Empowering Refugees through Cash and Agriculture: A Regression Discontinuity Design *

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October 2020

Abstract

Assistance to refugees is shifting from a humanitarian model, which focuses on protection, emergency relief, and shelter, to a development model promoting refugee self-reliance through income-generating activities, market development, and cash transfers. Evidence on the effects of this paradigm shift is limited. Exploiting a regression discontinuity design, this paper tests whether the adoption of a development approach to refugee assistance in a new settlement in Kenya has a positive impact. We find that refugees benefiting from the new approach have better diets and perceive themselves as happier and more independent from humanitarian aid. We find no effect on assets and employment. These effects appear to be driven by the switch from food rations to cash transfers and by the wider promotion of small-scale agriculture. Our findings argue in favor of the development approach to refugee assistance, which is cheaper and leads to better outcomes.

Keywords: Refugee economies, Humanitarian aid, Cash transfers, Agriculture, Self-reliance

JEL Classification: O12, O15, I38, Q12

*The analysis presented in this paper reflects the views of the authors but not necessarily the views of the institutions employing them. All errors are ours. We acknowledge funding from the World Food Program.

1 Introduction

In 2016, the United Nations General Assembly adopted the New York Declaration for Refugees and Migrants, which recognizes that refugees can be self-reliant[1] and make positive contributions to the communities hosting them provided they are given access to labor markets, livelihood opportunities, education, and health care without discrimination. The New York declaration's commitment to a development approach to refugee assistance marked a major paradigm shift from the humanitarian model that had prevailed for decades. The humanitarian model assumes that refugee situations are temporary, implying that assistance can simply focus on protection, emergency relief, and shelter while crises are being resolved. The premise of the humanitarian model is however flawed: only 2.5 percent of refugee crises are resolved within 3 years (Cosgrove et al. 2016), and approximately 78 percent of all the refugees worldwide were living in a protracted situation at the end of 2018 (UNHCR 2019).[2]

Concurrently with the New York declaration, a few host countries initiated pioneering policy experiments to enhance refugee agency and foster local development. In 2016, both Jordan and Ethiopia agreed to grant thousands of work permits to refugees in exchange for concessional financing and different forms of development support.

In this paper, we assess the impact of a third experiment in the development approach to refugee policy: the Kalobeyei settlement in North-West Kenya. The refugee legislation in Kenya is viewed as one of the most restrictive worldwide (Betts et al. 2019; Jaji 2011). Kenya's encampment policy requires refugees to reside in camps and restricts their freedom of movement and right to work. Until May 2016, the bulk of incoming refugees had to settle in two massive refugee camps created in the early nineteen-nineties to host refugees escaping civil conflicts in Southern Sudan and Somalia: Kakuma and Dadaab. Both of these camps became symbols of the humanitarian approach to refugee assistance (Jansen 2015; Abdi

[1]Self-reliance is defined by UNHCR as *"the social and economic ability of an individual, a household or a community to meet essential needs (including protection, food, water, shelter, personal safety, health and education) in a sustainable manner and with dignity"* (UNHCR 2005).

[2]UNHCR defines protracted refugee situations as those in which at least 25,000 refugees from the same country have been living in exile for more than five consecutive years.

2005), with refugees waiting for years in limbo and surviving on monthly food rations.

In May 2016, a third refugee hosting site, the Kalobeyei settlement, was opened in Kenya, just 3.5 kilometers away from the old Kakuma camp (Figure 1). The Kalobeyei development plan proposes a radically different approach which would transform "the humanitarian model of assistance for refugees towards the development-oriented solutions that enhance the self-reliance of refugees and host communities" and "boost the local economy" (UNHCR 2018). However, in practice, the Kalobeyei settlement shares many of the same challenges that limit economic opportunities in the neighboring Kakuma camp. Yet the Kalobeyei settlement differentiates itself from the Kakuma camp by proposing a series of programs aiming to foster economic development through the promotion of self-reliance and integration. Two programs were particularly notable at the time of our survey in August 2017. First, in-kind food rations had been almost entirely replaced by a system of mobile-money transfers called Bamba Chakula. Second, rain-fed agriculture was more widely promoted in the Kalobeyei settlement, as a way of supplementing and diversifying refugee diets.

We use a regression discontinuity design to assess the short-run effect of the development approach promoted in Kalobeyei. We take advantage of the rule used by the United Nations High Commissioner for Refugees (UNHCR) to assign newly arriving refugees between the Kakuma camp and the Kalobeyei settlement. Households who arrived before the 13th of May 2016 were invited to settle in the Kakuma camp, while those who arrived after the 14th of May 2016 went to live in Kalobeyei. This analysis draws on data from a representative household survey of refugees who were living in Kakuma camp and Kalobeyei settlement in September and October 2017. We exploit the discontinuity in the UNHCR assignment rule to compare the average outcomes of refugees who arrived shortly before and after the cutoff date, and interpret any concurrent discontinuity in average outcomes as resulting from the differing programs between the two sites. We use both a parametric and a non-parametric approach to estimate treatment effects (Jacob et al. 2012; Calonico et al. 2019).

The results of this regression discontinuity analysis indicate that refugees who arrived shortly after the cutoff date do better in terms of dietary diversity, calorie intake, and food security than those arriving just before. By contrast, we find no effect on assets and on non-food spending. While refugees living in Kalobeyei are more likely to be involved in agriculture, we find no effect on other income-generating activities. We also find suggestive evidence that refugees living in Kalobeyei feel happier and more independent from aid than their counterparts in Kakuma. These results are robust to various tests and specification changes.

One key challenge in our study is to attribute the observed effects to specific differences between Kakuma and Kalobeyei. Yet this part of the analysis is also the most interesting, as it sheds light on some of the barriers and opportunities that shape refugees' socio-economic lives. We explore the possible mediating role of different variables, including involvement in productive activities, health, education, finance, remittances, spending on non-essential goods, prices, and food assistance modalities. Our analysis suggests that the "Kalobeyei effect"[3] is not driven by differences in employment, by differences in accumulation of human or physical capital, nor by access to finance or remittances. We find suggestive evidence that improvements in dietary variety and food security in Kalobeyei are partly attributable to involvement in kitchen gardens.[4] However, there is no significant difference in calorie intake between those that grow their own food and those that do not. This is likely because the type of foods grown are dense in nutrients but not in calories. We argue that the bulk of the "Kalobeyei effect" can be attributed to the different modes of food assistance offered in Kakuma and Kalobeyei. In Kakuma, the monthly entitlement per refugee is mostly in-kind, constituted of 13 kilograms of a mix of cereals, pulses, and oil. It is very common for refugees to resell part of their food rations at a low price to allow for purchase of other types of food and non-food items. By contrast, refugees living in Kalobeyei can choose to buy the food they prefer using Bamba Chakula, without additional transaction costs.

[3]In what follows, we use the label "Kalobeyei effect" when referring to the significant discontinuities estimated for nutrition outcomes, subjective well-being, and perception of independence.

[4]A kitchen garden is a garden or area where vegetables, fruit, or herbs are grown for domestic use.

Our research contributes to the literature on refugee economies (Betts et al. 2019, 2018; Alloush et al. 2017; Jacobsen 2005) and refugee livelihoods (Jacobsen 2014; Horst 2006). The paper carefully describes the socio-economic lives of refugees living in the Kakuma refugee camp and the Kalobeyei settlement (Alix-Garcia et al. 2019; Betts et al. 2019; Alix-Garcia et al. 2018). The bulk of the economic literature on refugees measures the impact of refugees on host populations, showing that refugees can stimulate host economies (Alix-Garcia et al. 2018; Maystadt and Duranton 2018; Taylor et al. 2016) but also have negative impacts, for example by favoring the propagation of diseases (Baez 2011; Montalvo and Reynal-Querol 2007) or competing for scarce resources and jobs (Depetris-Chauvin and Santos 2018; Tumen 2016; Ruiz and Vargas-Silva 2015). The resulting effects are complex and mixed, with some benefiting from the arrivals of refugees while others end up worse off (Fallah et al. 2019; Maystadt and Verwimp 2014; Alix-Garcia and Saah 2009). The economic literature on refugees themselves is surprisingly scarce. Our research examines how assistance to refugees can be best provided. It therefore contributes to the literature on the relative impacts of providing food aid in-kind, as cash, or as vouchers to refugees. Findings on the differential impacts of food-aid modalities have been far from conclusive,[5] and may depend heavily on the specific contexts in which they were researched (Gentilini 2015). For example, two studies found in-kind aid to have a larger impact on increasing calorie intake than cash or vouchers in Ecuador and Uganda (Hidrobo et al. 2014; Hoddinott et al. 2013). One study in Yemen found the opposite to be true (Schwab 2020). Cash and vouchers led to greater dietary diversity than did in-kind in almost all studies, most likely because those recipients preferred to spend the transfer on a wide range of less energy-dense food while in-kind recipients mostly consumed the large quantities of staples they received. Our findings highlight the benefits of cash transfers that can only be spent on food items. Finally, our results – which suggest that kitchen-garden agriculture improves refugee diets – also contribute to the scarce literature on small-scale agriculture in refugee

[5]See for example Aker (2017) in the Democratic Republic of Congo, Cunha (2014) in Mexico, Hidrobo et al. (2014) in Ecuador, Hoddinott et al. (2018) in Niger and Hoddinott et al. (2013) in Uganda, Mohiddin et al. (2007) in Sri Lanka, and Schwab (2020) in Yemen.

contexts (Betts et al. 2019; Strunk and Richardson 2019).

The paper is organized as follows. Section 2 introduces the context and the history of the Kakuma refugee camp and the Kalobeyei settlement, highlighting similarities and differences between the two sites. Section 3 introduces the new dataset used in this study, and presents the method of regression discontinuity used to analyze it. The main results of this analysis are presented and their robustness is discussed in Section 4. Channels of impact are explored in Section 5. Section 6 concludes the study.

2 The Kalobeyei quasi-experiment

The Kakuma refugee camp is situated in Turkana County in North-West Kenya, approximately 40km from the Kenyan border with South Sudan. It was created in 1991 when $12,000$ unaccompanied minors known as the 'Lost Boys' settled there after fleeing civil war in neighboring Southern Sudan. Since then, it has grown to host more than $145,000$ refugees, under the joint jurisdiction of the United Nations High Commissioner for Refugees (UNHCR) and the Government of Kenya's Refugee Affairs Secretariat (RAS). While the majority of the camp's population originate from South Sudan, the camp also hosts large numbers of Somali, Sudanese, and Congolese refugees (table 1). As of August 2017, the average household in Kakuma had spent 7 years in the camp.

The Kakuma camp offers limited opportunities for agriculture or other income-generating activities, first, because the camp is situated in a remote, poor, and arid area, and second, because Kenya's encampment policy imposes legal restrictions on refugees' right to work and freedom of movement. To be sure, some businesses thrive in Kakuma, especially in the oldest parts of the camp where the liveliest markets are located (Delius and Sterck 2020; IFC 2018). But success is for the few, not the many. Only 24% of adult refugees have an income-generating activity and, of these, a large proportion are employed by NGOs and international organizations (Betts et al. 2018). The median income of those working is low, about US$55 per month. Most refugees living in Kakuma therefore survive thanks to monthly food

Table 1 – Countries of origin (percentage), by site and arrival date

	All refugees		Recent arrivals (post March 2015)
	Kalobeyei	Kakuma	Kakuma
	%	%	%
South Sudan	71	52	70
Ethiopia	13	4	2
Burundi	9	4	8
DR Congo	4	6	9
Uganda	2	1	2
Sudan	1	6	8
Somalia	0	26	1
Other nationalities	0	1	0
Total in %	100	100	100
Total population	37,471	145,406	17,814

Source: UNHCR registration data from August 2017

rations distributed by the World Food Program (WFP). As summarized by Jansen (2015) "A camp like this is first and foremost a humanitarian economy."

Recognizing the limits of the humanitarian model, the Government of Kenya and UNHCR agreed, in 2015, *"to pilot a new approach by developing a settlement promoting the self-reliance of refugees and the host population by enhancing livelihood opportunities and promoting inclusive service delivery"* (UNHCR 2018). The Kalobeyei settlement was opened in May 2016 for the joint benefit of refugees and the local host community, approximately 3.5 kilometers to the West of Kakuma refugee camp (Figure 1). The Kalobeyei Integrated Socio-Economic Development Program (KISEDP) aims *"to allow refugees and the host population to maximize their potential in an enabling environment [...] in which inclusive service delivery and local capacities are strengthened, legal frameworks and policies are improved, a conducive environment for investment and job creation is promoted and communities' resilience is strengthened."* In contrast with Kakuma's humanitarian model, the Kalobeyei model recognizes the importance of market-based development. It aims to boost the local economy while promoting self-reliance and refugee-host integration.

Initially, the Kalobeyei settlement was to receive up to 60,000 refugees who

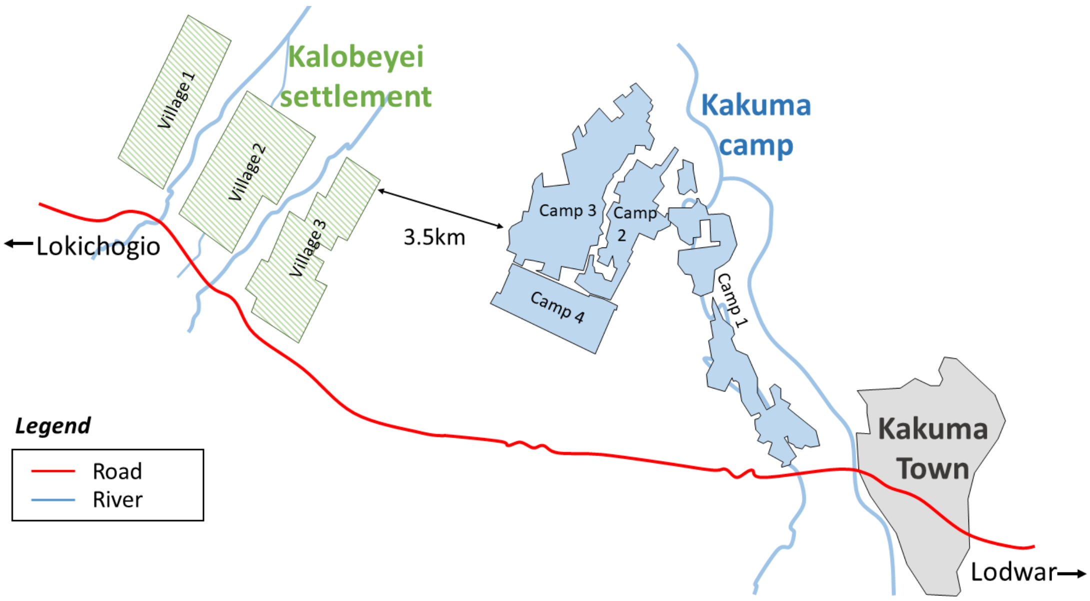


Figure 1 – Map of the Kakuma refugee camp and Kalobeyei settlement

would voluntarily relocate from Kakuma to benefit from self-reliance programs. However, this plan was adapted in 2016 to provide emergency relief to large influxes of refugees fleeing outbreaks of violence in South Sudan and Burundi. The Kalobeyei settlement is now home to around 37,500 refugees, the bulk of whom fled conflict in South Sudan (table 1). The Kalobeyei settlement also hosts a number of Burundian refugees as well as some Ethiopian refugees who were relocated from Dadaab refugee camp in the east of Kenya.

In terms of geographical and legal environment, the Kalobeyei settlement was virtually indistinguishable from the Kakuma camp at the time of our survey, in August 2017 (Betts et al. 2020). Two important differences relating to aid were however noticeable: the more extensive use of a cash-assistance program called Bamba Chakula (which means ‘get your food’ in Swahili), and the greater promotion of kitchen gardens.

The World Food Program (WFP), the largest humanitarian organization globally providing food assistance, distributes comprehensive food aid to all registered refugee households in Kakuma refugee camp and Kalobeyei settlement with the aim of meeting the entire macronutrient needs of residents: 2,100kcal per person per day. There is a growing movement in the international humanitarian community to provide aid in cash or near-cash forms directly to beneficiaries. The rationale for this movement includes a lower cost of distribution, development of local economies, and respect for the dignity of consumer choice. Globally, the WFP provides about 35% of its aid - US$1.8 billion yearly - in different forms of cash-based transfers (WFP 2018b). In 2015, WFP Kenya introduced a mobile-money system of food-aid distribution called Bamba Chakula - translated literally as *'get your food'* in Swahili. Bamba Chakula entails monthly money transfers on SIM-cards given to each registered household. Beneficiaries can use their SIM-card to purchase food items from registered traders.[6] In Kakuma refugee camp, 70% of households' energy requirements are distributed in-kind monthly as a mixture of dry grains, pulses, and cooking oil.[7] An additional transfer via Bamba Chakula is calculated to ensure that the remaining 30% of energy requirements can be satisfied through purchase at local market prices, as detailed in Table 2. In Kalobeyei settlement, households receive a single monthly transfer via Bamba Chakula calculated to enable the purchase of 93% of basic energy requirements at local market prices; this amounts to $1,400$KES (about US$14) per person per month.[8] In both sites, refugees also receive a ration equivalent to one portion per day of micro-nutrient enriched corn-soy blend (CSB) which can be prepared as a porridge to avoid malnutrition.

Small-scale agriculture, in the form of kitchen gardens, is more widely promoted in Kalobeyei than in Kakuma by NGOs and international organizations. The Kalobeyei settlement was planned with wide spaces between houses to allow

[6]The initial intention of WFP was for Bamba Chakula to be as close to a cash system as possible. However, legal restrictions were imposed by Kenyan authorities due to concerns that cash transfers to refugees could be diverted to finance terrorist activities. For this reason, Bamba Chakula transfers can only be spent on food items with registered traders. Refugees in Kalobeyei settlement are also prevented from spending their transfer in Kakuma refugee camp to promote the development of adequate markets in Kalobeyei settlement. This means the law of one price need not always hold between Kakuma refugee camp and Kalobeyei settlement, since refugees cannot redirect their business to Kakuma refugee camp when prices are too high.

[7]The content of in-kind rations in Kakuma depends on what commodities WFP receives from donors, which in turn affects the value of in-kind rations. For example, at the time of our survey in September and October 2017, refugees in Kakuma received sorghum, which tends to be cheaper and slightly less nutritious than maize. WFP is also frequently forced to reduce the content of in-kind rations due to gaps in donations (Betts et al. 2018). For this reason, food rations were reduced in Kakuma from January to March 2017 and in October 2017.

[8]We use the exchange rate of 103KES for 1 US$ throughout the paper. When Kalobeyei was created in May 2016, WFP calculated that the cash transfer in Kalobeyei had to be equal to KES1377 ($\sim$ US$13) to be equivalent to the typical in-kind ration distributed in Kakuma. This amount was rounded-up to KES1400 ($\sim$ US$14).

for subsistence agriculture. A large majority of the South-Sudanese refugees in Kalobeyei settlement and Kakuma refugee camp have agricultural backgrounds. Many areas of South Sudan have a similar arid environment to Turkana, so South-Sudanese refugees with experience in farming are able to use their prior knowledge of cultivating plants in sunken beds which help to collect and conserve water in gardening. Controlling for arrival date in a fuzzy regression-discontinuity framework, we estimate that about 71% of the first households that settled in Kalobeyei were involved in small-scale agriculture at the time of our survey, while only 29% of comparable South-Sudanese households living in Kakuma had a kitchen garden. Typical produce includes cow-peas, okra, and leafy greens, which are micronutrient dense and are more easily grown in sandy soil and arid climates. Because of limited access to capital and water, refugees participating in kitchen gardening projects only produce small quantities to supplement and diversify their diets. About 84% of households self-consume all their own production (Betts et al. 2020).

Table 2 – Entitlements per person in the Kakuma refugee camp

Family Size	(1)		(2+)	
	Grams	Kcal.	Grams	Kcal.
Whole Wheat Grain	105	351	147	492
Maize	105	383	147	537
Pulses	60	205	60	205
Corn-Soy Blend	40	152	40	152
Vegetable Oil	35	309	35	309
Total per Day	345	1,400	429	1,695
Total per Month (30 days)	10,350	42,000	12,870	50,850
Bamba Chakula per Month	500 KES (∼ US$5)		300 KES (∼ US$3)	

Example of daily ration entitlements per person, June 2017

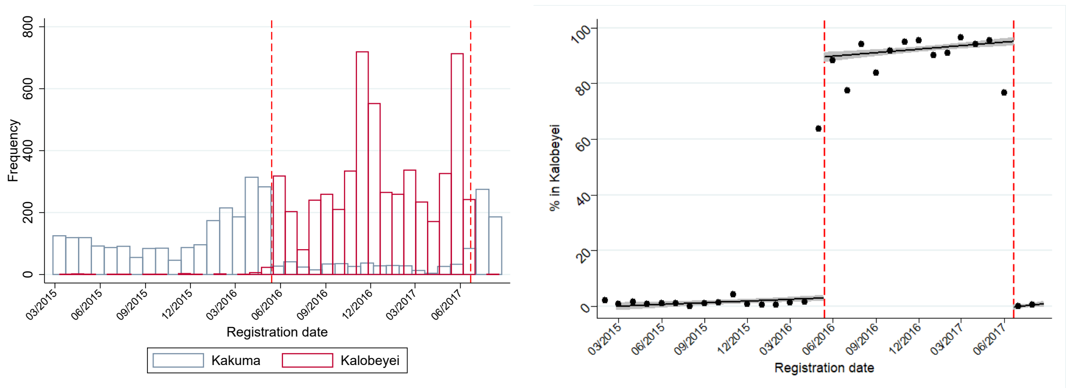
Source: WFP Entitlement Sheets

Not only is the Kalobeyei settlement a ground-breaking policy experiment, it also has the features of a quasi-experiment for South-Sudanese recent arrivals. Two distinct cutoff dates determined whether South-Sudanese recent arrivals live in Kakuma camp or Kalobeyei settlement. Three phases can be identified using

UNHCR registration data, which include information on households' registration date, nationality, and size:

1. Of South-Sudanese households who registered between the 1st of March 2015 and the 13th of May 2016, 98% live in Kakuma;
2. Of South-Sudanese households who registered between the 14th of May 2016 and the 21st of June 2017, 93% live in Kalobeyei;
3. Of South-Sudanese households who registered between the 22nd of June 2017 and the beginning of our survey on 24 August 2017, 99.8% live in Kakuma.

The cutoff dates were not determined by the characteristics of the population, but by logistical constraints of international organizations working under extreme strain due to the massive influx of refugees from South Sudan. Administrators authorized a few exceptions for refugees who registered at the reception center between the 14th of May 2016 and the 22nd of June 2017 and should therefore have been allocated to Kalobeyei, but who already had family members living in Kakuma and willing to host them. Additionally, there are a few cases of individuals who moved from Kakuma to Kalobeyei due to perceived safety concerns. The three phases are visible on figures 2(a) and 2(b), which illustrate where refugees live according to their registration date.



(a) Frequency

(b) % assigned to Kalobeyei

Figure 2 – Assignment of South-Sudanese households to Kakuma and Kalobeyei (Source: UNHCR registration data from August 2017)

3 Data and Methods

Using a regression discontinuity (RD) design, we propose to compare the socio-economic outcomes of South-Sudanese refugees living in Kalobeyei and Kakuma, exploiting the fact that their arrival dates almost perfectly predict where they live. In this section, we introduce the data (section 3.1), the variables of interest (section 3.2), and the RD design (section 3.3).

3.1 Survey Data

This analysis uses data from a representative household survey of refugees living in Kakuma camp and Kalobeyei settlement. The survey took place over five weeks between the 12th of September and 16th of October 2017. Data collection was carried out by a team of 24 trained refugee enumerators. The survey questionnaire, which was translated into local languages, included modules on household demographics, economic activities, networks, mobility, living standards, food consumption and production, household history, the regulatory environment, subjective well-being, and mental and physical health.

Our sampling strategy was designed to maximize comparability between respondents in Kalobeyei and in Kakuma. Because South-Sudanese refugees made up the vast majority of new arrivals during the study period (table 1), we decided to sample South-Sudanese households in each site. In addition, households from Burundian and Ethiopian communities were each sampled in Kalobeyei; we exclude them from our sample here because these communities were not surveyed in Kakuma, and we wish to ensure that the households compared across the two camps were as similar prior to arrival as possible. As our objective was to exploit the regression discontinuity, we focused on recent arrivals, defined as households who registered between the 24th of February 2015 and the 24th of August 2017, i.e. 15 months before and after the opening of Kalobeyei Settlement, or the 2.5-year period prior to data collection.

In the first instance, households were sampled from UNHCR registration data, which includes registration date, household size, nationality, ethnicity, and location in the camps. Once randomly selected by the research team, UNHCR provided the names of the selected household heads. This meant that we could locate households in Kakuma according to their camp, zone, and block. Within blocks, enumerators would have to search for individual households as there were no recorded house numbers. Because one block could include up to 200 households, we enlisted the help of community leaders, who are refugees responsible for community-level administration within their own block. In Kalobeyei, households are organized by village, neighborhood, and compound. Within a compound there are between 10 and 20 households. We enlisted the help of neighborhood leaders to identify households in Kalobeyei. However, during the first week of data collection, it became apparent that there was a large flaw in the list of addresses provided by UNHCR, especially in Kalobeyei settlement. During high-volume periods of refugee arrivals, administrators often recorded a default location for households rather than the actual plot they were settled in. This problem was much more salient in Kalobeyei than in Kakuma. In Kakuma refugee camp, while a small number of households were not at their recorded location, this seemed to be due to individual household decisions to leave their initial location, rather than a systematic flaw in the locations recorded by administrators. Where there were households which were misrecorded, many could be correctly located with the help of block leaders. Therefore, we decided to proceed with the initial sampling strategy in Kakuma refugee camp, rather than lose the surveys already completed and risk reducing the total number of responses collected. In Kalobeyei, $4,629$ South-Sudanese households (81%) were recorded wrongly as being settled in Village 1, Neighborhood 1, Compound 1. This made it very difficult to accurately locate most of the sampled households in Kalobeyei settlement.

It was clear that a new approach was needed in Kalobeyei. After one week of interviews, we decided to develop a new sampling strategy using satellite imagery. This required obtaining satellite images of the entire Kalobeyei settlement site and mapping each individual compound to record the locations of each building from the image. Simultaneously, we also visited each compound to note the building numbers and cross-referenced this mapping exercise with the satellite images. With complete maps of each compound, including missing buildings, we then randomly selected 10% of the buildings in Kalobeyei settlement for interview. The decision to use two different strategies in Kalobeyei and Kakuma could be problematic if it resulted in differences in the samples which were solely reflections of differences in these strategies. We tested for the presence of such differences by comparing the means of several personal characteristics for respondents in Kalobeyei settlement from each strategy and found there to be no significant differences. Because there was no discernible difference between the two strategies, the sample in Kalobeyei settlement includes responses from both sampling strategies.

In order to capture gender dynamics and complex household structures, we interviewed up to three adults within each selected household. When more than three adults were part of the household, we interviewed the household head, the person in charge of shopping and cooking, as well as one or two adults randomly selected.[9] Our final sample includes 1874 South-Sudanese refugees (960 in Kakuma and 914 in Kalobeyei), who are living in 1126 households. Sampling weights are accounted for in the analysis below.

3.2 Outcomes, predetermined variables, and mediators

We consider eight outcome variables, four of which measure the quantity and quality of food intake. We also consider a measure of non-food expenditures, an asset index, a measure of subjective well-being, and – because self-reliance is closely related to autonomy (Betts et al. 2020) – a measure of perceived independence from aid. The eight outcome variables are constructed as follows (descriptive statistics are presented in table 3).

- **Dietary Diversity Score (in log):** The dietary diversity score is a measure of the variety of food intake, which is calculated by counting the number of twelve different food types which have been consumed at any time within the seven days preceding the survey, resulting in a score from $0 - 12$. The

[9] When the household head was also in charge of food preparation, up to two additional adults were randomly sampled.

FAO presents guidelines for its use and interpretation, without setting out specific categorical thresholds for acceptable levels of dietary diversity (Food and Agriculture Organization 2010).[10]

- **Calories per adult equivalent (in log):** The WFP aims to ensure that all refugees living under its remit, including children, have access to $2,100$kcal per day to meet their basic energy requirements. In each household, the primary food preparer was asked for extensive details on the food consumption of their household for 18 specific foods. For each of these foods, the food preparer was asked whether any household member consumed that food within the past seven days; the quantity of that food consumed, the source of the food (Bamba Chakula, cash, food rations, own production, gift), and the price paid for the food if it was bought using money or Bamba Chakula. We use the average number of calories consumed per adult equivalent per day in the household as a measure of the quantity of food available to refugees.[11]

- **Value of food consumption per household member (in log):** Using the same data, we construct a measure of the value of food consumption per household member. For each of the 18 types of commodity, we multiply the quantity consumed expressed in kilos per day by the median price per kilo in our data. We then aggregate the values calculated for the 18 commodities and divide the total by the number of household members.

- **Household Food Insecurity Access Prevalence:** We measure food insecurity using the Household Food Insecurity Access Prevalence (HFIAP), which aggregates respondents' perceptions of food vulnerability and the frequency

[10]Zero-valued observations are considered as unrealistic and excluded by the use of the logarithm transformation. We obtain similar results with the variable expressed in level or with the quantile transformation proposed by (Delius and Sterck 2020) to deal with variables that have zero-valued observations.

[11]We converted food consumption to calories using energy data from the U.S. Department of Agriculture (table A.2 in appendix). The conversion into calories per adult equivalent aims to account for the different needs of adults and children and for economies of scale. Adult equivalents are calculated according to the following formula $AE = [(1 + \beta(A-1)) + \alpha K]^{\theta}$, where A is the number of adults in the household, and K is the number of children. We use the following parametrization: $\alpha = 0.3$, $\beta = 1$, and $\theta = 0.9$ (Deaton and Zaidi 2002; D'Aoust et al. 2018). We obtain similar results with an indicator of daily calories per household member. The correlation between these indicators is above 0.9.

with which shortages occurred (Coates et al. 2007). The primary food preparer in the household was asked whether each of nine worries had occurred, and if yes, whether that happened rarely, sometimes, or often. The HFIAP ranges from 1 for food secure households to 4 for severely food insecure households.

- **Non-food expenditures (ihs):** This variable aggregates household monthly expenditures on education, health, ceremonies, housing, transport, video halls, soda, alcohol, tobacco, and airtime. Because the sum of non-food expenditures has a large proportion of zero and is skewed to the right, we consider the inverse hyperbolic sine (ihs) transformation of non-food expenditures in regressions.

- **Asset index:** The asset index is a composite indicator that compiles information on household assets,[12] the type of stove used for cooking, access to electricity, and ownership of animals. We aggregate the different components of the index using the same weights as the ones used to construct the wealth index of the Kenya Demographic and Health Survey of 2014.

- **Subjective well-being:** For this variable, we consider the answers to the question "All things considered, how satisfied are you with your life as a whole these days?". Answers are ranging from 1 "Very unsatisfied" to "5 Very satisfied".

- **Perception of independence from aid:** This variable summarizes the answers to the question "How dependent do you think your household is on support from UNHCR, WFP or any other NGOs?" Answers range from 1 "Completely dependent" to 4 "Not at all dependent".

In the analysis below, we also make use of 9 variables that are categorized as *predetermined* and 24 *possible mediators*. Variables are categorized as *predetermined* if we have strong reasons to believe that they have not been affected

[12] The list of assets includes: radio, television, computer, refrigerator, solar panel, generator, table, chair, sofa, bed, cupboard, clock, DVD-player, mobile-phone, MP3-player, watch, bicycle, motorcycle, and car

Table 3 – Summary statistics

	Kakuma			Kalobeyei		
	Mean	Std Dev	N	Mean	Std Dev	N
Outcomes variables in level						
Dietary diversity	4.48	(1.58)	960	5.20	(1.25)	914
Daily calories per adult equivalent	2239.77	(1987.15)	448	4874.06	(2635.04)	625
Value of daily food consumption per HH member	33.96	(44.24)	462	68.56	(67.41)	625
Food insecurity (HFIAP)	3.90	(0.42)	468	3.64	(0.81)	632
Non-food expenditures	468.46	(1608.72)	437	189.95	(856.24)	610
Assets	-0.66	(0.29)	468	-0.86	(0.17)	636
Subjective well-being	2.50	(1.16)	960	2.51	(1.33)	914
Dependence on aid	1.13	(0.40)	960	1.34	(0.61)	914
Predetermined variables						
Gender (1=female)	0.51	(0.50)	960	0.74	(0.44)	914
Age	25.93	(9.06)	959	28.89	(9.64)	914
Married	0.46	(0.50)	960	0.60	(0.49)	914
# parents alive	1.04	(0.78)	960	0.90	(0.81)	914
Father's years of education	1.58	(4.09)	955	2.06	(4.38)	885
Mother's years of education	0.43	(1.81)	955	0.34	(1.61)	908
Agricultural background	0.90	(0.31)	960	0.88	(0.33)	914
Equatoria region	0.34	(0.47)	960	0.96	(0.20)	914
Bahr el Ghazal Region	0.09	(0.28)	960	0.01	(0.09)	914
Great Upper Nile Region	0.57	(0.49)	960	0.03	(0.18)	914
Possible mediators						
Involvement in productive activities						
Job	0.08	(0.27)	960	0.06	(0.24)	914
Kitchen Garden	0.25	(0.43)	468	0.36	(0.48)	632
Animal husbandry	0.11	(0.31)	468	0.02	(0.15)	636
Mobility and household composition						
Traveled within Kenya (dummy)	0.05	(0.21)	960	0.00	(0.05)	914
Traveled to origin country (dummy)	0.05	(0.22)	960	0.01	(0.07)	914
# HH members	6.78	(5.01)	466	5.39	(2.46)	626
# on ration cards	6.31	(4.49)	467	5.66	(2.35)	627
Rations per members	1.05	(0.65)	930	1.17	(0.87)	886
Human and physical capital						
Years of education	4.91	(4.24)	959	3.36	(4.06)	914
Vocational training dummy	0.15	(0.36)	960	0.11	(0.32)	914
Currently in education	0.53	(0.50)	960	0.31	(0.46)	912
Assets	-0.66	(0.29)	468	-0.86	(0.17)	636
Health index	6.55	(5.21)	945	6.79	(5.06)	891
Mental health index	6.09	(4.85)	897	6.18	(5.77)	854
English dummy	0.35	(0.48)	960	0.20	(0.40)	914
Swahili dummy	0.09	(0.28)	960	0.03	(0.16)	914
Access to services						
Has savings account	0.01	(0.09)	960	0.00	(0.07)	914
Has a loan	0.01	(0.09)	960	0.00	(0.07)	914
Remittances (dummy)	0.12	(0.32)	957	0.06	(0.23)	910
Time needed to access water	53.63	(43.37)	468	63.06	(61.50)	624
Water fetched daily	61.28	(41.73)	468	61.92	(39.01)	632
Access to electricity	0.04	(0.19)	468	0.01	(0.08)	636
Perception of insecurity	2.63	(0.80)	955	2.57	(0.95)	905
Non-essential spending (dummy)	0.12	(0.33)	960	0.03	(0.17)	914

Note: The construction of variables is described in table A.1 in appendix.

Source: our survey data.

by programmatic or contextual differences between Kakuma and Kalobeyei. Predetermined variables are to be distinguished from *possible mediators* or *channels of impact*, which are variables for which we have some evidence suggesting they may have been affected by programmatic or contextual differences between the sites and could affect outcomes variables. In other words, while predetermined variables were fixed pre-intervention, mediators are intermediate outcomes.

Predetermined variables and possible mediators are listed in table 3 with their summary statistics. Their construction is described in table A.1 in appendix. The vector of predetermined variables includes a gender dummy, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. Predetermined variables will be included as control variables in regression analysis, in order to increase the precision of RD estimators (Calonico et al. 2019). To assess the validity of the RD design, we will also test the null hypothesis of a zero average effect on predetermined variables (see section 4.2). The 24 possible mediators relate to four domains that are likely to differ between Kakuma and Kalobeyei: (1) involvement in productive activities, (2) mobility and household composition, (3) human and physical capital, (4) and access to services. Possible mediators will be exploited in section 5, when exploring channels of impact.

The classification of variables into the *predetermined* and *mediator* categories is largely context dependent and mostly relies on our in-depth knowledge of the field. We recognize that the classification is ambiguous for a few possible mediators, that were partly determined before refugees' registration in Kakuma and Kalobeyei. For example, human capital was partly accumulated by refugees back in South Sudan, before their migration. Similarly, the composition of households partly depends on decisions taken in South Sudan. The variables that relate to these domains are therefore partially predetermined. Yet, as explained in section 5, we also have strong evidence that contextual and programmatic differences between Kakuma and Kalobeyei have shaped these variables, which is why they are classified as possible mediators. As discussed below, this classification choice is largely inconsequential because differences in possible mediators that are partly predetermined – notably differences in human capital and in the composition of households – do not seem to drive our results (see section 5).

3.3 Regression discontinuity design

The rule used by UNHCR to assign refugees between Kakuma and Kalobeyei creates two discontinuities (figure 2), which pose a possible identification strategy for the effects of differing programs between the two camps. Regression discontinuity (RD) is a useful method for identifying the causal impact of a treatment assigned according to a known rule that consist of a cutoff in an assignation or forcing variable. It makes use of the assumption that individuals who just qualify for treatment are similar to those who just miss out on treatment, such that average differences in the outcomes of those individuals sufficiently close to either side of the cutoff point can be attributed to the treatment.

Two cutoff dates almost perfectly predict the allocation of refugees between Kakuma and Kalobeyei. Almost all refugees who registered before the 14th of May 2016 or after the 22nd of June 2017 live in the Kakuma camp. Most of those who registered between these two dates live in the Kalobeyei settlement. Our analysis focuses on the first cutoff date, the 14th of May 2016.[13] The second cutoff date can unfortunately not be exploited in the present study: our representative sample only includes 58 refugees who arrived after the second cutoff date as our survey was organized only two months after that date. The few exceptions to the allocation rule are explained by refugees who arrived at the reception center between the two cutoff dates, but who had family members already living in Kakuma and willing to host them. We therefore use the earliest arrival date in the household as the forcing variable. In section 4.2, we show that results are robust to using the arrival date of each respondent as the forcing variable. The presence of a few exceptions to the allocation rule means that the regression discontinuity design is fuzzy, and

[13]UNHCR stopped registering new arrivals in Kakuma around the 14th of May 2016. The registration process was then put on hold for 10 days between the 14th and the 24th of May (only 4 households registered during that period, all in Kalobeyei) while UNHCR was moving its operations to Kalobeyei. On the 24th of May, registration really started in Kalobeyei, with more than 20 households registered per day. Households which arrived after the 14th of May 2016 are registered in Kalobeyei, which is why this date was selected as the cutoff date. In section 4.2, we show that results are robust to using the 24th of May 2016 as the cutoff date.

that we estimate the local average treatment effect (LATE) for compliers at the cutoff i.e. for those residing in their assigned camp.

We use both a parametric and a non-parametric approach to estimate the treatment effect (Jacob et al. 2012). The parametric approach uses all relevant observations to model the outcome variable Y as a function of the forcing variable - the registration date r in this study - and a treatment dummy T equal to 1 for refugees living in Kalobeyei and 0 for those living in Kakuma:

$$Y_i = \alpha + \beta_0 T_i + f(r_i) + X_i + \epsilon_i, \tag{1}$$

where X_i is the vector of predetermined covariates.

Because we have a fuzzy regression discontinuity design, the treatment dummy T is instrumented by a cutoff dummy D equal to 1 for those who registered after the 14th of May. We focus on South-Sudanese refugees who registered between the 24th of February 2015 (the initial date of our sampling strategy) and the 22nd of June 2017 (the second cutoff date).[14] In the main results table, we estimate a linear model that includes an interaction term between the registration date r_i and the cutoff dummy D. In appendix, we show that similar results are obtained with different functional forms for the function f of the registration date (Table A.4).[15] Results are also robust to excluding observations that are distant from the cutoff date (figures A.4(a) to A.4(h) in appendix). Inference is based on cluster-robust standard errors to account for the sampling frame.[16]

[14]While our sampling strategy focused on recent arrivals, who registered after the 24th of February 2015, our sample includes 188 South-Sudanese refugees who reported arriving in the camp before the 24th of February 2015. This is possible because we interviewed multiple adults per households and some recent arrivals are staying with family members who were already living in Kakuma.

[15]We focus on a linear model with an interaction term between the registration date r_i and the cutoff dummy D for three reasons. First, this functional form is similar in spirit to the functional form used in the non-parametric approach (Calonico et al. 2014b, 2019). Second, we were keen to avoid higher-order models, which increase the risk of overfitting (Gelman and Zelizer 2015; Gelman and Imbens 2019). Third, the interaction term between the cutoff dummy and the registration date is statistically significant and contextually justified for a number of variables. In the robustness checks, we use linear and quadratic specifications with and without the interaction term $r_i D$ (Gelman and Zelizer 2015; Gelman and Imbens 2019).

[16]Our sampling strategy had two randomization stages: the random selection of households, and the random selection of respondents in household with more than 3 adults. Given this

The non-parametric approach only considers observations that lie within a small bandwidth of the cutoff date, where the functional form is more likely to be close to linear (Jacob et al. 2012). A local linear regression is then estimated using the reduced sample. The main challenge with this approach is to select an optimal bandwidth that balances precision and bias. With a smaller bandwidth, the linear approximation is more accurate, but sample size and hence precision are reduced. On the contrary, a larger bandwidth yields more precise estimates but the bias resulting from the linear approximation is usually more important. Various authors have proposed methods to calculate optimal bandwidths in RD designs (Calonico et al. 2014b; Imbens and Kalyanaraman 2012). In our main results table, we use the same bandwidth for the eight outcome variables, to ensure that results are comparable and not driven by bandwidth selection. For each outcome variable, we estimated the optimal bandwidth using the mean squared error (MSE)-optimal bandwidth selector of Calonico et al. (2014a). Optimal bandwidths range between 98 and 135 days. The bandwidth we use is the maximum value of the estimated bandwidths.[17] In section 4.2, we show that results are robust to bandwidth selection by estimating the treatment effect for any bandwidth between 70 and 420 days (figures 5(a) to 5(h)). We use the robust bias-corrected approach of Calonico et al. (2014b, 2019) with a triangular kernel to estimate the local average treatment effects and consistent cluster-robust standard errors, with and without controlling for predetermined variables.

4 Results

In this section, we present the results of the parametric and non-parametric RD estimations (section 4.1) and assess their robustness by implementing a number of specification tests and sensitivity analyses (section 4.2). Channels of impact are then discussed in section 5.

sampling strategy, households can be considered as clusters and standard errors are therefore clustered at the household level.

[17]Opting for a smaller bandwidth could lead to power or overfitting issues.

4.1 Benchmark results

Our baseline estimates are given in table 4. The results of the parametric approach are presented in panels A and B, without and with predetermined variables respectively. The results of the non-parametric approach are presented in panels C and D, also without and with predetermined variables. Our preferred specification is the non-parametric estimation with predetermined variables (Calonico et al. 2019). The local-linear regressions are also represented in figures 3(a) to 3(h). These figures are useful to visually assess whether RD estimates could be driven by specification choices.

South-Sudanese refugees living in the new Kalobeyei settlement have better diets than their counterparts in the Kakuma camp. First, their diets are more varied. Their Dietary Diversity Scores are 20% higher on average, which corresponds to one more type of food eaten during the week preceding the survey, out of a list of 12 categories of food commodities. This result is largely driven by large discontinuities at the cutoff date in the proportion of people eating vegetables and fish (+46% and +18.3% respectively).

Second, they eat more food. Point estimates are extremely large, both when consumption is measured in calories per adult equivalent and in monetary terms. These large effects do not seem to be driven by measurement or misspecification issues.[18] When distinguishing different categories of food, we find large positive effects on calorie intake from starchy food, beans, vegetable and fruits, and meat and fish (Figures A.1(a)-1(f) in appendix). The effect on oil is positive and almost significant at conventional thresholds (p-value = 0.12). We find no significant effect on dairy and eggs. Overall, these observations suggest that the large effect we find on consumption is not driven by one particular type of food.

Third, households living in Kalobeyei are less food insecure. Nevertheless, food insecurity is extremely high in both camps. Among recently arrived South-

[18] The effects are not driven by a few outliers, by overfitting, or by the selection of a specific bandwidth (figures 3(b), 3(c), 5(b), and 5(c)). Considering the monetary value of consumption leads to higher point estimates, suggesting that the conversion from quantities to calories does not drive the results. We also obtain similar regression coefficients when considering daily calories per household member, which shows that the conversion in adult equivalent does not drive the results.

Sudanese households, 92% can be categorized as food insecure in Kakuma, versus 79% in Kalobeyei. The regression discontinuities associated with the consumption indicators are very apparent in figures 3(a) to 3(d). The steep slope of the local-linear fit on the right-hand side of the cutoff in figure 3(d) suggests that the result related to food insecurity might be partly driven by the choice of functional form and bandwidth. Reassuringly, the discontinuity remains strongly significant when considering larger bandwidths or a local-quadratic regression, which suggests that issues of overfitting are not driving the effect on food security (section 4.2).

Table 4 – Benchmark results

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Non-food expenditures (ihs) (5)	Asset index (6)	Subjective well-being (7)	Independence from aid (8)
Panel A - Parametric approach without predetermined variables								
RD	0.173***	0.949***	0.972***	-0.461***	-0.00561	-0.119***	0.214	0.246***
	(0.0319)	(0.0811)	(0.0960)	(0.0927)	(0.352)	(0.0232)	(0.132)	(0.0650)
Panel B - Parametric approach with predetermined variables								
RD	0.144***	0.965***	1.078***	-0.469***	0.0567	-0.0360	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.397)	(0.0267)	(0.157)	(0.0726)
Panel C - Non-parametric approach without predetermined variables								
Robust RD	0.269***	1.009***	1.254***	-0.752***	-0.877	-0.0223	0.823***	0.160
	(0.0794)	(0.282)	(0.300)	(0.249)	(1.030)	(0.0599)	(0.293)	(0.141)
Panel D - Non-parametric approach with predetermined variables								
Robust RD	0.269***	1.021***	1.328***	-0.731***	-0.704	0.0118	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(1.025)	(0.0591)	(0.298)	(0.145)
N param. RD	1642	961	961	985	936	1016	1648	1648
N non-param. RD (right)	178	128	128	133	130	130	178	178
N non-param. RD (left)	282	159	159	167	155	168	284	284
Mean in Kakuma	1.44	7.31	2.99	3.9	3.36	-.66	2.5	1.13

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In Panel B and D, the following predetermined variables are included as controls in all regressions: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We find no effect whatsoever on non-food expenditures and on assets. The absence of effect on these variables is clearly visible in figures 3(e) and 3(f). Only 49% of households reported positive non-food expenditures, which is consistent with the extremely high levels of poverty in Kakuma and Kalobeyei. Asset holding is very low, especially for the most recent arrivals. Most refugees fled conflict, without being able to take belongings with them. Betts et al. (2020) report the following story from a South-Sudanese refugee, which is particularly telling: *"We fled in panic. Suddenly our village was attacked. We grabbed whatever was around us and ran away. No time to carry assets or money or even to meet family members."* Given the high levels of poverty, very few refugees are able to buy assets. Consistent with this story, our data shows that South-Sudanese recent arrivals have almost nothing: for example, only 0.5% of households have a television, 0.4% have a generator, 2.3% have solar panels, 9% have a table, 17% have at least one chair, and 4% have animals (mostly chickens). The only assets which are quite common in Kakuma and Kalobeyei are mobile phones, owned by 47% of South-Sudanese households in our sample. The null effects on non-food expenditures and assets are very robust to bandwidth selection and specification changes (section 4.2).

There is some evidence of a positive effect on subjective well-being. All coefficients are positive but their magnitudes vary substantially from one specification to another. With the non-parametric approach, the effect is large and statistically significant at the 1% threshold. With the parametric approach, however, coefficients are insignificant, but p-values are low (0.10 without controlling for predetermined variables, and 0.20 with predetermined variables). While the discontinuity is salient in figure 3(g), most of the variation in subjective well-being is left unexplained by the regression discontinuity and predetermined variables. The adjusted-R^2 of the parametric regression with predetermined variables is only 0.01 (table A.3 in appendix). Similarly, we find some evidence of a positive effect on the perception of independence from aid. All coefficients are positive, but the coefficients of the non-parametric approach are insignificant at conventional thresholds (the p-values are 0.26 without controlling for predetermined variables and 0.22 with predetermined variables). Figure 5(h) shows that the estimated effect is statistically significant with slightly narrower or larger bandwidths. The discontinuity is visible, but variability across households seems important (figure 3(h)). Overall, there is some evidence of positive effects on subjective well-being and on perception of independence from aid, but these effects are not fully robust. The subjective nature and variability of these measures warrant caution when interpreting results.

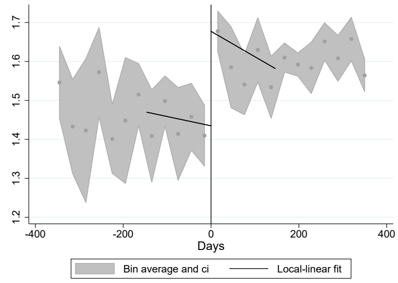
In what follows, we use the label "Kalobeyei effect" to refer to the positive discontinuities in dietary diversity, calorie intake, food consumption value, food security, subjective well-being, and perception of independence from aid at the cutoff.

4.2 Robustness checks

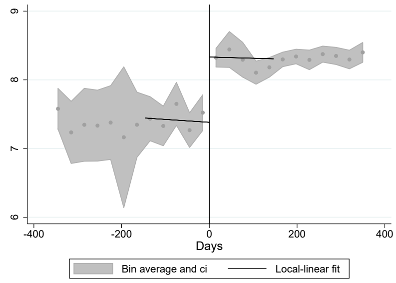
In this section, we implement various tests to assess the internal validity of the RD design (Imbens and Lemieux 2008; Jacob et al. 2012): (a) the McCrary (2008)'s test of manipulation in the forcing variable, (b) tests of discontinuities in the average values for predetermined covariates, (c) robustness tests to variations in the bandwidth, (d) various specification tests, and (e) two placebo tests examining discontinuities in the average outcomes at other values of the forcing variable.

The RD approach relies on the hypothesis that units of observation cannot manipulate the forcing variable to be on one side of the cutoff rather than the other (Imbens and Lemieux 2008). This hypothesis is difficult to test directly because manipulations are difficult to measure accurately. McCrary (2008) proposes an indirect test of the no-manipulation hypothesis, which examines the presence of a jump in the density of the forcing variable at the cutoff point. If some refugees indeed manipulated their registration date in order to be assigned to one site rather than the other, one might expect to observe a discontinuity in the density of registration dates at the cutoff date. We apply this test using UNHCR registration data. Results are illustrated in figure 4. We do not reject the null hypothesis of continuity of the density of the forcing variable (t-test = -0.3), which suggests that there was no manipulation in refugees' registration date. Because the McCrary test has some limitations,[19] we also visually inspect a histogram of registration dates (figure 4(a)). The density of registration dates varies dramatically from one week to another, especially in 2016 and 2017 as refugees were arriving in successive waves. Figure 4(b) shows that discontinuities are driven by violent events against

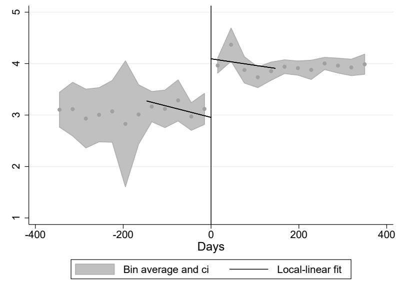
[19] The McCrary test assumes that the density of the forcing variable is continuous in the absence of manipulation. The histogram of registration dates suggests that the continuity assumption might not hold (figure 4(a)), implying that the McCrary (2008) might be of limited value in this study. See Jacob et al. (2012) for a discussion of other limitations.



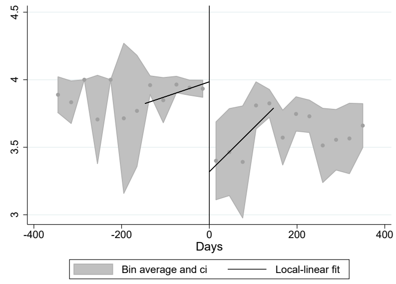
(a) Dietary variety (log)



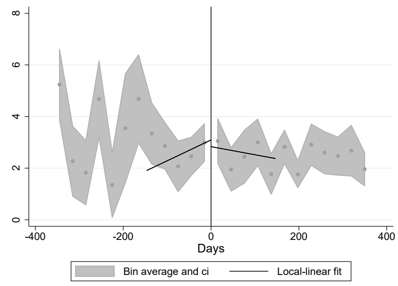
(b) Daily calories per adult equivalent (log)



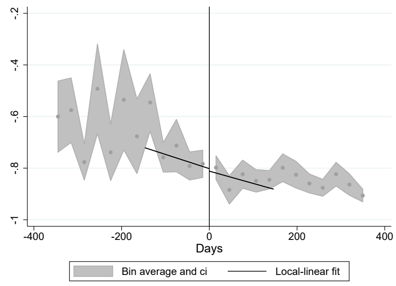
(c) Value of daily food consumption per HH member (log)



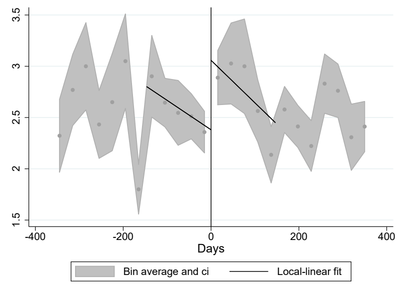
(d) Food insecurity (HFIAP)



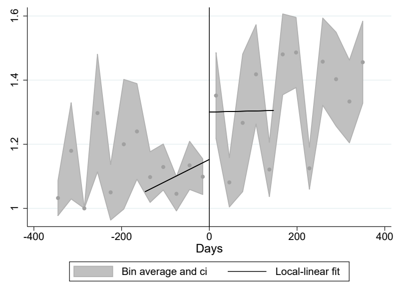
(e) Non-food expenditures (ihs)



(f) Asset index



(g) Subjective well-being



(h) Perception of independence from aid

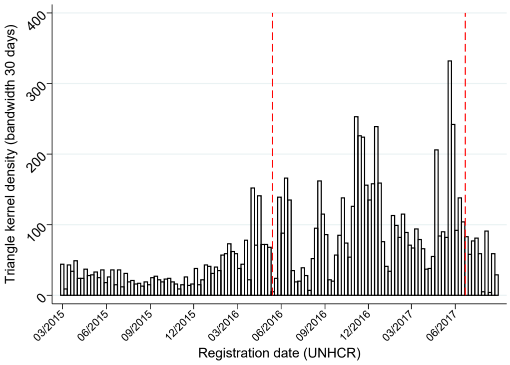
Figure 3 – Discontinuities in outcome variables

Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.

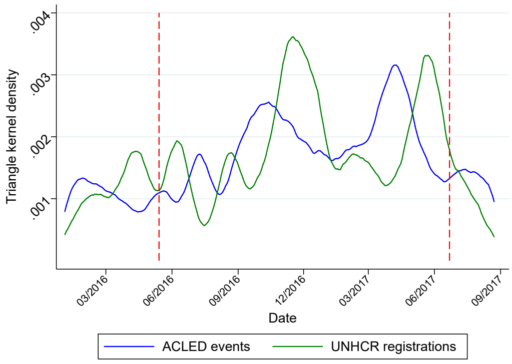
civilians in South Sudan, as measured by ACLED data. The correlation between the frequency of arrivals in a given month and the two-month lag of violence against civilians in South Sudan is as high as 0.69. Overall, these results suggest that the successive waves of refugee arrivals were driven by waves of violence in South Sudan and that manipulation or the creation of the Kalobeyei settlement had little influence on refugee movements.

A second category of tests involves testing the null hypothesis of a zero average effect on predetermined variables, which are variables that are unlikely to have been affected by programmatic or contextual differences between Kakuma and Kalobeyei (Imbens and Lemieux 2008). Discontinuities in predetermined variables at the cutoff do not necessarily invalidate the RD design. However, if predetermined variables that are strong predictors of the outcomes of interest are discontinuous at the cutoff, the continuity of the potential outcome function is unlikely to hold, which would cast doubt on the validity of the RD design (Cattaneo et al. 2017). In table 5, we use the non-parametric approach with the same bandwidth as in the main analysis to test for the presence of discontinuities in predetermined variables. Coefficients are not statistically significant at conventional thresholds, which is a positive sign of the validity of our design. Some coefficients are however statistically significant with much narrower or wider bandwidths. This is not surprising given the sensitivity of RD designs to bandwidth selection and overfitting (Imbens and Kalyanaraman 2012; Gelman and Zelizer 2015; Gelman and Imbens 2019). Reassuringly, the adjusted-R^2 with and without controlling for predetermined variables are not very different (table A.3 in appendix), suggesting that predetermined variables are relatively weak predictors of the outcome variables. Controlling for predetermined covariates does not significantly change the estimated effects (table 4).

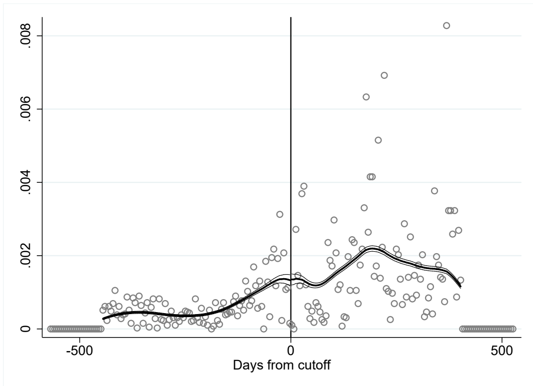
Results of RD designs can be highly sensitive to the choice of bandwidth. And the bandwidth selection methods proposed by Imbens and Kalyanaraman (2012) and Calonico et al. (2014b) often lead to very different optimal bandwidths. We therefore verify the robustness of the results to different choices of bandwidth.



(a) Histogram of registration data



(b) Kernel density of violence against civilians and registration data



(c) Manipulation test of McCrary (2008)

Figure 4 – Registration date of South-Sudanese refugees (UNHCR registration data from August 2017), violence against civilians in South Sudan (ACLED data), and test of manipulation of McCrary (2008)

Table 5 – Balance tests for predetermined variables

	Gender (1=female) (1)	Age (2)	Married (3)	Parents alive (4)	Years educ. father (5)	Years educ. mother (6)	Agriculture background (7)	Equatoria (8)	Bahr el Ghazal (9)	Greater Upper Nile (10)
Robust RD	0.135	3.453	0.099	-0.254	-0.514	-0.445	0.066	0.165	-0.008	-0.156
	(0.094)	(2.588)	(0.126)	(0.200)	(0.876)	(0.324)	(0.074)	(0.103)	(0.022)	(0.102)
Observations	1874	1873	1874	1874	1840	1863	1874	1874	1874	1874
Eff. obs. (right)	187	187	187	187	178	186	187	187	187	187
Eff. obs. (left)	289	289	289	289	286	286	289	289	289	289
Mean in Kakuma	.51	25.93	.46	1.04	1.58	.43	.9	.34	.09	.57

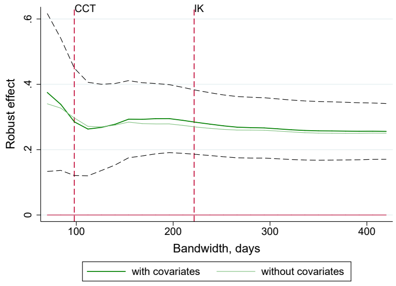
Data source: our survey data. Notes: The table reports the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b) and a bandwidth of 135 days. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Results are shown in figures 5(a) to 5(h).[20] Results related to dietary variety, calorie intake, food consumption value, and food insecurity are very robust to bandwidth selection. The effects on non-food expenditures and on the asset index are statistically insignificant for any bandwidth. The effects on subjective well-being and on independence from aid are positive for any bandwidth, but the degree of significance varies with the bandwidth. For all outcome variables, estimates with and without predetermined variables are similar. We conclude that our results are robust to bandwidth selection.

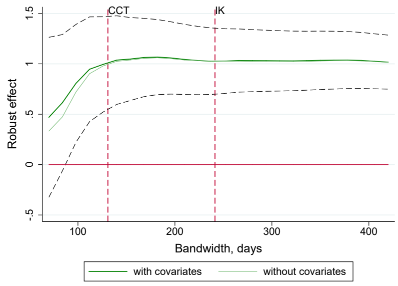
In tables A.4 and A.5 in appendix, we further assess the robustness of results to various specification tests. Results are broadly similar when considering different functional forms representing the relationship between the forcing variable and the outcomes (table A.4). Results are similar when the forcing variable is the arrival date of each respondent instead of the earlier arrival date in the household, but the effect on perception of independence from aid becomes statistically significant (table A.5, panel B). Manipulation in the forcing variable is more likely to occur around the cutoff (Cattaneo et al. 2017). Dropping refugees who arrived between the 7th and the 31st of May 2016 does not affect key results (table A.5, panel C). Conclusions are also similar if the cutoff date is set as the 24th of May instead of the 14th of May 2016 (table A.5, panel D).[21] We obtain similar results when restricting the sample to refugees from Equatoria, region in South Sudan the closest to the

[20]Similar figures are available in appendix for the parametric approach (figures A.4(a) to A.4(h)).

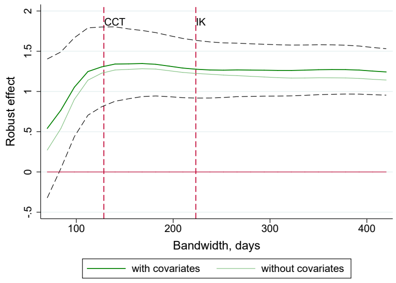
[21]While registration in Kakuma stopped around the 14th of May 2016, registration in Kalobeyei really kicked off on the 24th of May.



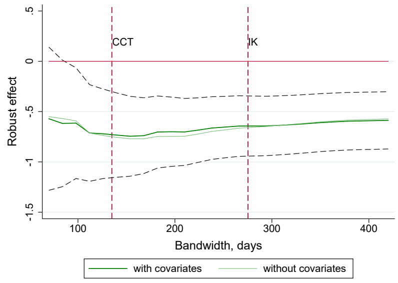
(a) Dietary variety (log)



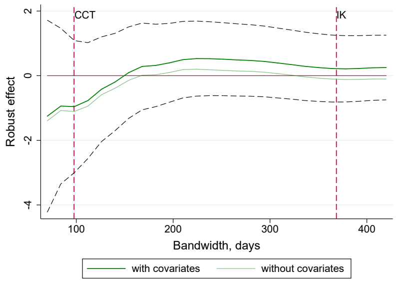
(b) Daily calories per adult equivalent (log)



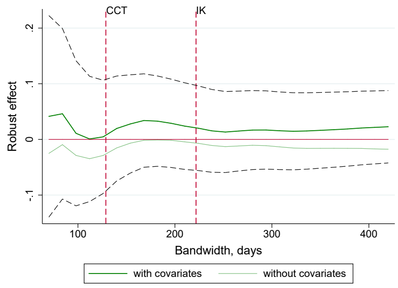
(c) Value of daily food consumption per HH member (log)



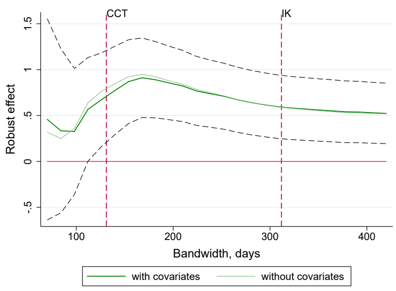
(d) Food insecurity (HFIAP)



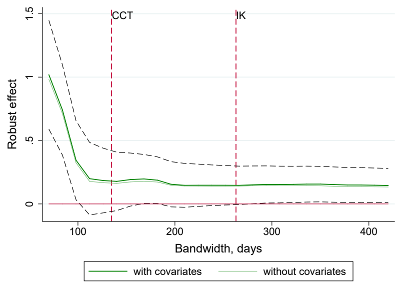
(e) Non-food expenditures (ihs)



(f) Asset index



(g) Subjective well-being



(h) Perception of independence from aid

Figure 5 – Robustness of the non-parametric approach to variation in the bandwidth

Data source: our survey data. Notes: We use the robust bias-corrected approach of Calonico et al. (2014b, 2019) with a triangular kernel to estimate the local average treatment effects for bandwidths between 70 and 420 days and increments of 14 days. Light green lines = estimated treatment effects, without controlling for predetermined variables. Dark green lines = estimated treatment effects, controlling for predetermined variables. Black dashed lines = confidence intervals for the specifications with predetermined variables. Red dashed lines: optimal bandwidths of Calonico et al. (2014a) (labeled CCT) and Imbens and Kalyanaraman (2012) (labeled IK).

refugee sites, which accounts for 64% of our sample (table A.5, panel E). In October 2017, food rations in Kakuma were reduced to 70% of their usual content (see Section 5.6 for more details). Results are also broadly similar if the data collected in Kakuma in October 2017 is dropped from the sample (table A.5, panel F). The different timing of fieldwork in Kakuma and in Kalobeyei could affect the results if consumption smoothing is imperfect and if refugees in Kakuma received food assistance longer ago on average than refugees in Kalobeyei. Reassuringly, we find similar results when controlling for the number of days since respondents last received in-kind assistance in Kakuma and Bamba Chakula transfers in Kalobeyei (table A.5, panel G).

Finally, we implement two placebo tests, which consist of searching for jumps at points where there should be no jumps. We follow Imbens and Lemieux (2008) and test for jumps at the median of the two sub-samples on either side of the cutoff date. We use the same specification and the same bandwidth as in our preferred specification (the parametric approach with predetermined variables). Results, presented in table A.5 in appendix, show that 13 out of 16 coefficients are statistically insignificant at conventional thresholds. The coefficients in the regression on the independence from aid variable are significant at the 1% threshold, which is probably due to the high variability of this subjective measure and might explain why the findings for this variable are not fully robust.

5 Channels of impact

The exploration of channels of impact is the most challenging but also the most interesting part of this study. It is challenging, not least because of the absence of random or quasi-random variation in possible mediators, and because some of the factors that may drive the effects are uniformly distributed across all refugees in each of Kakuma or Kalobeyei (e.g. the Bamba Chakula program of cash transfers). Given these caveats, the evidence presented below should be interpreted as suggestive. But exploring the channels of impact is also insightful, as it encourages us to delve deeper into the data to understand how refugees live in Kakuma and Kalobeyei and how refugee economies there function.

We will study 24 possible mediators, which are grouped into four categories: involvement in productive activities (section 5.1), mobility and household composition (section 5.2), human and physical capital (section 5.3), and access to services (section 5.4).[22] We will also study differences in prices (section 5.5) and in the modalities of food assistance (section 5.6).

To be a mediator, a variable should satisfy two conditions. First, it should be affected by the treatment, and hence be discontinuous at the cutoff date. Second, it should capture part of the "Kalobeyei effect": the mediator should be statistically significant when included in the RD regressions as a control variable and it should induce a change in the estimate of the discontinuity towards zero.[23].

5.1 Productive activities

The promotion of income-generating activities and employment is central to self-reliance programming. Yet, we find no evidence of a positive effect of the Kalobeyei model on the proportion of refugees with an income-generating activity (figures A.5(a) and A.8(a)). In fact, employment is dramatically low in both camps: only 7% of South-Sudanese recent arrivals have an income-generating activity. Employment levels are particularly low for very recent arrivals.

The agriculture dummy is clearly discontinuous at the cutoff (figures A.5(b) and A.8(b)). While 71% of households who arrived less than a month after the cutoff date had a kitchen garden at the time of our survey, this percentage is only 33% for those who arrived less than one month before the cutoff date. This confirms that the wider promotion of small-scale agriculture in Kalobeyei is one of the key differences between Kakuma and Kalobeyei.[24] In table A.6, we add the

[22]The construction of possible mediators is described in table A.1 in appendix. Descriptive statistics are presented in table 3.

[23]We use the non-parametric local-linear approach with predetermined variables to test for discontinuities in possible mediators at the cutoff date and test whether including the possible mediator in the list of covariates affects the RD estimates. We use the parametric approach to test whether the mediator is statistically significant when included in the RD regressions as a control variable.

[24]The progressive roll-out of small-scale agriculture in Kalobeyei explains why we observe a decreasing trend on the right-hand side of the cutoff in Figure 5(b) in appendix. NGOs started promoting small-scale agriculture in Village 1, the oldest and the most developed of the three villages in Kalobeyei at the time of our survey. By contrast, small-scale agriculture was not yet very prevalent in the Village 3 of Kalobeyei, where most refugees had just settled and had not

agriculture dummy to the list of control variables to assess whether this variable partly explains the "Kalobeyei effect". We find that involvement in agriculture is positively correlated with dietary diversity and with food security. The correlation with calorie intake is low and insignificant. Households indeed produce small quantities of cow-peas, okra, and leafy greens, which is useful to diversify diets, but does not much increase calorie intake. Interestingly, controlling for the agriculture dummy substantially reduces the estimate of the discontinuity in average dietary diversity at the cutoff date. The coefficient drops from 0.268 to 0.198 according to the non-parametric approach (-0.26%). Involvement in agriculture seems to partly explains the higher levels of dietary diversity in Kalobeyei. For food insecurity, we also observe a drop, albeit smaller, in the estimate of the discontinuity (-12%).

By contrast, we find no discontinuity in animal husbandry. Only 4% of refugee households actually own animals. This is partly due to restrictions on livestock ownership imposed by the Turkana host population (Betts et al. 2018). Refugees are only allowed to own small animals, such as chickens or doves, to avoid conflictual competition with the Turkana, who have a strong tradition of nomadic pastoralism.

5.2 Mobility and household composition

Refugees are mobile populations. Qualitative accounts suggest that South-Sudanese refugees frequently travel to South Sudan for family reasons, and within Kenya for medical or educational reasons (Betts et al. 2018). Such movements have implications on the composition of households, which in turn affects the quantity of food aid received per person. We find no significant difference in mobility patterns between sites. In fact, only 2.1% of South-Sudanese recent arrivals reported traveling back to South Sudan the year before the survey, and less than 2% reported traveling to another city in Kenya.[25]

Household composition influences both needs and the amount of assistance received. We study discontinuities in the number of household members elicited

yet had time to set up a kitchen garden.

[25]Note that under-reporting is likely, as refugee movements are frequently not notified to authorities.

during the survey – this relates to needs – and in the number of household members recorded on ration cards – this determines food assistance. The correlation between these two numbers is large (0.73) but not perfect: these two numbers can differ if household members have moved in or out since registration,[26] or if births or deaths have not been recorded. We find a slight discontinuity in the average number of household members at the cutoff – households in Kalobeyei appear to be slightly smaller in size– but no significant discontinuity in the number of household members recorded on ration cards (figures A.5(f)-5(g) and A.8(f)-8(g)). We also find some evidence of a discontinuity in the ratio of the number of people on the ration card to the number of household members (figures A.5(h) and A.8(h)). On average, the number rations per household member is 1.05 in Kakuma and 1.17 in Kalobeyei.[27] In table A.7, we introduce both the number of household members and the number rations per household member as supplementary controls in our main regressions. Larger households have lower calorie intake per adult equivalent. The per capita value of what they consume is also lower. By contrast, having extra people on ration cards is positively correlated with calorie intake, with the value of food consumption, and with subjective well-being. We find some evidence that part of the "Kalobeyei effect" on calorie intake ($\approx 13\%$) and on the value of food consumption ($\approx 24\%$) could be driven by the composition of households and, in particular, by changes that might have occurred between the registration of households and the time of our survey. However, the bulk of the "Kalobeyei effect" remains unexplained by the composition of households and by secondary movements.

5.3 Human and physical capital

We study whether differences in human and physical capital could explain our findings. We find weak evidence of a possible discontinuity in the average number of years of education (figures A.6(a) and A.9(a)). This discontinuity could be ex-

[26]To avoid suffering from a reduction in food aid, households rarely report when their members move out.

[27]Ratios larger than 1 imply that households receive more than one ration of food aid per member, which usually indicate that some household members have passed away or moved out of the household without reporting the changes to UNHCR.

plained by the fact that adult education is more widely available in the Kakuma camp, which is older and has greater infrastructure. The proportion of South-Sudanese recent arrivals enrolled in an educational program is 55% in Kakuma versus 32% for those in Kalobeyei. The discontinuity in education years is however statistically insignificant with large bandwidths. We also find evidence of a discontinuity in the poor health index (figures A.6(e) and A.9(e)). Only one clinic existed in Kalobeyei at the time of our survey, and refugees had to travel to Kakuma camp or Kakuma town to access a hospital. We do not find evidence of discontinuities in education program enrollment, vocational training, asset holding, mental health, and language skills.

It seems unlikely that differences in education and health are driving our results, simply because educational levels and health are worse in Kalobeyei compared to Kakuma and these factors should, at least in theory, be associated with better outcomes. Tables A.8 and A.9 confirm that education and health do not explain the different outcomes we observe in Kakuma and Kalobeyei.

5.4 Access to services

We examine whether our results could be driven by differential access to finance, water, electricity, security, and markets. We find no significant discontinuities in access to financial services around the cutoff date (figures A.7(a)-A.7(c) and A.10(a)-A.10(c)). In fact, access to finance is poor in both Kakuma and Kalobeyei. Only 0.6% of South-Sudanese recent arrivals had a bank account with savings at the time of our survey, only 0.5% had a pending loan, and only 7% had received remittances.

We identify a strong discontinuity in the average time needed to collect water (figures A.7(d) and A.10(d)). At the time of our survey, access to water was much better in Village 1 of Kalobeyei - the oldest part of the settlement - compared to Village 2 and Village 3. In table A.10, we show that differences in access to water do not account for the observed differences in nutrition, subjective well-being, and perception of independence between the camps. We find no significant discontinuity in the quantity of water fetched daily, access to electricity, and a measure of perception of insecurity (figures A.7(e)-A.7(g) and A.10(e)-A.10(g)).

Access to more developed markets in Kakuma could lead to increased spending on leisure and non-essential goods and, therefore, reduced spending on food and other essential items. We find no discontinuity in non-essential spending on soda, alcohol, tobacco, or video halls (figures 7(h) and 10(h)). In fact, only 6% of South-Sudanese recent arrivals reported spending money on these non-essential goods, which is not surprising given high levels of food insecurity.[28]

We conclude that differential access to services does not seem to drive differences in outcomes between Kakuma and Kalobeyei.

5.5 Prices

Different factors could lead to price differences between Kakuma and Kalobeyei. At the time of our survey, markets in Kalobeyei were relatively new and less developed than markets in the oldest part of Kakuma camp. Food retailers in Kalobeyei faced higher transaction costs, as most of them had to rely on wholesalers located in Kakuma camp or Kakuma town (Betts et al. 2019). The Kalobeyei settlement is less densely populated than the Kakuma camp, which could affect competition and prices (Capozza and Van Order 1977). The different modalities of food assistance are also likely to influence prices (Delius and Sterck 2020).

In table 6, we use OLS and quantile regressions and data from the consumption module of our survey to study price differences between Kakuma and Kalobeyei. The dependent variable is the price paid per kilo divided by the average price paid per kilo for that good in Kakuma. Our main variable of interest is a dummy equal to 1 for transactions that occurred in Kalobeyei. In columns 2-3 and 5-6, we also control for a dummy equal to 1 for cash payments (versus Bamba Chakula payments), and a measure of the quantity consumed. Results from OLS regressions suggest that prices are about 15% higher in Kalobeyei than in Kakuma. Estimates are positive but close to zero with quantile regressions. We conclude

[28] Figure 7(h) offers weak evidence that non-essential spending might be more prevalent in Kakuma, possibly because bars, hotels (i.e. cafes), shops, and video halls are more numerous in the old camp. The discontinuity is however statistically insignificant for any bandwidth. Controlling for non-essential spending does not affect our main results (table A.11). We conclude that "the Kalobeyei effect" is not related to non-essential spending.

Table 6 – Analysis of price differences between Kakuma and Kalobeyei

	Dependent variable: prices, expressed in % of the mean price of each product in Kakuma					
	OLS regression			Quantile regression		
	(1)	(2)	(3)	(4)	(5)	(6)
Kalobeyei	0.147***	0.146***	0.172***	0.000	0.034***	0.030*
	(0.026)	(0.022)	(0.043)	(0.012)	(0.012)	(0.018)
Cash dummy		-0.311***	-0.335***		-0.173***	-0.195***
		(0.035)	(0.035)		(0.017)	(0.020)
Quant (% mean, 99% trimmed)		-0.127***	-0.132***		-0.071***	-0.073***
		(0.012)	(0.012)		(0.006)	(0.007)
Controls	No	No	Yes	No	No	Yes
Observations	4362	4011	3859	4362	4011	3859
r2	0.0099	0.063	0.071			

Notes: Columns 1 to 3 report the results of OLS regressions. Columns 4 to 6 report the results of quantile regressions. The dependent variable is the price paid per kilo divided by the average price paid per kilo in Kakuma for that commodity. In columns 3 and 6, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. Data source: our survey data. Sampling weights are accounted for. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

that prices are similar in Kakuma and Kalobeyei and, if anything, they are slightly higher in Kalobeyei. Therefore, differences in prices cannot explain the "Kalobeyei effect". Interestingly, cash purchases appear to be much cheaper than Bamba Chakula purchases. Different market imperfections explain this result, including the strong barriers to entry in the Bamba Chakula market and the complex credit relationships between refugees and Bamba Chakula food retailers (Sterck et al. 2020; Betts et al. 2019).

5.6 In-kind versus cash aid

Food assistance is supposed to be of equal value in Kakuma and in Kalobeyei. But the modalities of assistance differ. At the time of our survey, refugees in Kalobeyei were receiving 93% of food assistance through the Bamba Chakula program of cash transfers. Refugees in Kakuma were receiving about 70% of their food ration in-kind and only 30% through Bamba Chakula.[29] Attributing part of the "Kalobeyei effect" to these different modalities is challenging because there is

[29]The amount provided through Bamba Chakula is slightly higher for single-person households.

little variation in the modalities of food assistance within sites. Contrarily to other mediators, we cannot simply add one more control variable in regressions to assess whether the variable mediates the effect. Still, different observations suggest that a substantial part of the "Kalobeyei effect" is due to the greater importance of the Bamba Chakula program in the settlement.

The positive effects on nutrition and the null effects on assets and non-food spending are consistent with the fact that Bamba Chakula mobile money can only be spent on food items. Given this restriction, refugees cannot directly buy non-food items using Bamba Chakula. Refugees willing to purchase non-food items with Bamba Chakula money have to buy food items at registered Bamba Chakula shops first, and then resell the items at a discounted price to obtain cash (Sterck et al. 2020).

The positive effects of the Bamba Chakula program on dietary diversity, subjective well-being, and perception of independence also make sense theoretically. Refugees receiving cash transfers can directly and independently buy the food they prefer, including fruits and vegetables, meat, fish, and dairy. The diets of those on in-kind rations is constrained by the content of the monthly food baskets, which is determined by WFP. If the content of in-kind rations is less diverse than the preferred diet of beneficiaries, cash transfers are expected to increase dietary diversity. In Kakuma, the in-kind rations usually consist of 13kg of a mix of cereals, pulses, and oil. Vegetables, fruits, meat, fish, dairy and other commodities are absent from the food basket. The effect of cash transfers on dietary diversity is therefore quite logically positive. Refugees receiving cash transfers feel happier and more independent from aid as they are entitled to buy the food they like.

The relative effect of cash versus in-kind transfers of equal values on calorie intake and on the value of consumption is theoretically ambiguous. The consumption patterns of refugees depend on how they spend their Bamba Chakula allowance, which in turn depends on food preferences and on prices. Some commodities are more or less nutritious. For example, 1 dollar spent on maize gives 32 times more calories than 1 dollar spent on fish. We estimate the minimum and maximum quantity of calories per person that households can theoretically afford in each site (see figure A.12 in appendix for details). [30] We find that refugees can all consume 2,100kcal per day provided they purchase nutritious food and provided food rations are not reduced. But we also find that the range of possibilities is much broader for refugees in Kalobeyei. If refugees living in Kalobeyei spend their entire Bamba Chakula allowance on cereals, they can consume as much as 3300kcal per day. By contrast, the calorie content of their diet can be very low if they spend their Bamba Chakula allowance on less energy-dense food, such as fish, meat, vegetables, or fruits. Refugees receiving cash transfers have the opportunity to consume more calories than those on in-kind transfer if they spend a large part of their allowance on nutritious food. Whether refugees realize this possibility is an empirical question, and our results suggest they do.

Our results showing that food insecurity is less prevalent in Kalobeyei can be easily explained by the fact that food insecurity is negatively correlated with dietary diversity and with calorie intake. Another practice associated with Bamba Chakula may reinforce this effect. Although explicitly forbidden by WFP, some Bamba-Chakula retailers extend credit to their regular customers in exchange for keeping their Bamba Chakula SIM cards at the shop (Sterck et al. 2020). For Bamba-Chakula retailers, keeping the SIM cards of customers acts as a guarantee of re-payment and ensures their loyalty. In exchange, customers often receive goods on credit when they face difficulties or when Bamba Chakula payments are delayed, which is very frequent. This practice is therefore likely to favor consumption smoothing and reduce food insecurity. While a staggering 82% of Kalobeyei households store their SIM card at a Bamba Chakula shop, only 38% of households in Kakuma use this practice (Delius and Sterck 2020).

Finally, our findings should have a cause, and the only channel that we have not been able to rule out yet relates to the Bamba Chakula program. By elimination, we conclude that this is the most likely explanation for our findings. Importantly,

[30] The estimation does not take into account the fact that refugees receiving in-kind aid often resell part of their food ration at discounted prices in order to purchase the food they like or to buy non-food items. Qualitative accounts suggest that the resale of food rations is a very common practice in refugee camps around the world, including in Kakuma (Betts et al. 2018; WFP 2018a). This practice negatively affects the amount of calories consumed by refugees receiving in-kind transfers.

we rule out that our results are driven by mismeasurement problems or by sampling error. In line with our results, an observational study carried out two months after our survey also concludes that levels of dietary diversity, food expenditures, and food security are higher in Kalobeyei, while asset holding and non-food spending are higher in Kakuma (WFP 2018a).

6 Conclusion

Assistance to refugees is gradually evolving from a humanitarian model, based on care and maintenance, to a development model that promotes refugee self-reliance through income-generating activities, market development, and cash transfers. In this paper, we exploited a regression discontinuity design to assess whether the development approach to refugee assistance leads to better socio-economic outcomes for refugees. We compared refugees living in two hosting sites in North-West Kenya. The old Kakuma camp is a "humanitarian economy", in which the bulk of the refugees survive thanks to in-kind food rations that are distributed monthly. The new Kalobeyei settlement was opened in May 2016, with the aim of fostering local economic development through self-reliance programming, market development, and monthly cash transfers. We exploited a cutoff date in the allocation of refugees between the two neighboring sites. Our results suggest that refugees living in Kalobeyei have better diets and feel happier and more independent from humanitarian aid. They are also more likely to be involved in small-scale agriculture. We find no effect on non-food spending, assets, and employment. These effects appear to be driven by the switch from food rations to cash transfers and, to a smaller extent, by the wider promotion of kitchen gardens.

The current study has some limitations that future research could try to overcome. First, our data was collected about 16 months after the opening of the Kalobeyei settlement, implying that our study focuses on short-run effects. Long-term effects could be stronger or weaker, depending on how programs evolve and how markets develop. Second, regression discontinuity designs have their limitations. They are local in nature, as treatment effects are only estimated at the cutoff. Results can be sensitive to specification and bandwidth selection. While our estimates of the "Kalobeyei effect" on consumption indicators are very robust, results related to subjective well-being and perception of independence are more variable and should be interpreted with caution. Finally, the study of channels of impact is by nature exploratory and context dependent. The links we have identified would need further experimental investigation to determine causal effects. The lack of variation in the modalities of food assistance within Kakuma or Kalobeyei implies that it is impossible to formally attribute the "Kalobeyei effect" to the wider use of Bamba Chakula in the settlement. However, the irrelevance of other channels and the absence of effect on non-food expenditures and assets suggest that differences in the modalities of food assistance do drive the bulk of the observed differences between the two sites. More complex and costly research designs could attempt to test this hypothesis.

Our results suggest that the development approach to refugee assistance in Kalobeyei is having positive effects, possibly thanks to the wider promotion of cash assistance and kitchen gardens. Cash assistance is not only associated with better nutrition outcomes for refugees, it is also more cost efficient than in-kind transfers. In 2017, WFP Kenya estimated that the total cost of delivering US$1 to beneficiaries was US$1.18 for Bamba Chakula transfers compared to US$1.94 for in-kind food transfers (WFP 2018a). We calculate that WFP Kenya could save US$17 million if it were to replace in-kind aid by Bamba Chakula transfers in Kakuma and Dadaab camps. The money could be used to increase the amount received by all refugees living in Kakuma, Kalobeyei, and Dadaab by about 22%, from KES1400 ($\sim$ US$14) to KES1708 ($\sim$ US$17) per person per month. This calculus does not take into account the likely positive spillovers on local communities. In Lebanon, WFP (2014) estimated a multiplier value of 1.51 in the food products sector for a similar program of cash transfers offered to Syrian refugees. In 2018, WFP, which is the world's largest humanitarian organization providing food assistance, still provided 65% of its aid in-kind. As cash assistance is cheaper and seems more effective than in-kind aid, and as agriculture promotion is relatively inexpensive and is associated with more diverse diets, we believe that these programs should be rolled-out where possible, after a careful assessment of context-specific factors that might interfere with them.

However, it is worth noting that the development approach is not a magic bullet. Levels of food security, employment, and asset holding remain extremely low in Kalobeyei. The retail market heavily depends on Bamba Chakula aid. The labor market is, for a large part, dependent on international organizations and NGOs, which provide the bulk of employment opportunities. While cash transfers and gardening may improve diets and empower refugees, there is still a long way to go before the settlement could be labeled as self-reliant.

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A Online Appendix

Table A.1 – Construction of variables

Variable	Construction
Outcome variables	
Dietary Diversity Score	The dietary diversity score is a measure of the variety of food intake, which is calculated by counting the number of twelve different food types which have been consumed at any time within the seven days preceding the survey, resulting in a score from $0 - 12$. Zero-valued observations are considered as unrealistic and excluded.
Calories per adult equivalent	For 18 types of commodity, we converted the quantity consumed expressed in kilos per day using energy data from the U.S. Department of Agriculture (table A.2 in appendix). Adult equivalents are calculated according to the following formula $AE = [(1 + \beta(A - 1)) + \alpha K]^{\theta}$, where A is the number of adults in the household, and K is the number of children. We use the following parametrization: $\alpha = 0.3$, $\beta = 1$, and $\theta = 0.9$ (Deaton and Zaidi 2002; D'Aoust et al. 2018).
Value of food consumption per household member	For 18 types of commodity, we multiply the quantity consumed expressed in kilos per day by the median price per kilo in our data. We then aggregate the values calculated for the 18 commodities and divide the total by the number of household members.
Household Food Insecurity Access Prevalence	Food insecurity is measured using the Household Food Insecurity Access Prevalence (HFIAP), which aggregates respondents' perceptions of food vulnerability and the frequency with which shortages occurred (Coates et al. 2007). The primary food preparer in the household was asked whether each of nine worries had occurred, and if yes, whether that happened rarely, sometimes, or often. The HFIAP ranges from 1 for food secure households to 4 for severely food insecure households.
Non-food expenditures	The variable aggregates household monthly expenditures on education, health, ceremonies, housing, transport, video halls, soda, alcohol, tobacco, and airtime.
Asset index	The asset index is a composite indicator that compiles information on household assets(radio, television, computer, refrigerator, solar panel, generator, table, chair, sofa, bed, cupboard, clock, DVD-player, mobile-phone, MP3-player, watch, bicycle, motorcycle, and car), the type of stove used for cooking, access to electricity, and ownership of animals (cattle, donkeys, camel, goat, sheep, chicken or ducks, and doves). We aggregate the different components of the index using the same weights as the ones used to construct the wealth index of the Kenya Demographic and Health Survey of 2014.
Subjective well-being	The variable stores answers to the question "All things considered, how satisfied are you with your life as a whole these days?" Answers are ranging from 1 "Very unsatisfied" to "5 Very satisfied".
Perception of independence from aid	The variable stores answers to the question "How dependent do you think your household is on support from UNHCR, WFP or any other NGOs?" Answers range from 1 "Completely dependent" to 4 "Not at all dependent".

Continued on next page

Variable	Construction
Predetermined variables	
Gender	The dummy variable is equal to for female and zero otherwise.
Age	The variable stores answers to the question “How old are you?”
Married	The dummy variable is equal to one for married individuals and zero otherwise.
# parents alive	The variable is equal to zero if for respondents who answered “No” to the question “Are your parents still alive?” and equal to the answer to the follow-up question “How many parents do you still have?” otherwise.
Father’s years of education	The variable captures the number of years of education completed by the respondent’s father.
Mother’s years of education	The variable captures the number of years of education completed by the respondent’s mother.
Agricultural background	The variable is equal to one if the respondent answered “Yes” to the question “Before displacement, was your family involved in agriculture?” and equal to zero otherwise.
Equatoria region	The variable is equal to one if the respondent answered “Equatoria region” to the question “What region in South Sudan are you originally from?” and equal to zero otherwise.
Bahr el Ghazal Region	The variable is equal to one if the respondent answered “Bahr el Ghazal Region” to the question “What region in South Sudan are you originally from?” and equal to zero otherwise.
Great Upper Nile Region	The variable is equal to one if the respondent answered “Great Upper Nile Region” to the question “What region in South Sudan are you originally from?” and equal to zero otherwise.
Possible mediators	
Job dummy	The dummy is equal to one for refugees with an income-generating activity and equal to zero otherwise.
Agriculture dummy	The dummy is equal to one for households involved in agriculture (kitchen garden, community garden, or large farm) and equal to zero otherwise.
Animal husbandry	The dummy is equal to one for respondents who answered “yes” to the question “Does your household own any livestock, herds or poultry?” and equal to zero otherwise.
Years of education	The variable captures the number of years of education completed by the respondent.
Vocational training dummy	The dummy is equal to one if the respondent completed any vocational training and equal to zero otherwise.?

Continued on next page

Variable	Construction
Health index	The health index is constructed using six questions from the 12-item WHO-DAS scale. The six questions relates to difficulties that respondents may have faced over the 30 days preceding the survey when doing the following activities: standing for a long period, taking care of household responsibilities, learning a new task, joining community activities, concentrating for ten minutes, walking a long distance). Answers are ranging from 0 "No difficulty" to "4 Extreme difficulty". The index is the sum of the 6 answers and ranges between 0 and 24.
Mental health index	We measure the prevalence of common mental disorders using the Patient Health Questionnaire-9 (PHQ-9). Respondents were asked how often they have been bothered by symptoms of depression over the 2 weeks preceding the survey (e.g. sleeping or eating disorders, thoughts of suicide). Responses range from 0 "Not at all" to 3 "nearly every day". The index is the sum of the 9 answers and ranges between 0 and 27.
English dummy	The dummy is equal to one for respondents who answered "well" or "very well" to the question "How well can you understand and speak English?" and equal to zero otherwise.
Swahili dummy	The dummy is equal to one for respondents who answered "well" or "very well" to the question "How well can you understand and speak Swahili?" and equal to zero otherwise.
Has savings account	The dummy is equal to one for respondents who answered "Yes" to the question "Do you currently have any savings in a bank account, or at a micro-finance institution?" and equal to zero otherwise".
Has a loan	The dummy is equal to one for respondents who answered "Yes" to the question "Do you currently have a loan in a bank, a micro-finance institution, a private lender, or any friend or family member?" and equal to zero otherwise".
Remittances (dummy)	The dummy is equal to one for respondents who reported receiving remittances at least once per year from their network (brothers, sisters, children, parents, husbands or wives, or any other person) and equal to zero otherwise.
# HH members	The variable is the number of household members, including children, adults, and the elderly.
# on ration cards	The variable stores answers to the question "How many people are on the ration card(s) of your household?"
Rations per members	The variable is the ratio of the number of people on the ration cards household to number of household members.
Traveled within Kenya (dummy)	The dummy is equal to one for respondents who responded 1 or more to the question "Last year, how many times did you travel to another city in Kenya?" and equal to zero otherwise.

Continued on next page

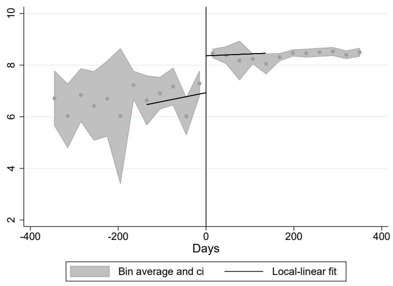
Variable	Construction
Traveled to origin country (dummy)	The dummy is equal to one for respondents who responded 1 or more to the question "Last year, how many times did you travel to your origin country?" and equal to zero otherwise.
Time needed to access water	The variable aggregates the time needed to go back and forth to the water source (measured as the double of the answer to the question "How many minutes does it take to get from your house to your main water source?") and the usual waiting time at the water source (measured as the answer to the question "How many minutes does your household usually have to wait at the water source?").
Water fetched daily	The variable stores answers to the question "How much water do you fetch per day?"
Currently in education	The dummy is equal to one for respondents who answered "yes" to the question "Are you currently attending school, college or University?" and equal to zero otherwise.
Access to electricity	The dummy is equal to one for respondents who answered "yes" to the question "Does your household have electricity?" and equal to zero otherwise.
Perception of insecurity	The variable stores answers to the question "Do you agree with the following statement: the level of security is good?" Responses range from 1 "Strongly agree" to 4 "Strongly disagree".
Non-essential spending (dummy)	The dummy is equal to one for respondents who spent some money on cinema, soda, alcohol, or tobacco in the 30 days preceding the survey and equal to zero otherwise.

Table A.2 – Caloric Values of Selected Foods

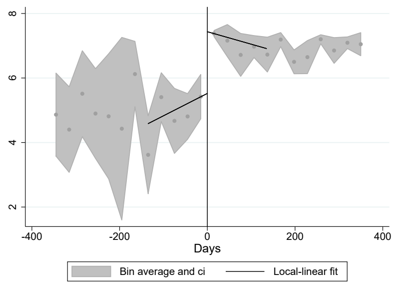
	kcal/100g	USDA Number	Notes
Sorghum & Sorghum Flour	329	20067	
Millet	378	20031	
Maize Flour	361	20316	
Corn-Soy Blend	380	110200*	
Wheat & Wheat Flour	340	20080	
Rice & Rice Flour	362	20042	
Irish (white) & Sweet Potato	91	11354; 11507; 11601	Mean of white, sweet, and yam
Peas & Beans	330	16027	Kidney beans are the most common
Onions	40	11282	
Kale & Okra	41	11233; 11278	Mean of kale and okra
Meat	200	13001; 17168	Mean of beef and goat carcass
Chicken & Poultry	258	5123	
Fish & Seafood	94	15060; 15261	Mean of raw perch and tilapia
Vegetables	72	11583	Mixed unprepared vegetables
Fruit	99	9040; 9200; 9037	Mean of banana, orange, and avocado
Milk & Yoghurt	67	1078; 1106	Mean of cow and goat milk
Eggs	143	1123	63kcal per medium egg
Oil	793	4513	per 100ml

Source: U.S. Agency for International Development (2018)

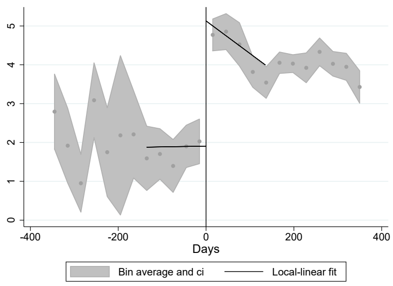
*Corn-soy blend information from U.S. Department of Agriculture (2008)



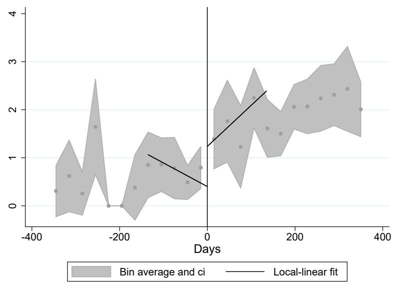
(a) Starchy food



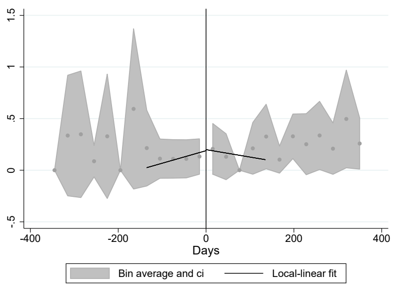
(b) Beans



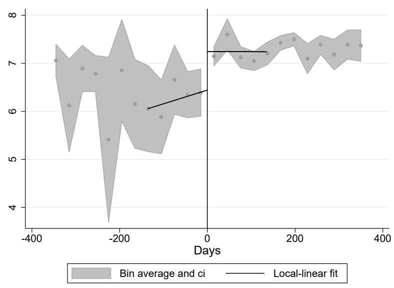
(c) Fruits and vegetables



(d) Meat and fish



(e) Dairy and eggs



(f) Oil

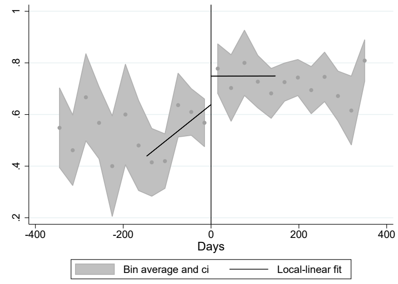
Figure A.1 – Decomposition of the "Kalobeyei effect" on calorie intake for 6 catogories of food

Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.

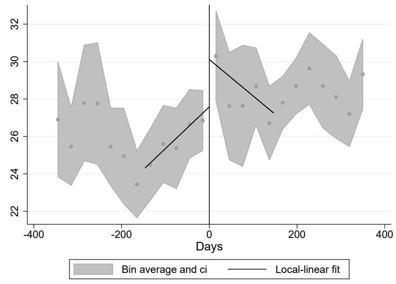
Table A.3 – Parametric approach without and with controlling for predetermined variables

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Non-food expenditures (ihs) (5)	Asset index (6)	Subjective well-being (7)	Independence from aid (8)
Panel A - Parametric approach without predetermined variables								
RD	0.173***	0.949***	0.972***	-0.461***	-0.00561	-0.119***	0.214	0.246***
	(0.0319)	(0.0811)	(0.0960)	(0.0927)	(0.352)	(0.0232)	(0.132)	(0.0650)
Forcing	0.0000228*	0.0000284	-0.0000136	0.000140*	-0.000716***	-0.0000159	0.0000798**	0.00000673
	(0.0000121)	(0.0000519)	(0.0000623)	(0.0000753)	(0.000205)	(0.0000104)	(0.0000406)	(0.0000138)
Forcing × cutoff dummy	-0.000116	0.000394**	0.000101	0.000609*	-0.00226**	-0.000227***	-0.00114**	-0.000101
	(0.0000899)	(0.000196)	(0.000245)	(0.000315)	(0.00107)	(0.0000561)	(0.000449)	(0.000213)
N	1642	961	961	985	936	1016	1648	1648
R^2	0.079	0.30	0.20	0.030	0.030	0.13	0.0079	0.032
Adjusted R^2	.08	.3	.2	.03	.03	.13	.01	.03
Panel B - Parametric approach with predetermined variables								
RD	0.144***	0.965***	1.078***	-0.469***	0.0567	-0.0360	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.397)	(0.0267)	(0.157)	(0.0726)
Forcing	0.0000194	0.0000186	-0.0000427	0.000147**	-0.000752***	-0.0000178*	0.0000822*	0.0000148
	(0.0000125)	(0.0000494)	(0.0000598)	(0.0000745)	(0.000200)	(0.00000972)	(0.0000475)	(0.0000145)
Forcing × cutoff dummy	-0.000128	0.000363*	0.0000907	0.000583*	-0.00244**	-0.000242***	-0.00115**	-0.0000792
	(0.0000891)	(0.000191)	(0.000239)	(0.000309)	(0.00106)	(0.0000567)	(0.000449)	(0.000211)
Female	0.0147	0.114	-0.245**	0.118	0.431	-0.0977***	0.131*	-0.0389
	(0.0143)	(0.0792)	(0.0999)	(0.111)	(0.382)	(0.0168)	(0.0742)	(0.0366)
Age	-0.000730	0.00219	-0.000211	0.00617**	-0.0103	0.000823	-0.00264	0.00290
	(0.000749)	(0.00218)	(0.00254)	(0.00313)	(0.0114)	(0.000701)	(0.00381)	(0.00206)
Married	0.0209	-0.110***	-0.119**	0.0739	0.285	0.0297**	-0.0155	-0.0102
	(0.0144)	(0.0417)	(0.0512)	(0.0612)	(0.223)	(0.0136)	(0.0768)	(0.0391)
# parents alive	-0.00117	-0.0529**	-0.0409	0.106***	0.111	-0.00734	-0.0482	-0.00836
	(0.0105)	(0.0263)	(0.0319)	(0.0369)	(0.137)	(0.00828)	(0.0495)	(0.0232)
Father's years of education	0.00863***	0.00748	0.0134**	0.00132	0.0996***	0.00424**	0.0104	-0.00168
	(0.00182)	(0.00506)	(0.00616)	(0.00588)	(0.0277)	(0.00165)	(0.00997)	(0.00397)
Mother's years of education	0.00611	-0.0123	-0.0187	0.0124	0.0225	0.00253	0.0153	0.00241
	(0.00452)	(0.0132)	(0.0150)	(0.0102)	(0.0624)	(0.00425)	(0.0248)	(0.0103)
Agricultural background	-0.0314	-0.309***	-0.431***	0.115	-0.604**	-0.0368*	-0.115	0.154***
	(0.0290)	(0.0618)	(0.0814)	(0.0863)	(0.296)	(0.0203)	(0.134)	(0.0433)
Bahr el Ghazal Region	0.0195	0.0308	0.121	0.0940	0.751	0.0341	0.603***	0.127
	(0.0785)	(0.173)	(0.205)	(0.108)	(0.606)	(0.0426)	(0.226)	(0.0940)
Great Upper Nile Region	-0.0520	0.0702	0.0688	0.0391	0.0632	0.125***	-0.0733	0.0746*
	(0.0368)	(0.0901)	(0.106)	(0.0906)	(0.324)	(0.0256)	(0.124)	(0.0453)
N	1642	961	961	985	936	1016	1648	1648
R^2	0.10	0.34	0.26	0.055	0.066	0.20	0.022	0.045
Adjusted R^2	.1	.33	.25	.04	.05	.19	.01	.04

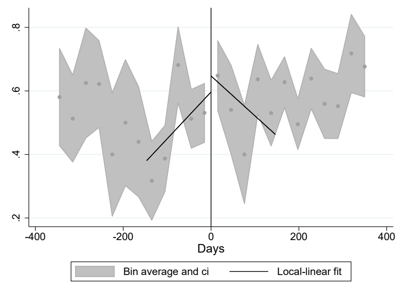
Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.



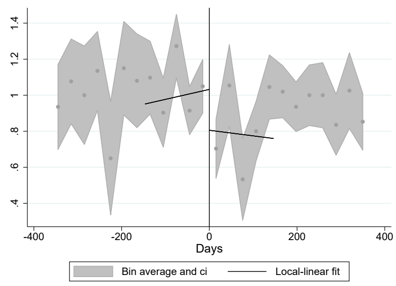
(a) Gender (1=female)



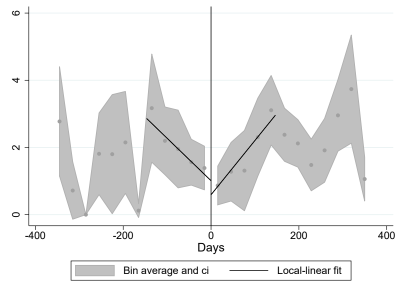
(b) Age



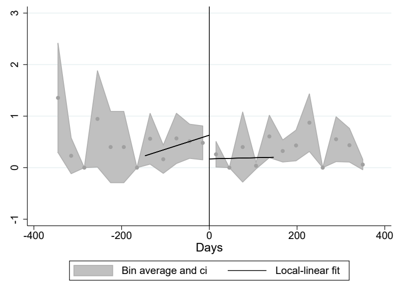
(c) Married



(d) Parents alive



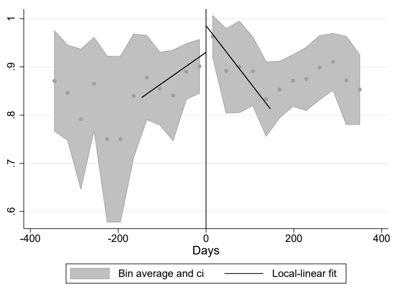
(e) Years educ. father



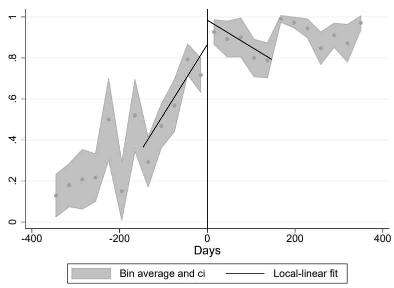
(f) Years educ. mother

Figure A.2 – Robustness checks: discontinuities in predetermined variables

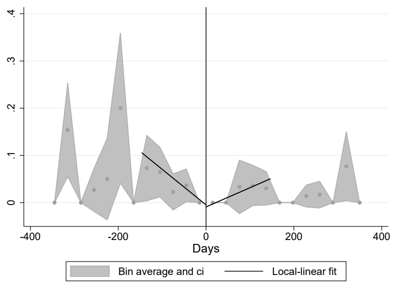
Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.



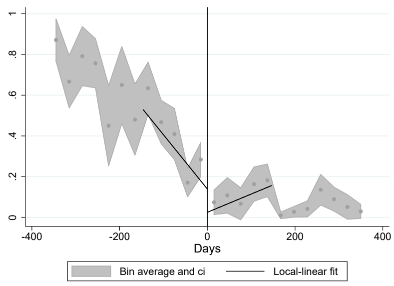
(a) Agriculture background



(b) Equatoria



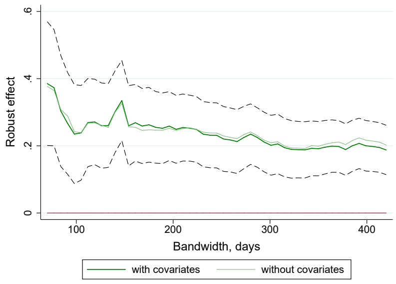
(c) Bahr el Ghazal



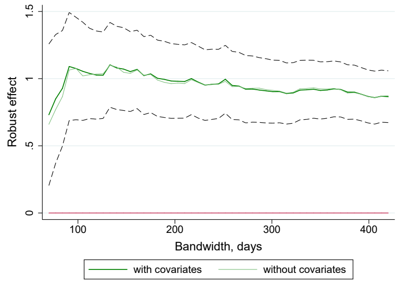
(d) Greater Upper Nile

Figure A.3 – Robustness checks: discontinuities in predetermined variables (continued)

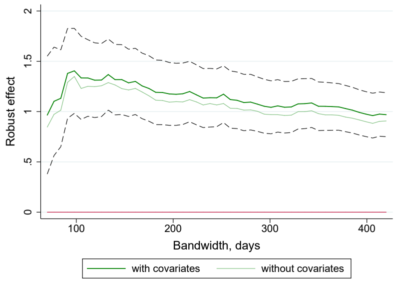
Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.



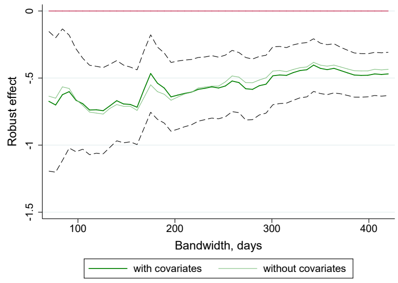
(a) Dietary variety (log)



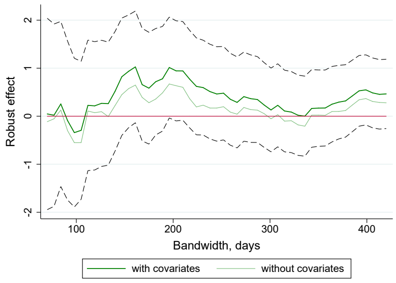
(b) Daily calories per adult equivalent (log)



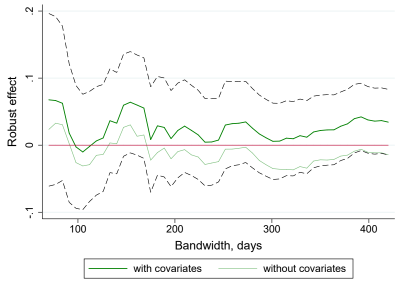
(c) Value of daily food consumption per HH member (log)



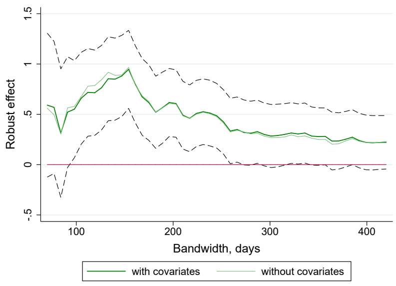
(d) Food insecurity (HFIAP)



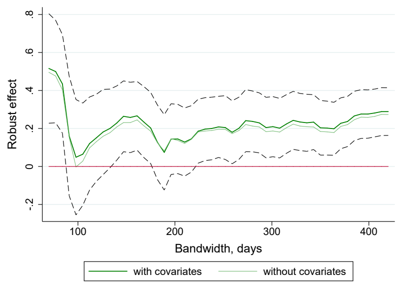
(e) Non-food expenditures (ihs)



(f) Asset index



(g) Subjective well-being



(h) Perception of independence from aid

Figure A.4 – Robustness of the parametric approach to dropping observations distant from the cutoff

Data source: our survey data. Notes: We use IV regressions in which the treatment dummy is instrumented by the cutoff dummy to estimate treatment effects. We consider restricted samples that include observations between 70 and 420 days from the cutoff and consider increments of 14 days. Light green lines = estimated treatment effects, without controlling for predetermined variables. Dark green lines = estimated treatment effects, controlling for predetermined variables. Black dashed lines = confidence intervals for the specifications with predetermined variables. Red dashed lines: optimal bandwidths of Calonico et al. (2014a) (labeled CCT) and Imbens and Kalyanaraman (2012) (labeled IK).

Table A.4 – Robustness to changes in the functional form

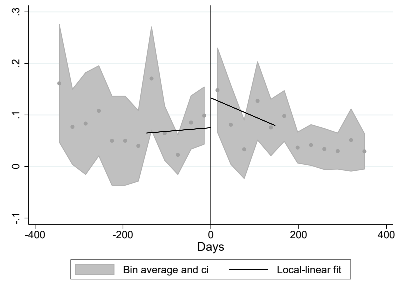
	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Non-food expenditures (ihs) (5)	Asset index (6)	Subjective well-being (7)	Independence from aid (8)
Panel A - Parametric approach with linear time trend								
RD	0.116***	1.029***	1.094***	-0.365***	-0.371	-0.0863***	-0.0520	0.274***
	(0.0339)	(0.0879)	(0.0996)	(0.0691)	(0.326)	(0.0220)	(0.115)	(0.0457)
Panel B - Parametric approach with a linear time trend and its interaction with the cutoff dummy								
RD	0.144***	0.965***	1.078***	-0.469***	0.0567	-0.0360	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.397)	(0.0267)	(0.157)	(0.0726)
Panel C - Parametric approach with quadratic time trend								
RD	0.133***	0.910***	1.016***	-0.450***	0.225	-0.0407	0.0290	0.257***
	(0.0391)	(0.102)	(0.117)	(0.0962)	(0.413)	(0.0254)	(0.124)	(0.0537)
Panel D - Parametric approach with linear and quadratic time trends and their interactions with the cutoff dummy								
RD	0.182***	1.028***	1.240***	-0.508***	-0.00115	-0.0536	0.371*	0.0963
	(0.0503)	(0.121)	(0.140)	(0.161)	(0.562)	(0.0347)	(0.200)	(0.0983)
Panel E - Non-parametric approach with local linear regression								
Robust RD	0.269***	1.021***	1.328***	-0.731***	-0.704	0.0118	0.741**	0.176
	(3.45)	(3.73)	(4.61)	(-2.82)	(-0.69)	(0.20)	(2.48)	(1.22)
Panel F - Non-parametric approach with local quadratic regression								
Robust RD	0.249**	0.956***	1.270***	-0.742**	-1.709	0.014	0.614	0.304
	(0.100)	(0.361)	(0.370)	(0.325)	(1.404)	(0.081)	(0.394)	(0.197)

Data source: our survey data. Notes: Panels A to D report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels E and F report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

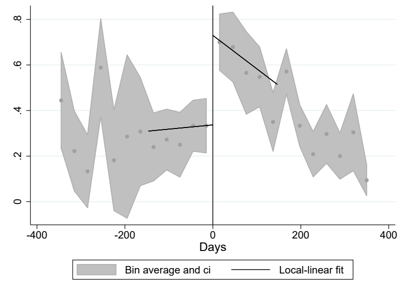
Table A.5 – Robustness and placebo tests

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Non-food expenditures (ihs) (5)	Asset index (6)	Subjective well-being (7)	Independence from aid (8)
Panel A - Non-parametric approach with predetermined variables								
Robust RD	0.269***	1.021***	1.328***	-0.731***	-0.704	0.0118	0.741**	0.176
	(3.45)	(3.73)	(4.61)	(-2.82)	(-0.69)	(0.20)	(2.48)	(1.22)
Panel B - Non-parametric approach - forcing variable = arrival date of each respondent								
Robust RD	0.300***	0.967***	1.267***	-0.661***	-0.369	0.0439	0.728**	0.348***
	(3.13)	(3.99)	(4.69)	(-2.85)	(-0.40)	(0.88)	(2.45)	(2.68)
Panel C - Non-parametric approach - dropping one week on each side of cutoff window								
Robust RD	0.246***	0.980***	1.274***	-0.995**	-1.183	0.0278	0.665*	-0.110
	(0.0837)	(0.274)	(0.293)	(0.399)	(1.221)	(0.0686)	(0.341)	(0.193)
Panel D - Non-parametric approach - cutoff date = 24th of May 2016								
Robust RD	0.268***	0.973***	1.269***	-0.708***	-1.368	-0.0342	0.756**	0.142
	(0.0889)	(0.344)	(0.353)	(0.233)	(1.130)	(0.0672)	(0.297)	(0.144)
Panel E - Non-parametric approach - only refugees from Equatoria region								
Robust RD	0.196**	0.859***	1.106***	-0.710***	-1.110	-0.0180	0.691**	0.0909
	(0.0832)	(0.328)	(0.325)	(0.274)	(1.125)	(0.0604)	(0.321)	(0.144)
Panel F - Non-parametric approach - Dropping interviews done in Kakuma in October 2017								
Robust RD	0.308***	1.036***	1.400***	-0.758***	-0.797	0.0261	0.602*	-0.0119
	(0.0999)	(0.359)	(0.356)	(0.280)	(1.170)	(0.0716)	(0.363)	(0.172)
Panel G - Non-parametric approach - Controlling for # days since food assistance last received								
Robust RD	0.262***	1.014***	1.319***	-0.737***	-0.711	0.00762	0.797***	0.184
	(0.0800)	(0.277)	(0.291)	(0.258)	(1.023)	(0.0579)	(0.305)	(0.139)
Panel H - Non-parametric approach - Placebo test (cutoff = median of left subsample)								
Robust RD	-0.0711	0.153	0.0128	0.219	-0.0685	-0.267**	-0.329	-0.312**
	(0.116)	(0.332)	(0.366)	(0.200)	(1.339)	(0.121)	(0.420)	(0.139)
Panel I - Non-parametric approach - Placebo test (cutoff = median of right subsample)								
Robust RD	0.0645	0.0650	0.154	0.0343	0.775	-0.0452	-0.353	-0.412***
	(0.0500)	(0.123)	(0.161)	(0.141)	(0.735)	(0.0340)	(0.262)	(0.0934)

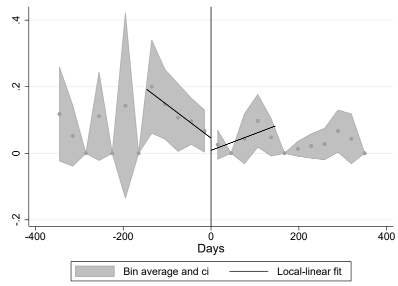
Data source: our survey data. Notes: All panels report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. The following predetermined variables are included as controls in all regressions: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.



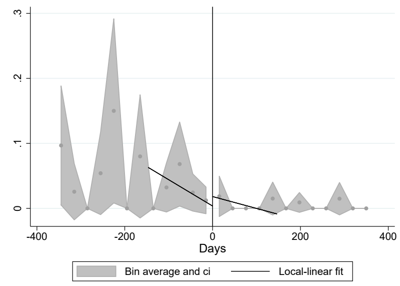
(a) Job dummy



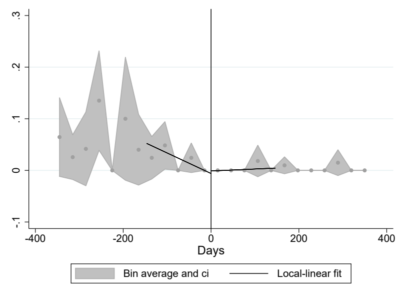
(b) Agriculture dummy



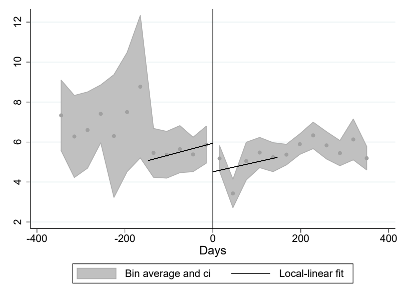
(c) Animal husbandry dummy



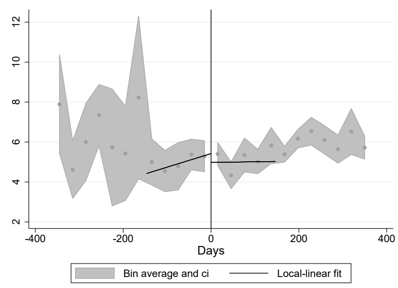
(d) Traveled within Kenya (dummy)



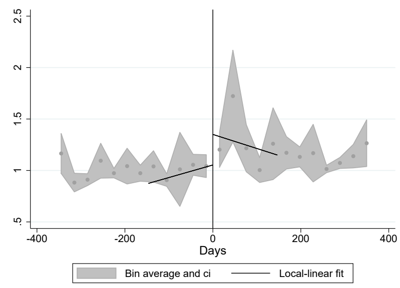
(e) Traveled to SSD (dummy)



(f) # of household members



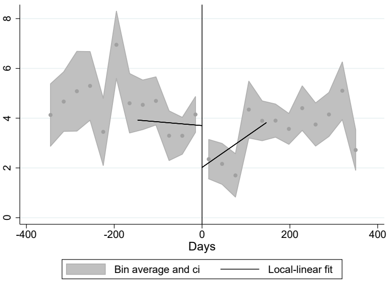
(g) # on ration cards



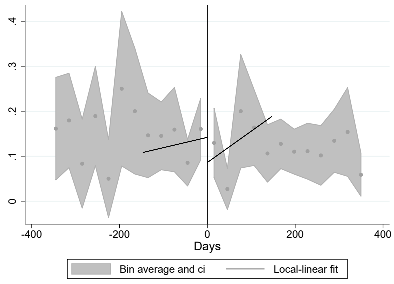
(h) Rations per household member

Figure A.5 – Channels of impact: discontinuities in possible mediators

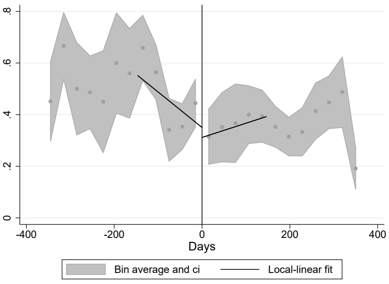
Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.



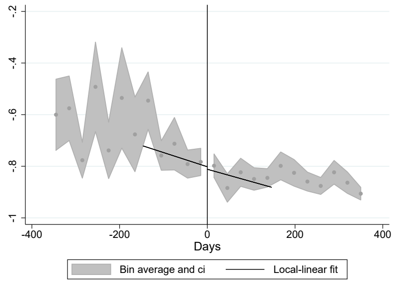
(a) Years of education



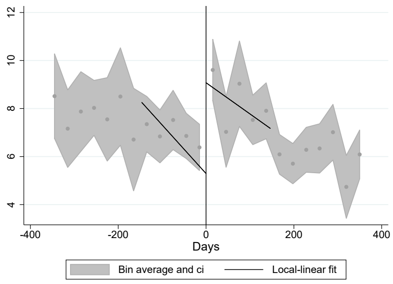
(b) Vocational training dummy



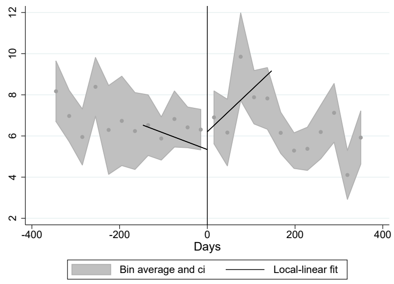
(c) Currently studying (dummy)



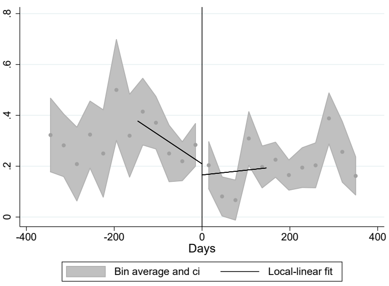
(d) Asset index



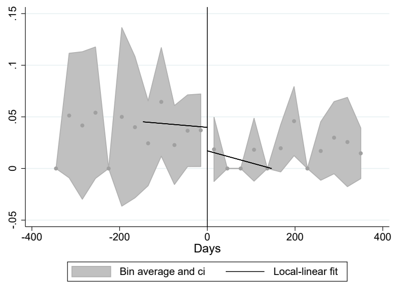
(e) Poor health index



(f) Poor mental health index (PHQ-9)



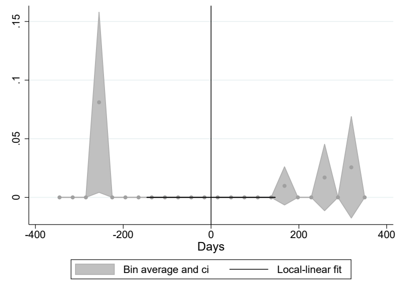
(g) English dummy



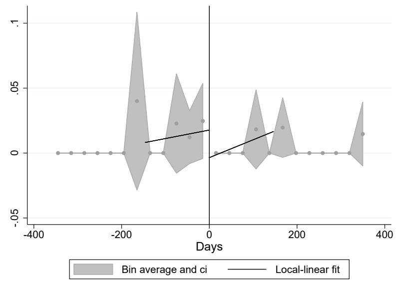
(h) Swahili dummy

Figure A.6 – Channels of impact: discontinuities in possible mediators (continued)

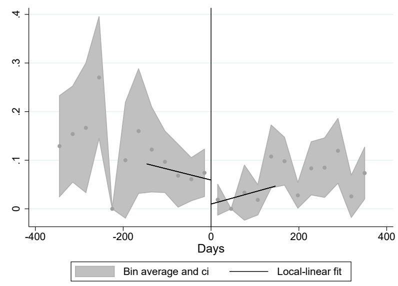
Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.



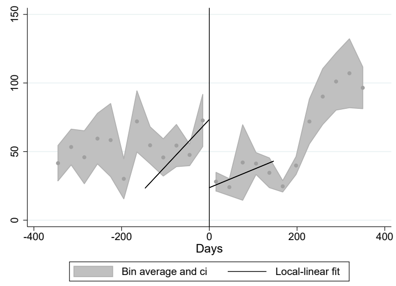
(a) Savings account dummy



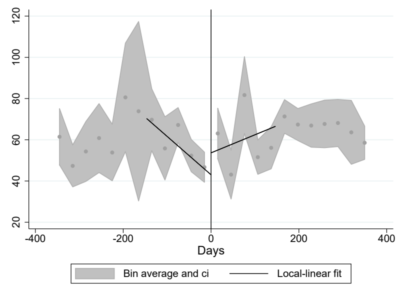
(b) Credit dummy



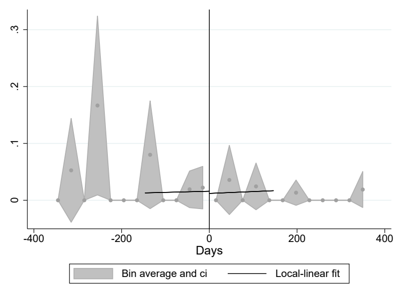
(c) Remittances dummy



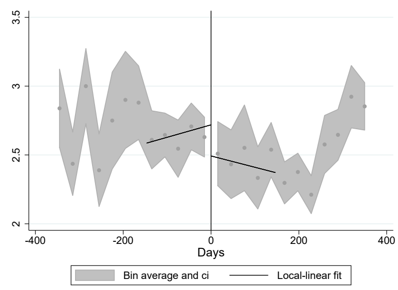
(d) Time needed to access water



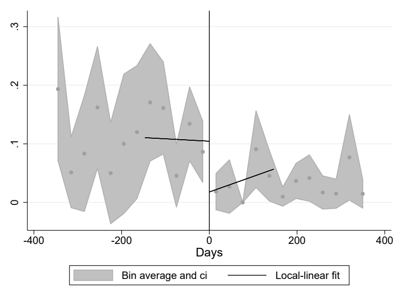
(e) Quantity of water fetched daily



(f) Access to electricity (dummy)

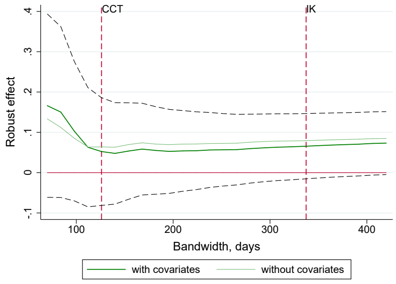


(g) Perception of insecurity

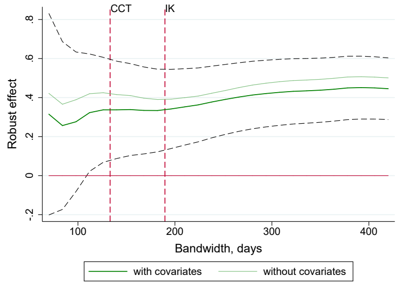


(h) Non-essential spending on soda, alcohol, tobacco, or cinema (dummy)

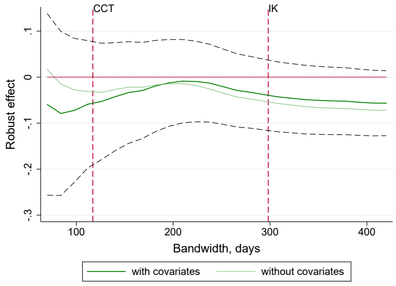
Figure A.7 – Channels of impact: discontinuities in possible mediators (continued)
Data source: our survey data. Notes: Each figure is constructed using the Stata command rdplot with 12 bins on each side of the cutoff and a local linear fit estimated using a uniform kernel. The 90% confidence intervals are represented by the shaded grey area.



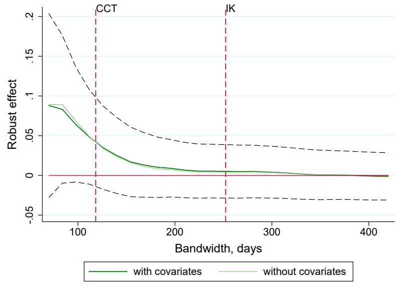
(a) Job dummy



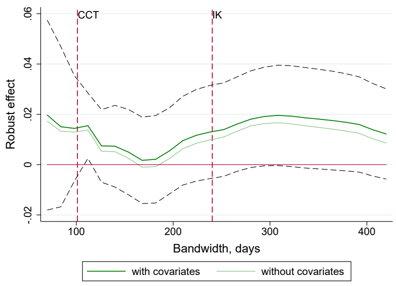
(b) Agriculture dummy



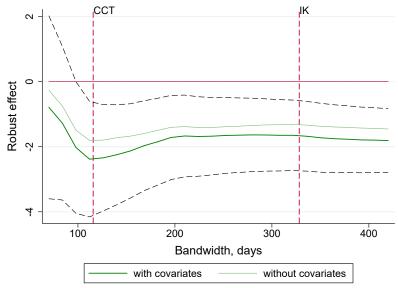
(c) Animal husbandry dummy



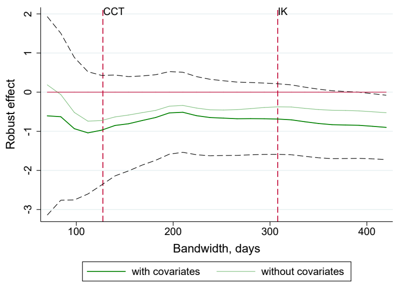
(d) Traveled within Kenya (dummy)



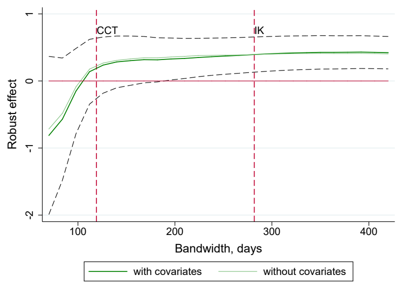
(e) Traveled to SSD (dummy)



(f) # of household members



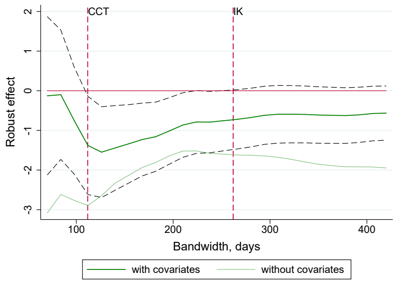
(g) # on ration cards



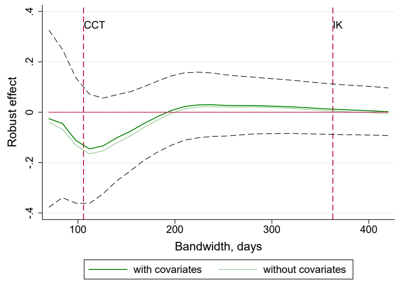
(h) Rations per household member

Figure A.8 – Channels of impact: discontinuities in possible mediators, robustness to bandwidth selection

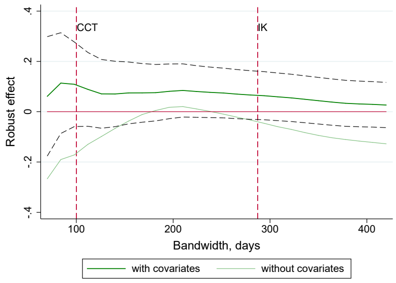
Data source: our survey data. Notes: We use the robust bias-corrected approach of Calonico et al. (2014b, 2019) with a triangular kernel to estimate the local average treatment effects for bandwidths between 70 and 420 days and increments of 14 days. Light green lines = estimated treatment effects, without controlling for predetermined variables. Dark green lines = estimated treatment effects, controlling for predetermined variables. Black dashed lines = confidence intervals for the specifications with predetermined variables. Red dashed lines: optimal bandwidths of Calonico et al. (2014a) (labeled CCT) and Imbens and Kalyanaraman (2012) (labeled IK).



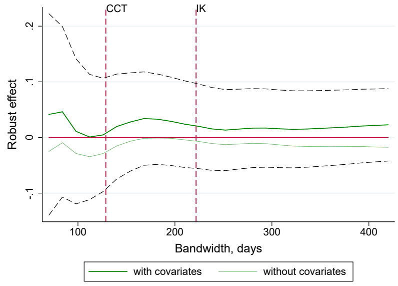
(a) Years of education



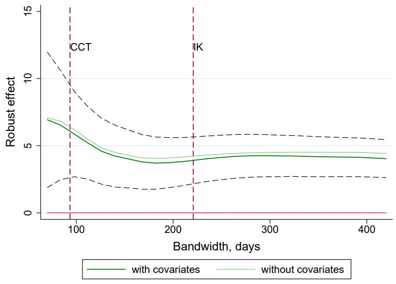
(b) Vocational training dummy



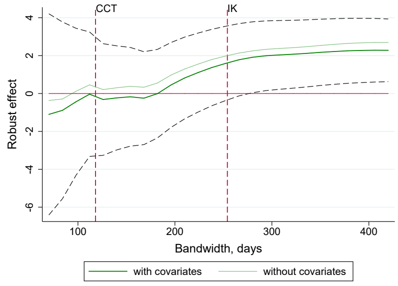
(c) Currently studying (dummy)



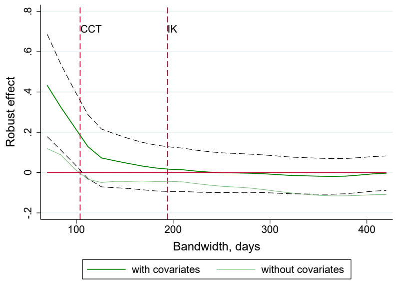
(d) Asset index



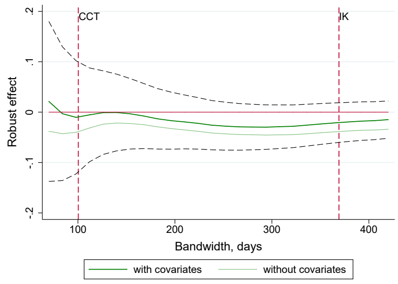
(e) Poor health index



(f) Poor mental health index (PHQ-9)



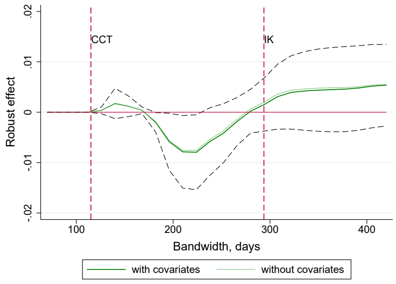
(g) English dummy



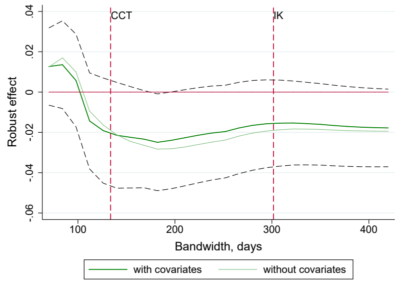
(h) Swahili dummy

Figure A.9 – Channels of impact: discontinuities in possible mediators, robustness to bandwidth selection (continued)

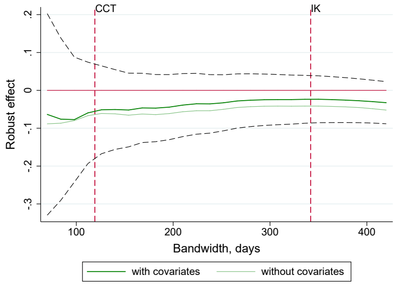
Data source: our survey data. Notes: We use the robust bias-corrected approach of Calonico et al. (2014b, 2019) with a triangular kernel to estimate the local average treatment effects for bandwidths between 70 and 420 days and increments of 14 days. Light green lines = estimated treatment effects, without controlling for predetermined variables. Dark green lines = estimated treatment effects, controlling for predetermined variables. Black dashed lines = confidence intervals for the specifications with predetermined variables. Red dashed lines: optimal bandwidths of Calonico et al. (2014a) (labeled CCT) and Imbens and Kalyanaraman (2012) (labeled IK).



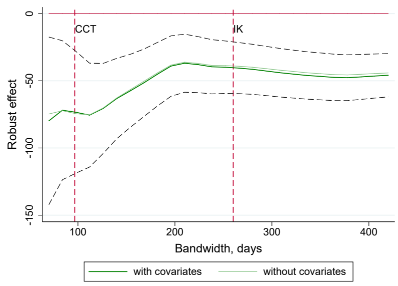
(a) Savings account dummy



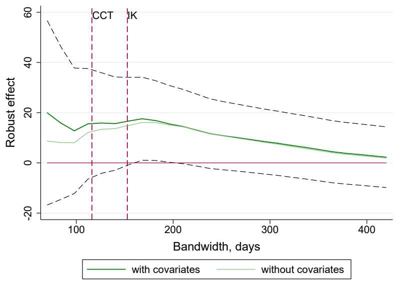
(b) Credit dummy



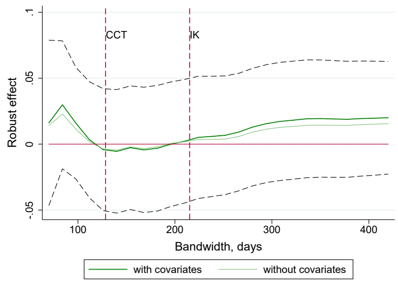
(c) Remittances dummy



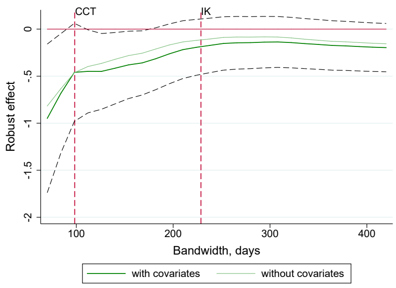
(d) Time needed to access water



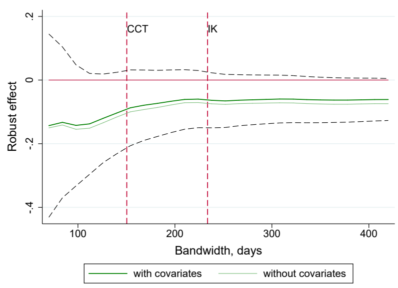
(e) Quantity of water fetched daily



(f) Access to electricity (dummy)



(g) Perception of insecurity



(h) Non-essential spending on soda, alcohol, tobacco, or cinema (dummy)

Figure A.10 – Channels of impact: discontinuities in possible mediators, robustness to bandwidth selection (continued)

Data source: our survey data. Notes: We use the robust bias-corrected approach of Calonico et al. (2014b, 2019) with a triangular kernel to estimate the local average treatment effects for bandwidths between 70 and 420 days and increments of 14 days. Light green lines = estimated treatment effects, without controlling for predetermined variables. Dark green lines = estimated treatment effects, controlling for predetermined variables. Black dashed lines = confidence intervals for the specifications with predetermined variables. Red dashed lines: optimal bandwidths of Calonico et al. (2014a) (labeled CCT) and Imbens and Kalyanaraman (2012) (labeled IK).

Table A.6 – Channels of impact: agriculture

	Dietary variety (log)	Calorie intake (log)	Value of consumption (log)	Food insecurity	Subjective well-being (ihs)	Independence from aid
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and agriculture:						
RD	0.115***	0.956***	1.063***	-0.407***	0.161	0.269***
	(0.0372)	(0.0949)	(0.111)	(0.0959)	(0.158)	(0.0709)
Agriculture	0.0910***	0.0262	0.0435	-0.171***	0.102	0.0290
	(0.0190)	(0.0458)	(0.0568)	(0.0623)	(0.0943)	(0.0458)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and agriculture:						
Robust RD	0.198***	0.976***	1.321***	-0.644**	0.695**	0.180
	(0.0754)	(0.270)	(0.288)	(0.254)	(0.293)	(0.137)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the agriculture dummy is added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7 – Channels of impact: composition of households, as captured by the number of household members and the number of rations per household member

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Subjective well-being (ihs) (5)	Independence from aid (6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and # HH members:						
RD	0.140***	0.848***	0.842***	-0.491***	0.144	0.219***
	(0.0395)	(0.0905)	(0.0935)	(0.102)	(0.160)	(0.0671)
# HH members	0.00179	-0.0362***	-0.0981***	-0.0188*	-0.00982	-0.00761**
	(0.00174)	(0.00761)	(0.00794)	(0.0102)	(0.00698)	(0.00311)
Rations per members	0.0184	0.154***	0.233***	0.000945	0.127***	0.0112
	(0.0122)	(0.0314)	(0.0444)	(0.0226)	(0.0468)	(0.0184)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and # HH members:						
Robust RD	0.293***	0.892***	1.005***	-0.673***	0.789**	0.164
	(0.0798)	(0.271)	(0.258)	(0.246)	(0.307)	(0.128)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the number of household members and the ratio of the number of people on the food ration cards to the number of household members are added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.8 – Channels of impact: education

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Subjective well-being (ihs) (5)	Independence from aid (6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and education:						
RD	0.141***	0.973***	1.081***	-0.461***	0.200	0.294***
	(0.0392)	(0.0954)	(0.111)	(0.0988)	(0.157)	(0.0728)
Years of education	0.00554**	-0.0122**	0.00157	-0.0114	0.00725	-0.00175
	(0.00240)	(0.00607)	(0.00750)	(0.00946)	(0.0112)	(0.00498)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and education:						
Robust RD	0.288***	1.031***	1.333***	-0.719***	0.829***	0.199
	(0.0764)	(0.274)	(0.289)	(0.261)	(0.292)	(0.144)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the number of years of education is added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9 – Channels of impact: health

	Dietary variety (log)	Calorie intake (log)	Value of consumption (log)	Food insecurity	Subjective well-being (ihs)	Independence from aid
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and health:						
RD	0.152***	0.959***	1.082***	-0.439***	0.224	0.343***
	(0.0407)	(0.0957)	(0.113)	(0.0990)	(0.158)	(0.0737)
Health index	-0.00212	0.00928**	0.00588	-0.00812	-0.0212***	-0.0325***
	(0.00160)	(0.00388)	(0.00478)	(0.00589)	(0.00714)	(0.00372)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and health:						
Robust RD	0.299***	0.973***	1.346***	-0.700***	0.812***	0.273*
	(0.0778)	(0.270)	(0.291)	(0.263)	(0.309)	(0.142)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the health index is added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10 – Channels of impact: access to water

	Dietary variety (log)	Calorie intake (log)	Value of consumption (log)	Food insecurity	Subjective well-being (ihs)	Independence from aid
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and time needed to access water:						
RD	0.145***	0.907***	1.009***	-0.462***	0.177	0.298***
	(0.0394)	(0.0970)	(0.112)	(0.101)	(0.163)	(0.0744)
Time needed to access water	-0.0000889	-0.00111***	-0.00129***	0.000258	-0.000205	0.000313
	(0.000147)	(0.000344)	(0.000400)	(0.000411)	(0.000972)	(0.000343)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and time needed to access water:						
Robust RD	0.250***	0.971***	1.237***	-0.614**	0.697**	0.221
	(0.0799)	(0.284)	(0.300)	(0.269)	(0.308)	(0.143)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the variable measuring the time needed to access water is added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.11 – Channels of impact: non-essential spending

	Dietary variety (log) (1)	Calorie intake (log) (2)	Value of consumption (log) (3)	Food insecurity (4)	Subjective well-being (ihs) (5)	Independence from aid (6)
Panel A - Parametric approach with predetermined variables:						
RD	0.144***	0.965***	1.078***	-0.469***	0.203	0.292***
	(0.0394)	(0.0951)	(0.111)	(0.0988)	(0.157)	(0.0726)
Panel B - Parametric approach with predetermined variables and non-essential spending:						
RD	0.157***	0.971***	1.099***	-0.483***	0.194	0.297***
	(0.0393)	(0.0957)	(0.112)	(0.0988)	(0.158)	(0.0721)
Non-essential spending (dummy)	0.184***	0.110	0.398***	-0.293*	-0.123	0.0695
	(0.0324)	(0.133)	(0.152)	(0.167)	(0.153)	(0.0583)
Panel C - Non-parametric approach with predetermined variables:						
Robust RD	0.269***	1.021***	1.328***	-0.731***	0.741**	0.176
	(0.0780)	(0.274)	(0.288)	(0.260)	(0.298)	(0.145)
Panel D - Non-parametric approach with predetermined variables and non-essential spending:						
Robust RD	0.296***	1.010***	1.319***	-0.740***	0.705**	0.186
	(0.0781)	(0.277)	(0.288)	(0.257)	(0.295)	(0.143)

Data source: our survey data. Notes: Panels A and B report the results of IV regressions in which the treatment dummy is instrumented by the cutoff dummy. Panels C and D report the results of local linear regressions using the robust bias-corrected estimator of Calonico et al. (2014b, 2019) and a bandwidth of 135 days. In all regressions, the following predetermined variables are included as controls: gender, age, a marital status dummy, father and mother's years of education, number of parents alive, an agricultural background dummy, and region of origin dummies. In panels B and D, the dummy for non-essential spending is added as a supplementary control variable. Sampling weights are accounted for. Cluster-robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

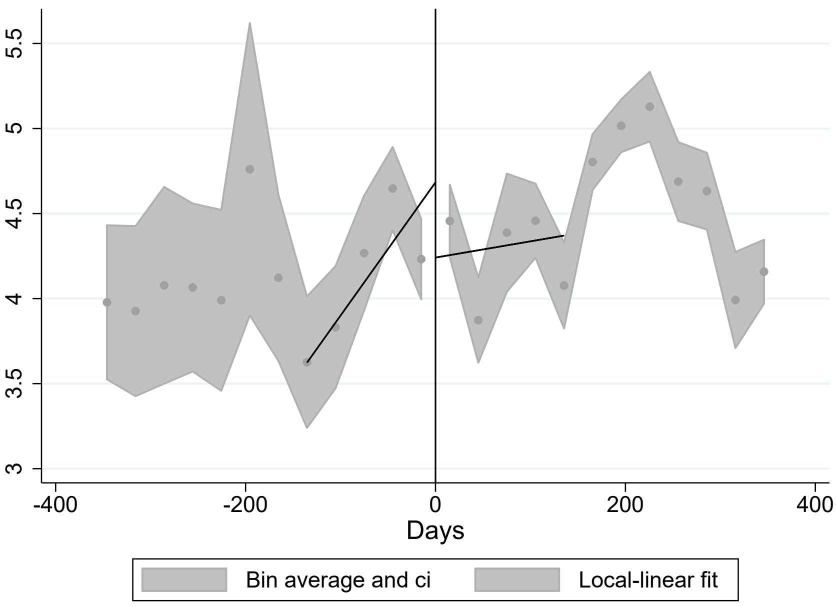


Figure A.11 – Discontinuity in household size at registration (Source: UNHCR registration data from August 2017)

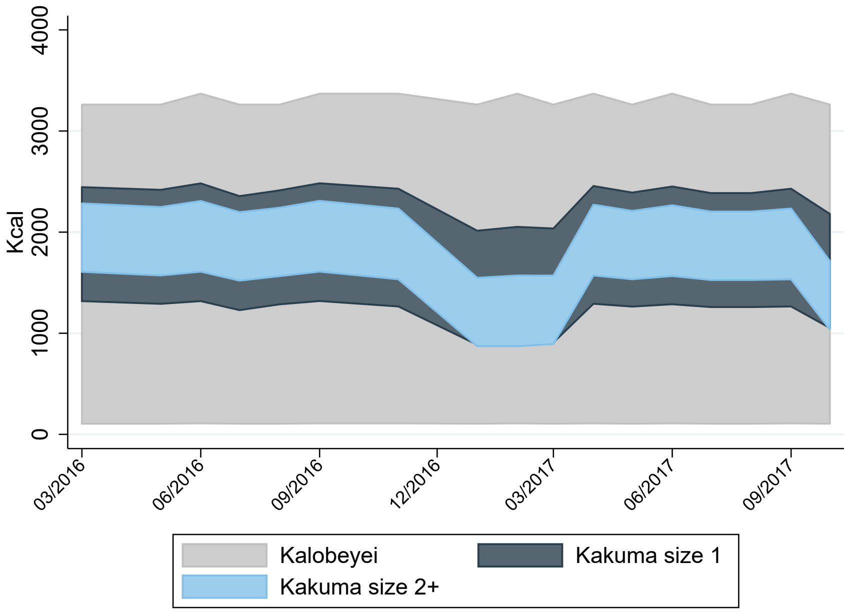


Figure A.12 – Amounts of calories that refugees could consume in Kakuma and Kalobeyei

Source: Authors' calculation based on data from WFP. Notes: The figure assumes no waste or gift of money or food and no savings. To calculate the maximum calorie intake in a context, we assume that all Bamba Chakula money is spent on maize. Maize is, according to our data, the commodity giving the highest number of calories for a given amount of money. To calculate the minimum calorie intake in a context, we assume that all Bamba Chakula money is spent on fish, which is the commodity giving the lowest number of calories for a given amount of money. CSB+ transfers are excluded from the calculation. In Kakuma, we distinguish households of size 1 and households of size 2 or more as they receive slightly different food rations.