.925***	1.913***
	(0.347)	(0.326)
Governorate: Tafilah	1.454***	1.434***
	(0.547)	(0.516)
Governorate: Zarqa	-0.289	-0.211
	(0.317)	(0.296)
Observations	20,566	20,567

The dependent variable is treatment take-up D_i. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Covariate sample means and balance tests at the threshold (round 1)

	Bandwidth	Mean non-beneficiaries	Mean beneficiaries	Difference at threshold
Household size	28.7	4.6	5.1	0.105
				(0.0808)
Working-age household members	29.4	3.0	2.8	-0.066
				(0.0810)
Female household head	33.9	0.06	0.04	0.021*
				(0.0114)
Household lives in rural area	33.2	0.06	0.07	-0.014
				(0.0122)
Household lives in an apartment	29.1	0.67	0.75	-0.034
				(0.0254)
Household owns property	31.1	0.06	0.04	-0.004
				(0.0113)
Household owns land	32.5	0.22	0.16	-0.006
				(0.0209)
Household cultivates land	32.1	0.21	0.16	-0.001
				(0.0208)
Household owns livestock	45.5	0.003	0.002	-0.001
				(0.0024)
Household owns a car	32.4	0.36	0.23	0.047*
				(0.0239)

Standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.05$

Table A.9: Covariate sample means and balance tests at the threshold (round 2)

	Bandwidth	Mean non-beneficiaries	Mean beneficiaries	Difference at threshold
Household size	31.9	4.6	5.2	0.015
				(0.145)
Working-age household members	31.6	3.1	2.9	-0.049
				(0.0242)
Female household head	32.5	0.06	0.04	0.016
				(0.1560)
Household lives in rural area	32.0	0.06	0.07	-0.027
				(0.0251)
Household lives in an apartment	41.2	0.66	0.74	-0.037
				(0.0397)
Household owns property	38.8	0.08	0.05	-0.015
				(0.0230)
Household owns land	40.7	0.24	0.19	-0.02
				(0.0370)
Household cultivates land	45.9	0.24	0.19	-0.014
				(0.0338)
Household owns livestock	39.2	0.003	0.002	-0.001
				(0.0044)
Household owns a car	36.6	0.36	0.24	0.052
				(0.0444)

Standard errors in parentheses

* $p<0.1$, ** $p<0.05$, *** $p<0.05$

Table A.10: Difference-in-differences: income and employment (round 2 baseline)

	Control		Treatment		DiD
	Baseline Mean	Difference Coef	Baseline Mean	Difference Coef	Coef
Household income					
Household income reported (log)	6.385	-0.103**	6.176	-0.160***	-0.072
	(0.019)	(0.044)	(0.017)	(0.041)	(0.061)
Per capita income reported (log)	4.874	-0.071**	4.632	-0.127***	-0.070
	(0.015)	(0.035)	(0.014)	(0.034)	(0.049)
Household income imputed (log)	7.190	0.018***	6.869	-0.034***	-0.053***
	(0.005)	(0.007)	(0.005)	(0.007)	(0.010)
Per capita income imputed (log)	5.625	0.022***	5.295	-0.036***	-0.060***
	(0.003)	(0.007)	(0.003)	(0.007)	(0.010)
Household head income					
Head has no income	0.689	0.008	0.226	-0.006	-0.012
	(0.007)	(0.012)	(0.008)	(0.014)	(0.019)
Head has irregular income	0.295	-0.011	0.724	-0.015	-0.005
	(0.007)	(0.012)	(0.008)	(0.015)	(0.020)
Head has regular income	0.016	0.003	0.049	0.020**	0.017*
	(0.002)	(0.003)	(0.004)	(0.009)	(0.009)
Employment					
Household head works	0.236	-0.005	0.595	0.022	0.029
	(0.006)	(0.011)	(0.009)	(0.017)	(0.020)
Head is in irregular employment	0.222	-0.010	0.541	0.011	0.022
	(0.006)	(0.010)	(0.009)	(0.017)	(0.020)
Head is a business owner	0.010	0.004	0.042	0.014*	0.011
	(0.001)	(0.003)	(0.004)	(0.008)	(0.008)
Nr. regular income sources in HH	0.329	-0.043***	0.491	-0.069***	-0.034
	(0.009)	(0.015)	(0.012)	(0.022)	(0.027)
Observations	4,585	9,170	3,086	6,172	15,342

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

Note: The results for household income are expressed as percentages, and all other results are expressed as percentage points, as the outcome variable is binary, except the number of regular income sources, which is expressed in absolute values.

Table A.11: Difference-in-differences: assets and schooling (round 2 baseline)

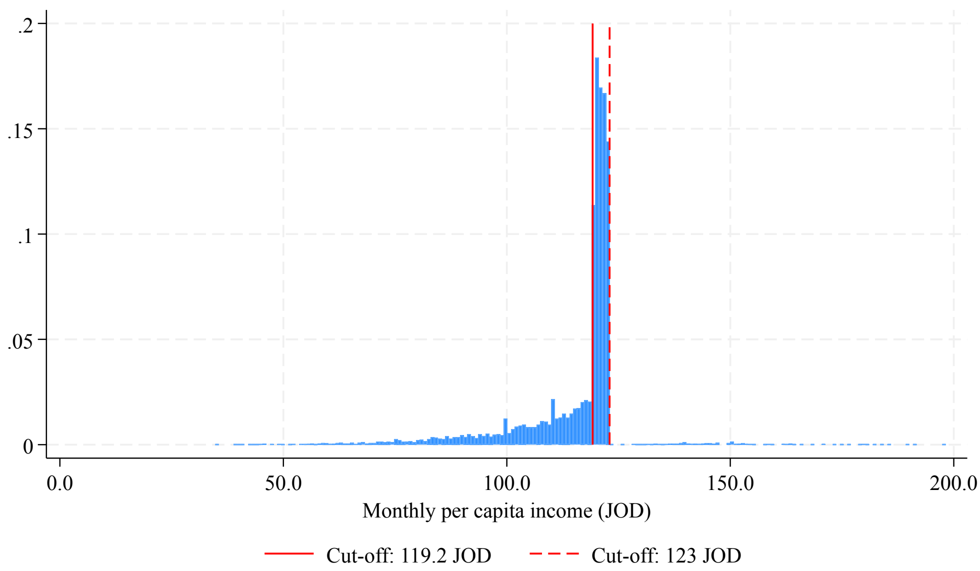
	Control		Treatment		DiD
	Baseline Mean	Difference Coef	Baseline Mean	Difference Coef	Coef
Assets					
Household has no assets	0.528	-0.037***	0.554	0.038**	0.078***
	(0.007)	(0.013)	(0.009)	(0.016)	(0.021)
Household has assets with revenue	0.246	0.003	0.242	-0.025	-0.026
	(0.006)	(0.011)	(0.008)	(0.016)	(0.019)
Household has any assets	0.472	0.037***	0.446	-0.038**	-0.078***
	(0.007)	(0.013)	(0.009)	(0.016)	(0.021)
Indicators in proxy-means test					
Household owns land	0.225	-0.001	0.228	-0.020	-0.019
	(0.006)	(0.011)	(0.008)	(0.015)	(0.019)
Household cultivates land	0.222	-0.003	0.225	-0.021	-0.017
	(0.006)	(0.011)	(0.008)	(0.015)	(0.019)
Household owns car	0.317	0.067***	0.294	-0.019	-0.087***
	(0.007)	(0.013)	(0.008)	(0.015)	(0.020)
Household owns property	0.058	0.004	0.057	-0.004	-0.008
	(0.003)	(0.006)	(0.004)	(0.009)	(0.011)
PMT asset index	0.165	0.005	0.164	-0.014	-0.019*
	(0.004)	(0.006)	(0.005)	(0.009)	(0.011)
Children's school attendance					
All children are enrolled	0.475	-0.008	0.936	-0.033***	-0.030
	(0.010)	(0.018)	(0.005)	(0.010)	(0.021)
Number of non-enrolled children	1.069	0.041	0.182	0.124***	0.153***
	(0.023)	(0.044)	(0.011)	(0.022)	(0.051)
Any child dropped out of school	0.353	0.233***	0.504	0.133***	-0.101***
	(0.016)	(0.027)	(0.013)	(0.022)	(0.035)
Number of children who dropped out	0.702	0.334***	0.883	0.253***	-0.086*
	(0.020)	(0.033)	(0.017)	(0.031)	(0.046)
Observations	4,585	9,170	3,086	6,172	15,342

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

Note: The results for assets and indicators in the proxy-means test are expressed as percentage points, as the outcome variable is binary, except for the PMT asset index, whose coefficient is expressed in absolute values. The results for children's schooling are expressed in percentage points, except the number of non-enrolled children or children who dropped out, which are expressed in absolute values.
[1]This PMT asset index was constructed by the authors to analyse changes in only the structural, non-demographic aspects in the PMT model. We construct this index through principal-component factor analysis using the indicators on livestock ownership, land ownership, land cultivation, car ownership, property ownership and stock ownership.

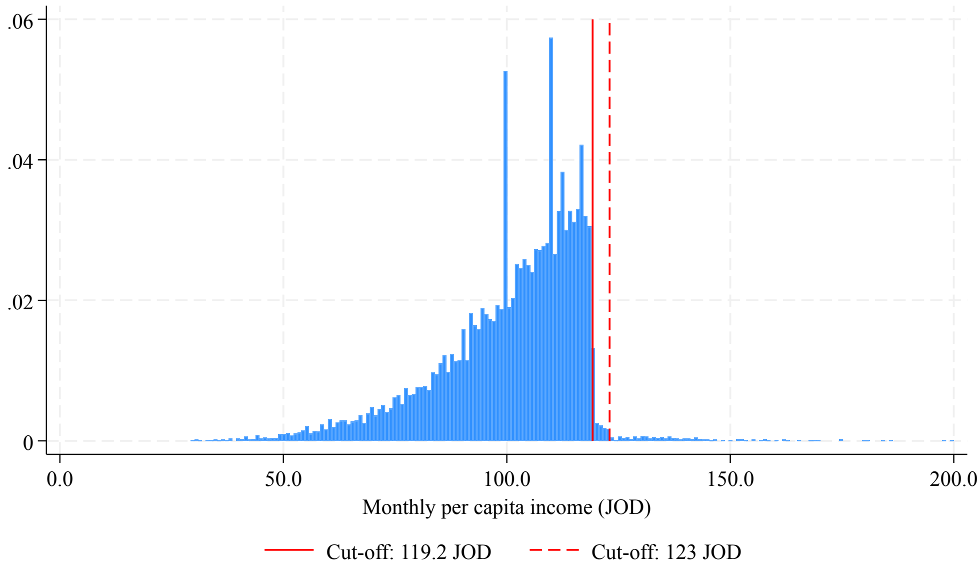
B Appendix

Figure B.1: Histogram of households deemed eligible in round 1 but did not receive UCT



Note: We limit the range of the running variable to monthly per capita incomes of 200 or less as data become relatively sparse for larger monthly per capita incomes.

Figure B.2: Histogram of households deemed eligible in round 1 who received 1-6 payments but were excluded from UCT in September 2022



Note: We limit the range of the running variable to monthly per capita incomes of 200 or less as data become relatively sparse for larger monthly per capita incomes.

Figure B.3: Regression discontinuity manipulation test

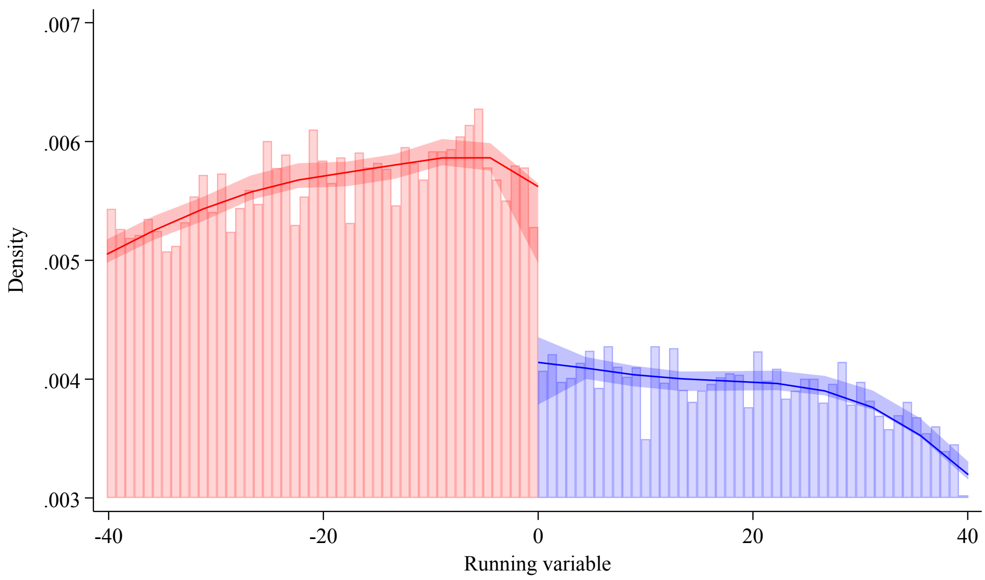
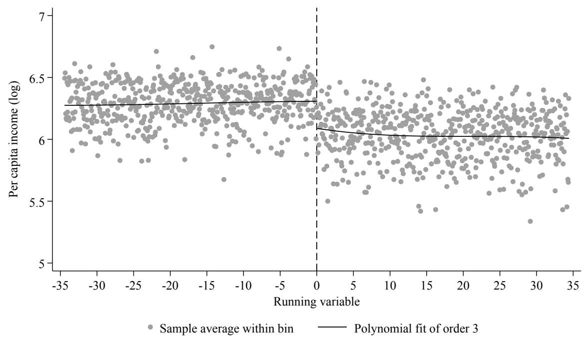
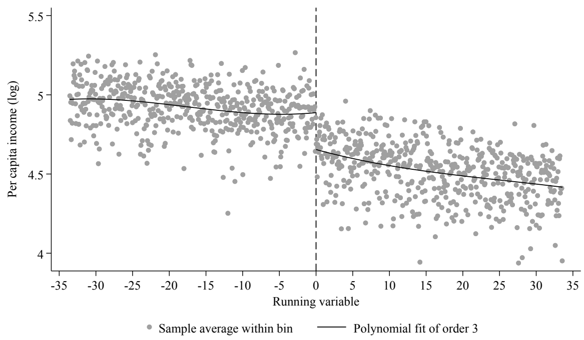


Figure B.4

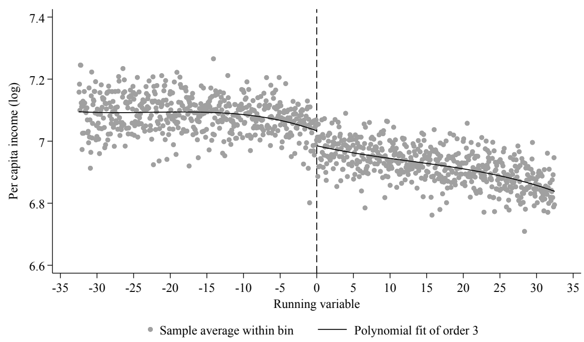
(a) Household (reported)



(b) Per capita (reported)



(c) Household (imputed)



(d) Per capita (imputed)

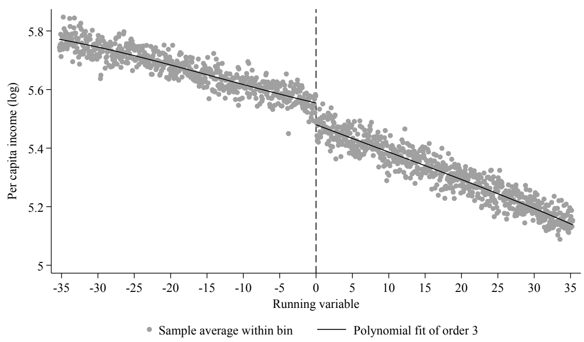
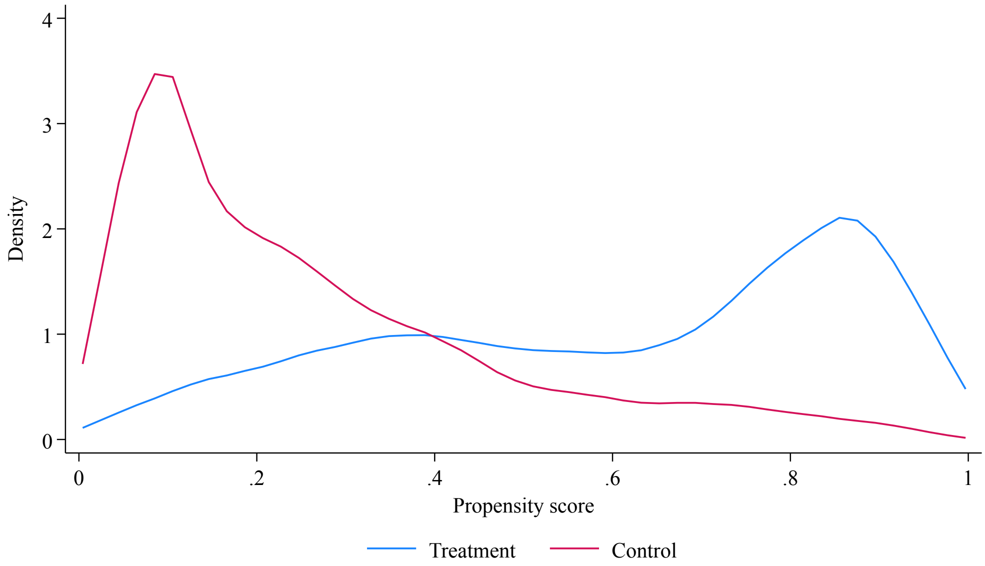


Figure B.5: Kernel density smoothing of propensity score across treatment and control group

(a) Unweighted



(b) Weighted

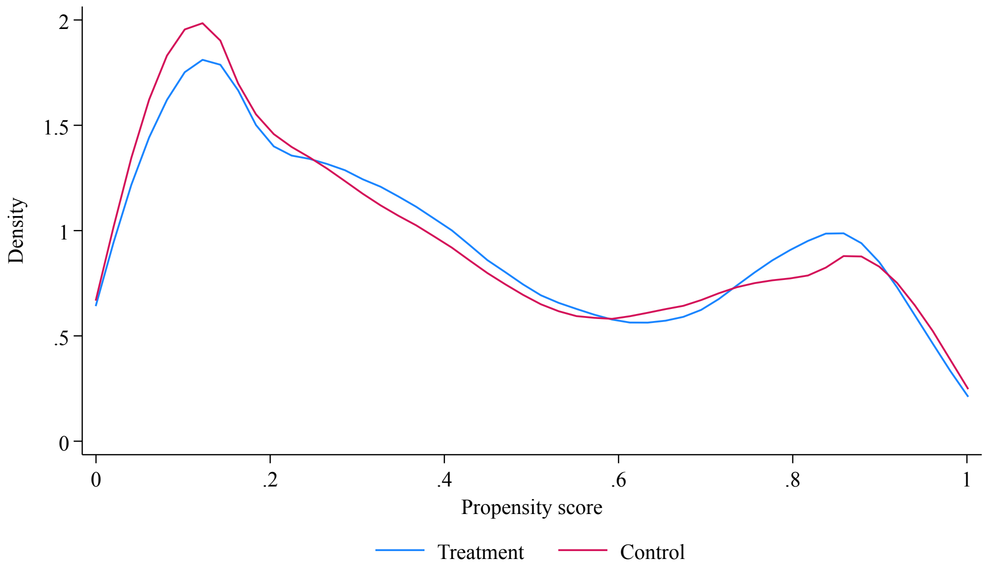
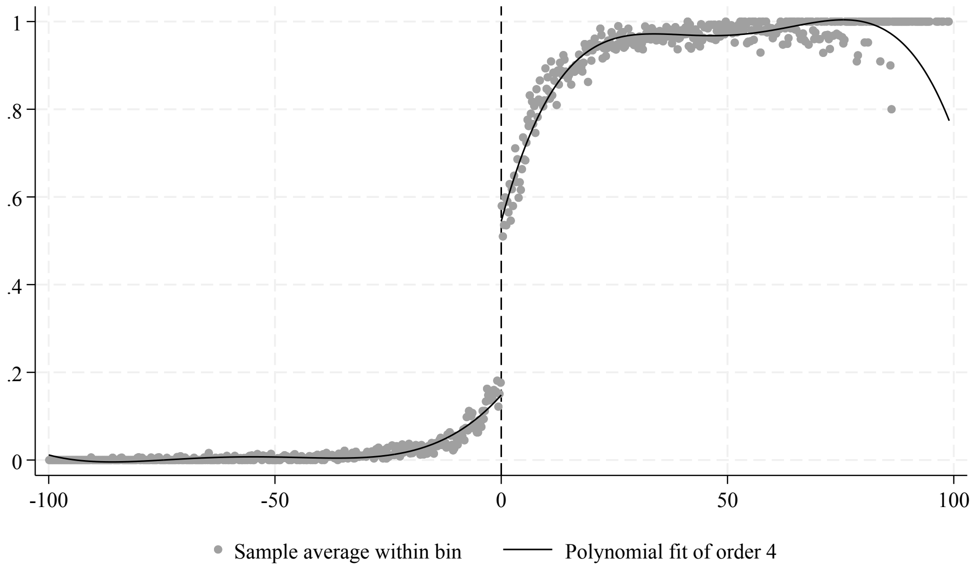
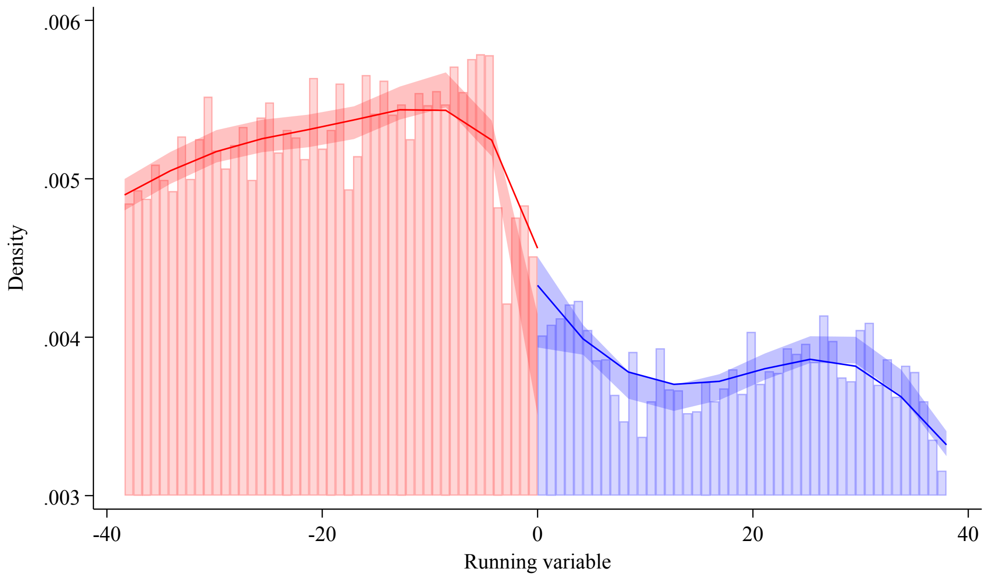


Figure B.6: Regression discontinuity plot: treatment take-up at round 2



Note: We limit the range of the running variable to monthly per capita incomes of 100 or less (in absolute terms) as data become relatively sparse for larger incomes. The eligibility threshold is JOD 119.175 monthly per capita income (imputed).

Figure B.7: Regression discontinuity manipulation test (round 2 baseline)



Note: x