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Effects of including refugees in local government schools on pupils' learning achievement: Evidence from West Nile, Uganda

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ABSTRACT

The paper analyses the effect of government school attendance on refugee pupils' learning achievement and the effect of refugee concentration in schools on the learning achievement of native pupils in government schools. The study uses learning assessment data collected in refugee settlements and host communities in West Nile, Uganda. The results show that refugee pupils attending government schools do not perform differently in English but score lower in math than those in non-government schools, while native pupils attending government schools with higher refugee concentrations score lower in both English and math under the context where massive refugee influx continues.

1. Introduction

The importance of refugee education has never been greater than it is today, as the world is facing the highest-ever number of forcibly displaced people and half of the refugee population consists of children below 18 years of age (UNHCR, 2018b, 2020). Refugees are explicitly included as a marginalized group targeted by Sustainable Development Goal (SDG) 4 and the Education 2030 Framework for Action (UNESCO, 2016, p. 9). Education generally used to be provided for refugees through parallel education systems, separate from the host country natives. However, given the protracted nature of displacement as well as the rising number of urban refugees, this approach is increasingly being viewed as impractical; since 2012, the inclusion of refugee learners within national systems has been mainstreamed as a sustainable alternative solution (Dryden-Peterson, 2016; UNESCO, 2018a).

Another important fact is that the majority of refugees are hosted in developing countries (UNHCR, 2020). In these countries, the use of development assistance funds, which are not intended primarily for refugees, to support both refugees and the host population can produce win–win outcomes (Betts et al., 2017). Allowing refugee children to have access to services such as education in the host country's national system is known as a general approach in implementing this scheme as well (Krause, 2016). In theory, host countries, whose education systems are already burdened with serious issues, can also benefit, since the donor funding can improve the quality of education in general, for both refugees and host community students. The United Nations High Commissioner for Refugees's (UNHCR's) updated education strategy towards 2030 explicitly supports this approach, calling it as "the best policy option" (UNHCR, 2019, p. 6) not only for refugees but also for host communities.

Utilizing learning assessment data, many empirical studies have been conducted to investigate issues faced by immigrant children in the education system in their new context, especially in developed countries. Efforts have been made to explain the poor performance of immigrant children and examine the effect of including them in public schools on their own and other children's educational outcomes. However, little rigorous evidence is available for refugee children, mainly due to the lack of largescale learning assessment data, particularly in developing countries, although there is a growing demand from policy-makers.

This study examines the effect of including refugee children in government schools on learning achievement of both refugee and native pupils using learning assessment data from Uganda, collected by Uwezo.[1] The learning achievements of refugees and natives are measured by the English and math tests commonly used in Uwezo

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[1] In this paper, "student" may refer to learners at any level. However, following the terminology used in the current education law in Uganda (The Education Act [Pre-Primary, Primary and Post-Primary] 2008), the term, "pupil" is used to represent a person receiving instruction in any subject at a primary school in Uganda.

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surveys. Exploring the determinants of these basic skills among refugees is becoming increasingly recognized as important, as general refugee management policies highlight the vital role education plays in promoting socioeconomic growth in host countries by equipping refugees with the skills and abilities to succeed within national systems.

The remainder of this paper is organized as follows. The next section reviews the existing literature on the effect of inclusion of refugee/immigrant children in schools. Section 3 describes the Ugandan refugee education policy context as well as the circumstances of the South Sudanese refugee influx in 2016. Section 4 describes the data used in the analysis, and the empirical approach is outlined in Section 5. The results and discussion are provided in Section 6. The last section concludes by discussing policy implications.

2. Literature review

Overall, there is a scarcity of largescale quantitative studies on the learning achievement of refugees and students in communities hosting refugees, mainly due to lack of data collected from refugees. However, a number of previous studies have been conducted to assess the non-refugee immigrant peer effect on the learning achievement of both immigrant and non-immigrant students at the primary education level especially in developed countries and has produced mixed results. A largescale dataset from Denmark was analysed by Jensen and Rasmussen (2011) to see to what extent the share of immigrant peers in school affects reading and math test scores of both immigrant and host country native students using the immigrant concentration in larger geographical area as an instrumental variable (IV). The study concludes that there is a negative effect of immigrant concentration in the school, stronger for native students than for immigrant students. Rigorous estimates from Italy also confirm negative effects on reading and math test scores of natives applying the IV estimation utilizing unique institutional rule of class formation in Italy (Ballatore et al., 2018). A study from Austria, while it shows zero effect on students who are Austrian natives, finds a negative effect on migrant students' educational outcomes other than test scores even after controlling for the within-school variation in the immigrant concentration between cohorts (Schneeweis, 2015).

On the other hand, several studies, which also mainly use cohort-by-cohort variation in immigrant presence within schools in identifying the effect, conclude that there is little evidence for a negative effect of immigrant peers on host country native students' performance in primary education. For instance, Geay et al. (2013) find zero correlation between the proportion of non-native English speakers in a year group and native students' test scores in reading, writing, and math in England. Ohinata and van Ours (2013) examined the effect of the proportion of immigrants in class on the reading, science, and math test scores of native students in the Netherlands and found no strong evidence for a negative effect. More recently, Brandén et al. (2016) conducted analysis in Sweden, finding almost zero effect on Swedish native students' grade scores. Although the effect size is weak, they also found a positive correlation between immigrants' learning achievement and the ratio of their peers in class who had the same national background. Another study from the Netherlands also concludes that there is no significant immigrant peer effect on native students' reading or math test scores (Bossavie, 2020).

The relatively rich evidence derived from migration studies mostly in developed countries might have some implications for the design of measures to enhance the educational performance of refugees and their hosts. However, effective inputs in refugee education settings may differ from effective inputs in migrant education, since there are fundamental differences between these two groups. In addition to the language acquisition issues frequently explored in migrant studies, inclusive education studies for resettled refugees in developed countries tend to focus on the effect of psychological trauma on refugees' learning achievement (Kaplan et al., 2016; Miller et al., 2018).

Moreover, reflecting the changes in international strategies, there has been an increasing number of studies which unveil the challenges in including refugees in the host country's basic education system in developing countries. Like the findings from the previous migrant studies, several case studies have pointed out that refugee students face difficulties in following the classes offered in the national language of the host country when it is different from their mother tongue (e.g., Dryden-Peterson, 2006). To mitigate this language barrier, older refugees are sometimes hired as teachers or assistant teachers, such as in Jordanian camps for Syrian refugees (Culbertson and Constant, 2015) and the Kakuma refugee camp in Kenya (Mendenhall et al., 2015). Another study from Kakuma unveiled that teachers play a critical role in creating inclusive classrooms and schools for children (Mendenhall et al., 2021). However, the majority of these studies have primarily relied on qualitative study methods (Mendenhall et al., 2018). The central contribution of this study is to fill the significant gap in quantitative research for refugees in developing countries applying relatively rigorous approaches similar to those conventionally used in quantitative non-refugee migrant studies which assess the effect of immigrant concentration on children's educational outcomes using learning assessment data.[2]

One of the exceptions to the general lack of quantitative studies is Delprato et al. (2019) which analysed relatively rich Early Grade Reading Assessment (EGRA) and Early Grade Mathematics Assessment (EGMA) data of Syrian refugee and host-community pupils in grades 2 and 3 at primary education level collected in Jordan in 2017. Although they only conducted descriptive analyses and their estimates are not conclusive, the study reveals some trends in the correlation between school type and refugee pupils' learning achievement. The study shows that refugee pupils in integrated schools, where the majority of pupils are Jordanians, perform worse in math compared with those in second shift and camp schools, where all pupils are refugees. Their finding on performance in Arabic is more complex. Refugee pupils in integrated schools perform significantly worse in Arabic compared with those in the two types of schools exclusive to Syrian refugees. In contrast to this, the result shows no achievement gap in Arabic between refugee pupils in regular schools with low refugee concentration and those in camp schools with high refugee concentration.

Piper et al. (2020) is the other exception, a quantitative analysis using the EGRA data of refugee pupils in grades 1–3 collected in all primary schools in Kakuma refugee camp (in Kenya). In this camp, which receives refugees from different countries, Piper et al. (2020) examine the correlation between refugees' country of origin and their learning achievement applying ordinary least squares (OLS) regression analysis. Their finding suggests that how long refugees have been in the Kenya education system and/or exposure level to English, which is one of the two official languages of instruction in Kenya, in their home countries potentially explain the statistically significant correlation between these two variables.

The present study uses learning assessment data collected from both refugee and host-community children at the household level in Uganda in 2017. While this study is the first to conduct in-depths quantitative analysis focusing on South Sudanese refugees and their hosts in West Nile sub-region, basic descriptive analyses have been conducted by Uwezo (2018) using the data from all surveyed districts. Uwezo (2018) revealed that refugee children's education is generally disrupted by their harsh learning environment, and their levels of English and math skills are poorer than those of their non-refugee counterparts in general.

[2] There is a growing literature which analyses the effect of refugee influx and/or proximity to refugee residence on educational outcomes of host country native pupils in developing countries (Assad, 2019; Bilgili et al., 2019; Tumen, 2021). This study is not directly related to that literature; instead, rather than identifying the effect of the presence of refugees in the community, this study focuses on examining the effect of refugee pupils within the school on pupils' learning achievement.

Uwezo (2018) also found that being a male, living in a household headed by females, and having lived in Uganda for more than a year positively correlated with learning achievement in English and math.

In the same year, the British Council conducted a different survey in 30 schools from three districts, collecting detailed school-level information on teaching process through classroom observations and interviews with teachers. Although the sample size of this survey was much smaller than that of the one conducted by Uwezo, the survey had a component assessing the English skills of primary three and primary five pupils. The study revealed that only English is used as a medium of instruction in the majority of classrooms, which generally consist of pupils who speak different home languages (Hicks and Maina, 2018). Hicks and Maina (2018) also confirm that refugee pupils' English skills are slightly poorer than the one of the pupils from host community.

3. Context of the study

3.1. Policy frameworks and the South Sudanese refugee influx

Since the country's first formal refugee settlements were established by the British colonial administration in the 1940s, to host Polish refugees, Uganda has been implementing a local settlement policy, in which the government allocates land to refugees for long-term habitation (Jallow et al., 2004; Orach and De Brouwere, 2006). Beginning with the Self-Reliance Strategy (SRS), introduced in 1998, Uganda has been implementing many initiatives based on development-oriented refugee aid, where aid to refugees is linked with their development projects, providing both refugees and host communities access to services in an integrated manner (Krause, 2016) and the role of refugees is explicitly mentioned in Uganda's national development plan (World Bank, 2016a).

There has also been evolution in Uganda's national legal framework for refugee management. One notable breakthrough was the enactment and enforcement of the Refugee Act of 2006, which gives refugees in Uganda comprehensive rights, including freedom of movement and the right to seek employment in principle. With regard to educational provision, the current refugee law explicitly gives all refugees in Uganda a right to get access to the same primary education provided to host country natives.

Uganda started to provide schools with grant, named capitation grant, to abolish fees in the target schools when the Universal Primary Education (UPE) policy was introduced in 1997.[3] This study, regardless of schools' founding bodies, refers to all primary schools that receive a capitation grant from the government under the UPE policy as government schools. In this sense, refugees in Uganda living in districts that receive such a grant have been meant to have access to government schools since SRS was introduced in 1998. Refugee children who live in refugee settlements can go to the neighbouring government schools, and there are also many cases in which non-state actors establish new schools within the refugee settlements, supported by donors (Dryden-Peterson, 2003).

In July 2016, intense conflicts erupted in Juba, the capital of South Sudan, after which Uganda experienced a massive influx of refugees from South Sudan, on a historically unprecedented scale. The number of refugees in Uganda increased from 0.2 million in June 2016 to more than 1.4 million by the end of 2017; the sharp increase was mainly attributed to arrivals from South Sudan. In 2017, Uganda became the largest refugee-hosting country in Sub-Saharan Africa and the third-largest refugee-hosting country in the world, after Turkey, which hosts most of the Syrian refugees, and Pakistan, which hosts most of the Afghan refugees (UNHCR, 2018a). As of October 2017, when the data used in this study were collected, the number of South Sudanese refugees/asylum-seekers had reached 1 million, accounting for three-quarters of total refugees/asylum seekers in Uganda (UNHCR Representation in Uganda, 2017).[4] At that time, nearly half of South Sudanese refugees who fled to neighbouring countries were staying in Uganda (UNHCR, 2017).[5] Looking at the breakdown of refugees by districts within Uganda, the majority of them are hosted in West Nile sub-region, which is one of the least-developed areas in Uganda, with the highest poverty rates (World Bank, 2016b).

Strangely enough, the landmark New York Declaration on Refugees and Migrants was adopted in Uganda in September 2016, meaning that precisely during the time the country was being tested by refugee influx on an unprecedented scale, Uganda became one of the first countries to apply the centrepiece of the United Nation's reform proposal for refugee management, called the Comprehensive Refugee Response Framework (CRRF), as stipulated in the declaration. As of 2017, Uganda's central national policy framework for refugees was the five-year government strategy called the Settlement Transformation Agenda (STA) and STA was integrated into the Second National Development Plan (NDPII) 2015/2016–2019/2020. The initiative, named the Refugee and Host Population Empowerment (ReHoPE) Strategic Framework, was also established for supporting STA and playing a critical role in applying CRRF in Uganda.

Moreover, in line with these overarching frameworks for refugee management strategy, Uganda has set a framework for action focused on refugee education, called the Education Response Plan for Refugees and Host Communities (ERP) in 2018 (MoES, 2018); it is positioned to be integrated into the Education Sector Strategic Plan. Uganda's response to the influx of South Sudanese refugees, especially given its cutting-edge refugee education policy framework, is being closely followed globally.

3.2. Provision of primary education for refugees and natives

In the context of this study, in West Nile sub-region during the recent South Sudanese influx, the Office of the Prime Minister (OPM) in Uganda established new refugee settlements. Then, UNHCR and its implementation partners, humanitarian non-governmental organizations (NGOs), opened new schools supported by donor agencies to provide education especially to refugee children who live in refugee settlements, where no government school exists nearby. These schools usually do not receive any capitation grants from the government and fully rely for their budget on donor support. It is also reported that refugee-hosting government schools may receive some support from donors, but there is no increase in the amount of capitation grant they receive to reflect the number of refugee children they host (MoES, 2018).

While teachers in government schools are certified by and on the government payroll in Uganda, non-government schools in refugee settlements hire teachers themselves using the funds from their donors. It is known that these schools generally hire host-community teachers who are qualified but have no job in a government school or are working as teaching assistants in government schools hired locally by parents or

[3] The amount of capitation grant used to be calculated allocated on a per-pupil basis. Although part of the grant is fixed after 2007, part of the capitation grant still depends on enrolment of each school. Some of the target schools also receive grant, named school facilitation grants, mainly for developing and/or maintaining school infrastructure under UPE policy (Kayabwe and Nabacwa, 2014).

[4] As of October 2017, in Uganda, there are also refugees/asylum seekers from the Democratic Republic of the Congo (DRC) (17%), Burundi (3%), Somalia (3%), and others (3%) which include Eritrea, Ethiopia, Rwanda, Sudan and other countries (UNHCR Representation in Uganda, 2017).

[5] As of October 2017, other South Sudanese refugees had fled to Sudan, Ethiopia, Kenya, DRC and the Central African Republic (CAR), which account for 21%, 20%, 5%, 4%, and 0.1% of South Sudanese refugees who fled to neighbouring countries, respectively (UNHCR, 2017).

as teachers in low-cost private schools (Kisira, 2008, p. 136; Sesnan et al., 2013, p. 44).[6] The issue of overcrowded classrooms due to shortage of teachers in donor-funded schools is constantly highlighted in previous studies (MoES, 2018; Uwezo, 2018).

Within the national curriculum of Uganda, children, including refugees, start with seven years of primary education, from 6 to 12 years old. Primary education is divided into three cycles: lower primary (from grade 1–3), transition year (grade 4), and upper primary (grade 5–7). While the medium of instruction is English for grades 4–7, use of local languages is suggested in the lower primary cycle. However, in a majority of classes in refugee settlements, English is used as a medium of instruction in the lower primary cycle as well—this is a practical approach, since English is also used as a medium of instruction in South Sudan (Hicks and Maina, 2018).[7]

Even though refugees' home country and host country share the same main language as a medium of instruction, handling classes with South Sudanese refugee pupils, whose first languages are largely not spoken in Uganda, may be tough for Ugandan teachers in refugee settlements, especially in lower primary cycle. Based on in-depth interviews and other qualitative methods, Hicks and Maina (2018) and Miyamoto (2020) reveal that refugee teaching assistants, who used to work as qualified teachers in their home country, are hired to facilitate and/or even lead the teaching in these classes. Although refugees' right to be employed is protected, refugees' qualification obtained in their home countries are not recognized by the Ministry of Education and Sports in Uganda (MoES, 2018). As a result, many of these refugee teachers, who obtained qualifications from countries other than Uganda, can only work as assistants in principle.

4. Data and descriptive statistics

4.1. Data

Uwezo, which is the largest citizen-led learning assessment initiative in East Africa, driven by Twaweza undertook largescale household surveys of the English and math competencies of school-aged children every year from 2009 to 2015. This paper relies on the data collected through the household survey conducted by Uwezo in refugee settlements and their host communities, in October 2017 (hereafter called Uwezo 2017), with financial support from the Humanitarian Emergency Refugee Response in Uganda (HERRU) and the United Kingdom's Department for International Development (DFID). Although the data were collected in the four districts with the highest population of refugees in 2016, this study only targets the three districts in the West Nile sub-region, namely Adjumani, Arua and Yumbe, excluding Isingiro in the Western region. This is because the study focuses on the case during the massive South Sudanese refugee influx and Isingiro district is little affected by this influx started from 2016: two of the country's oldest refugee settlements in Isingiro district are under substantially different context with refugees from several different countries (UN-HABITAT and UNHCR, 2020).

Uwezo normally used a two-stage cluster sampling design, in which 30 enumeration areas (EAs) were selected in each district at the first stage, with the probability of selection proportional to population size (Uwezo, 2016). However, in 2017, 15 EAs in refugee settlements as well as 15 non-refugee EAs were selected in each surveyed district at the first stage[8]; at the second stage, around 20 households were selected to be interviewed in each selected EA, as in all the survey rounds (Uwezo, 2018).[9]

During the survey, a questionnaire was administered to the household heads (or their representatives) to collect relevant information on the households and their children aged 16 and younger. English and math tests were administered to all the available children aged between 6 and 16, regardless of their school attendance.[10] In addition, Uwezo collected EA-level data; to do so, questionnaires were administered to the headteacher of one primary school selected from each EA.[11]

The study identifies the refugee status of each respondent based on their question whether they are refugee or native.[12] Checking the breakdown of refugees and Ugandan natives, the proportion of natives in the sample from refugee settlements and the proportion of refugees in the sample from non-refugee EAs are both extremely small: 1.0% and 1.4%, respectively. Thus, the Ugandan native sample in refugee settlements and the refugee sample in non-refugee EAs are excluded from the analysis. Moreover, since the main objective of this study is to explore the effect of school characteristics on children's learning outcomes, the sample was further restricted to children who were in grade 1–7.[13]

In this paper, there are two dependent variables: test scores in English and math measured using the competency scale commonly employed in Uwezo surveys. Based on the results of the language test, children were first categorized into one of the following five ascending levels: (1) can do nothing; (2) can identify a letter; (3) can identify a word; (4) can read a paragraph; and (5) can read a short story. Then, two comprehensive questions were asked to those who could read a story; the child was recognized to have the ability to do comprehension and have achieved full competence in English literacy at the grade 2 level if he or she could correctly answer at least one of these questions (Uwezo, 2016). With regard to the math tests, children were placed into one of the following seven ascending levels: (1) can do nothing; (2) can match numbers; (3) can recognize numbers; (4) can do addition; (5) can do subtraction; (6) can do multiplication; and (7) can do division. The child was recognized to have full competence in math at the grade 2 level if he or she could correctly answer all of these questions (Uwezo, 2016). Following Wakano (2016), test scores for English and math were defined to range from 0 to 5 and from 0 to 6, respectively. Further, in keeping with other studies (e.g., Jones, 2016; Wamalwa and Burns, 2018), test

[6] Shortage of qualified teachers in government primary schools is still a notable issue in Uganda (National Planning Authority, 2015). However, it is known that the main reason for this shortage has been shifted from the shortage of qualified teachers to government budget constraints limiting the hiring of adequate number of teachers, creating a large pool of unemployed qualified teachers (Mulkeen, 2010, p. 24).

[7] After gaining independence in 2011, South Sudan officially changed its national language and the medium of instruction in its education system from Arabic to English (UNESCO, 2011). Like Uganda, use of local language is suggested during the first three grades of primary education under the curriculum launched in 2015 (UNESCO, 2018b).

[8] Uwezo mainly uses the lowest layer of administrative unit in Uganda's local government structure, namely the "village," referred to as Local Council (LC) 1, as the EA in their sample selection, although the EA can also be interpreted to cover only part of LC 1 (Magoola, 2015). In refugee settlements, Uwezo 2017 uses the "block," which is the lowest layer of administrative unit in the decentralized governance structure of Uganda's refugee settlements, referred as Refugee Welfare Councils (RWCs), as an EA unit for the sample selection (JICA, 2018; Uwezo, 2018).

[9] The details of the sampling frame and sampling strategy used for this survey are explained in Uwezo (2018).

[10] Children who were attending boarding schools were not assessed (Uwezo, 2016, p. 12).

[11] Regardless of the type of ownership, the primary school which was attended by the largest proportion of children dwelling in the EA was selected. Even though the school that met this criterion was located outside the EA, it was nevertheless selected as a surveyed primary school for that EA (Uwezo, 2016, p. 12).

[12] Uwezo 2017 use the term, "national," to represent Ugandan natives in their questionnaire.

[13] Uwezo 2017 collects nationality information only for refugee respondents. Among 274 refugee households in the final sample, 272 households responded that they were South Sudanese and 2 gave other responses. Thus, unlike in Piper et al. (2020), the refugee sample used for this study is very homogeneous in terms of country of origin.

Table 1
Summary statistics for refugee and native pupils in surveyed school sample.

Variables	Refugees (n = 581)		Natives (n = 544)		Difference
	M	*SD*	*M*	*SD*	
Test score					
English	2.904	1.688	2.710	1.724	0.194*
Math	4.509	2.174	4.239	2.256	0.270**
Individual characteristics					
Age	11.63	2.897	10.69	2.893	0.940***
Female	0.437	0.496	0.461	0.499	–0.0242
Some disability	0.141	0.348	0.171	0.377	–0.0298
Attended preschool	0.484	0.500	0.149	0.356	0.335***
Current grade	3.343	1.776	2.919	1.731	0.423***
Household characteristics					
Household size	8.336	3.899	7.662	3.720	0.674***
Wealth index (refugees)	–0.138	0.899			
Wealth index (natives)			–0.163	0.854	
Main source of income					
UNHCR stipends/none	0.821	0.384			
Farming/fishing	0.105	0.307			
Trading/business/other	0.074	0.262			
Number of years in Uganda					
0–1 years	0.578	0.494			
2–8 years	0.146	0.354			
8 years or more	0.275	0.447			
Age of the household head	34.55	11.77	45.05	13.12	–10.50***
Household head is female	0.744	0.437	0.267	0.443	0.477***
Education level of the household head					
None	0.284	0.451	0.129	0.335	0.155***
Primary education	0.499	0.500	0.654	0.476	–0.155***
Post-primary education	0.217	0.412	0.217	0.413	–0.0000443
School characteristics					
Total enrolment	2150.1	1192.5	867.3	419.9	1282.8***
Pupil–teacher ratio	93.85	52.00	53.09	21.46	40.76***
Untrained teachers are hired	0.647	0.478	0.443	0.497	0.204***
Percentage of refugee pupils	84.45	20.85	4.637	11.01	79.81***
District dummies					
Adjumani	0.248	0.432	0.298	0.458	–0.0499*
Arua	0.244	0.430	0.250	0.433	–0.00559
Yumbe	0.508	0.500	0.452	0.498	–0.0555*

Notes: The refugee sample is restricted to those in refugee settlements; the Ugandan native sample is restricted to those in the host community. Both samples are further restricted to those attending sampled schools. The significance of the difference is reported based on the results of independent-means *t*-test. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

scores were standardized to the mean of zero and the standard deviation of one, separately for refugees and natives.

As one of the key explanatory variables, the percentage of pupils in a school who are refugees was constructed utilizing the school-level information in the dataset: dividing the number of refugee children enrolled by the total enrolment and multiplying it by 100. Another key explanatory variable in this study is school type. There are two school type variables in this study: type of school the pupil attends as collected by the household-level questionnaire and as collected by the school-level questionnaire. These school type variables commonly have three categories: government, private, and community. "Government school" in this study, following Uwezo (2018), represents schools receiving UPE capitation grants from the government. Then, as refugee samples are restricted to those in refugee settlements, this study integrates "private" and "community" schools into one category named "non-government," and all non-government schools are considered to be those funded by donors for refugees in this study.[14]

At the school level, Uwezo 2017 collects data on how many untrained teachers are employed by parents, sponsors, and NGOs. The study creates a dummy variable whose value takes one if a sample school has at least one untrained teacher. Although Uwezo 2017 does not collect information on the nationality of the untrained teacher, the variable serves as a proxy for the presence of refugee teaching assistants in refugee settlements, under the conditions described in Section 3.

As the key SES variable, the household wealth index was generated, applying the widely used approach proposed by Filmer and Pritchett (2001). The scores were calculated by Principal Component Analysis (PCA) based on kinds of consumer goods and livestock households own and housing characteristics such as wall materials of households' main house, main source of water and lightning, and ownership of toilets/latrines. These indicators were selected with reference to those used in the composite variable for the wealth index in the Uganda Demographic and Health Survey 2016 (UBOS and ICF, 2018). Following the strategies used in Vyas and Kumaranayake (2006), similar variables with low frequencies were combined together, and the mean value of that variable was imputed for variables with missing values. Considering that refugees, in the refugee settlement, and Ugandan natives, in non-refugee communities, have different ways of living, PCA was conducted separately for refugee and Ugandan native samples. Scoring factors and factor loadings calculated based on PCA and summary statistics for

[14] Strictly speaking, Uwezo 2017 does not have a variable which enables us to distinguish private/community schools, which primarily serve Ugandan children, and donor-funded schools, which primarily serve refugee children. However, it is reasonable to assume that these are all donor-funded schools, not regular private/community schools for natives, because Uwezo 2017 data showed that the proportion of refugee pupils is more than 90% in all surveyed non-government schools where refugees in refugee settlements attend. Specific details are reported in the next sub-section.

Table 2
Summary statistics for refugee pupils attending government schools and non-government schools in surveyed school sample.

Variables	Government school ($n = 242$)		Non-government school ($n = 339$)		Difference
	M	*SD*	*M*	*SD*	
Test score					
English	3.116	1.748	2.752	1.629	0.363**
Math	4.405	2.113	4.584	2.216	–0.179
English (standardized)	0.220	1.061	–0.000567	0.989	0.221**
Math (standardized)	–0.036	0.958	0.0456	0.046	–0.0812
Individual characteristics					
Age	11.71	2.839	11.58	2.942	0.125
Female	0.426	0.495	0.445	0.498	–0.0198
Some disability	0.128	0.335	0.150	0.358	–0.0223
Attended preschool	0.583	0.494	0.413	0.493	0.170***
Current grade	3.554	1.780	3.192	1.760	0.362**
Household characteristics					
Household size	8.434	4.232	8.265	3.647	0.168
Wealth index (refugees)	0.193	0.952	–0.374	0.779	0.567***
Main source of income					
UNHCR stipends/none	0.839	0.368	0.808	0.394	0.0306
Farming/fishing	0.099	0.300	0.109	0.312	–0.00997
Trading/business/other	0.062	0.242	0.083	0.276	–0.0206
Number of years in Uganda					
0–1 years	0.595	0.492	0.566	0.496	0.0287
2–8 years	0.174	0.380	0.127	0.333	0.0467
8 years or more	0.231	0.423	0.307	0.462	–0.0754**
Age of the household head	36.65	12.09	33.05	11.33	3.596***
Household head is female	0.860	0.348	0.661	0.474	0.199***
Education level of the household head					
None	0.430	0.496	0.180	0.385	0.250***
Primary education	0.467	0.500	0.522	0.500	–0.0552
Post-primary education	0.103	0.305	0.298	0.458	–0.195***
School characteristics					
Total enrolment	1329.8	777.3	2735.6	1088.0	–1405.7***
Pupil–teacher ratio	74.81	43.30	107.4	53.46	–32.63***
Untrained teachers are hired	0.785	0.412	0.549	0.498	0.236***
Percentage of refugee pupils	67.10	22.47	96.83	4.126	–29.72***
District dummies					
Adjumani	0.401	0.491	0.139	0.346	0.262***
Arua	0.471	0.500	0.0826	0.276	0.388***
Yumbe	0.128	0.335	0.779	0.416	–0.651***

Notes: Refugee sample is restricted to those in refugee settlements and attending surveyed schools. The significance of the difference is reported based on the result of the independent-means *t*-test. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

selected variables used in the computation of the first principal component are displayed in Table B1.[15]

Another key SES variable for refugees was based on responses to the question on the main source of income, which was unique to Uwezo 2017. The variable has three categories: UNHCR stipends/none, farming/fishing, trading/business/others.[16] The dataset also has a variable for the number of years households have lived in Uganda as refugees. From this continuous variable, a categorical variable with three categories, namely 0–1 years, 2–8 years, and 8 years and more, was created. Since data were collected in October 2017, one year after the start of the dramatic surge in the number of South Sudanese refugees in Uganda, the first category represents refugees who came to Uganda during the recent inflow.

As detailed in Section 5, in line with our method, the sample was further restricted to refugee or Ugandan native pupils attending the surveyed school (the "surveyed school sample") and refugee pupils in all surveyed households regardless of their attendance at the surveyed school (the "surveyed household sample"). The final surveyed school sample contains 581 refugee pupils and 544 Ugandan pupils; the final surveyed household sample contains 1096 refugee pupils.

4.2. Descriptive statistics

Table 1 shows means and standard deviations for all variables included for refugee and Ugandan native pupils in surveyed school sample. Interestingly, unlike the common finding in migrant studies of poorer performance by immigrant children compared with their native counterparts, descriptive analysis here reveals that refugee pupils perform better in both English and math than Ugandan pupils, which is similar to EGRA/EGMA studies by Ndijuye and Rao (2019) finding outperformance of naturalized refugees in Tanzania, who are mostly from neighbouring countries. This trend is observed despite the fact that refugee pupils are from households with less educated heads and continuing their learning in a poorer school environment with considerably higher pupil–teacher ratio (PTR) than Ugandan native pupils in non-refugee areas. This finding is inconsistent with Uwezo (2018), which uses the same data, potentially because our study restricts the sample to West Nile sub-region, known as one of the worst-performing areas educationally in Uganda, and the Ugandan native sample is also restricted to government school attendees.

Table 1 also interestingly shows that a significantly higher proportion of refugee pupils attended preschool compared to native pupils,

[15] The percentage of covariance explained by the first principal component is 11% and 14% in refugee and native data, respectively. With regard to the reliability of the scores calculated by PCA, Cronbach's alphas for the wealth index for refugees and the one for natives are 0.62 and 0.68, respectively, which exceed the minimum acceptable value of 0.6 (Hair et al., 1998, p. 88).

[16] In addition to responses saying that they have an "other" main source of income, responses with extremely low frequency, including "mining," "salary earner," and "remittances from relatives abroad," are also included in the third category: trading/business/others.

which could be mainly attributed to the fact that there is free preschool education provision though NGOs in refugee settlements. Instead, preschool education for native pupils is mainly provided through the private sector at an expensive price for host communities (MoES, 2018). Since some critical common variables, including the ones for SES, are missing in the data set, it is difficult to make the two groups comparable, so that this paper does not conduct further analysis on the sources of this reverse disparity in learning achievement; the results of independent-means *t*-tests are provided purely for reference.

Tables 2 and 3 present descriptive statistics for refugee samples attending local government schools and non-government schools. The tables basically show that there are both government and non-government attendees among refugee pupils in refugee settlements.[17] The majority of non-government school attendees are from the new refugee settlement in Yumbe District, where the largest proportion of refugees of 2016 influx are absorbed in less populated areas. Comparison of individual characteristics shows that more refugees in government schools attended preschool compared with their counterparts. With regard to SES, the significant difference in wealth index suggests that more refugees in government schools have living conditions exposed to non-refugee settings. Besides, the tables show that refugees who are from households with household heads completed higher level of education are more likely to be in non-government schools.

Significantly lower PTR, shown in Table 2, suggests that government schools have a relatively better learning environment than non-government schools. The table also shows the average refugee concentration in the schools the pupils attend. To obtain a clear picture, the study checks the difference in the distribution of refugees by school type in refugee settlements (see Fig. A1) and in government schools in non-refugee EAs (see Fig. A2) using the school level data created from the final surveyed school sample. Fig. A1 clearly shows that more than 90% of pupils are refugees in all the surveyed non-government schools in refugee settlements. There are three government schools with 100% refugee concentration, but it ranges from around 30%. In contrast, Fig. A2 shows that a majority of government schools in non-refugee EAs have no refugees; however, there are some schools whose refugee concentration exceeds 50%.

The result of descriptive analysis shows that refugee pupils in government schools perform better in English than those in non-government schools, while the achievement gap in math is insignificant. However, given the significant difference in the pupils' background between the two groups, further analysis is required to assess to what extent attending government schools including native pupils affects the learning achievement of refugee pupils.

5. Empirical strategies

The theoretical framework for this study is built on an educational production function model for pupils' learning achievement outlined by Todd and Wolpin (2003). The common research question asked about both refugee and native pupils in this study is to what extent refugee concentration affects their learning achievement. In the analysis using refugee pupil data, the study also asked what extent the type of school the pupil attends influences the refugee pupils' learning achievement.

First, an OLS regression analysis was conducted as a baseline using the surveyed school sample. In the model, it is assumed that each pupil's

Table 3
Summary statistics for refugee pupils in government schools and non-government schools in surveyed household sample.

Variables	Government school (n = 353)		Non-government school (n = 743)		Difference
	M	*SD*	*M*	*SD*	
Test score					
English	3.142	1.678	2.587	1.585	0.555***
Math	4.558	2.083	4.507	2.229	0.0507
English (standardized)	0.236	1.018	−0.101	0.962	0.337***
Math (standardized)	0.034	0.944	0.011	1.010	0.0230
Individual characteristics					
Age	11.70	2.729	11.25	2.953	0.455**
Female	0.445	0.498	0.472	0.500	−0.0276
Some disability	0.133	0.340	0.191	0.393	−0.0580**
Attended preschool	0.620	0.486	0.431	0.496	0.190***
Current grade	3.550	1.746	2.983	1.701	0.567***
Household characteristics					
Household size	8.314	3.962	8.343	3.691	−0.0288
Wealth index (refugees)	0.247	0.976	−0.096	0.961	−0.343***
Main source of income					
UNHCR stipends/ none	0.870	0.337	0.817	0.387	0.0527**
Farming/fishing	0.0652	0.247	0.075	0.264	−0.0102
Trading/business/ other	0.0652	0.247	0.108	0.310	−0.0425**
Number of years in Uganda					
0–1 years	0.504	0.501	0.587	0.493	−0.0826**
2–8 years	0.176	0.381	0.168	0.374	0.74
8 years or more	0.320	0.467	0.245	0.430	0.0752***
Age of the household head	37.74	12.35	34.64	12.43	3.099***
Household head is female	0.830	0.376	0.727	0.446	0.103***
Education level of the household head					
None	0.411	0.493	0.229	0.420	0.182***
Primary education	0.436	0.497	0.550	0.498	−0.114***
Post-primary education	0.153	0.360	0.221	0.415	−0.0678***
District dummies					
Adjumani	0.408	0.492	0.331	0.471	0.0768**
Arua	0.467	0.500	0.131	0.337	0.337***
Yumbe	0.125	0.331	0.538	0.499	−0.414***

Notes: Refugee sample is restricted to those in refugee settlements and surveyed households, attending schools but not necessary in surveyed schools. The significance of the difference is reported based on the result of independent-means *t*-test. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

test score in English or math can be specified as the following linear function of the explanatory variables:

$$A_i = \beta_0 + \beta_1 X_i^{'} + \beta_2 S_i^0 + \beta_3 S_i^{GOV} + \beta_4 S_i^{REF} + \beta_5 D_i + \varepsilon_i, \quad (1)$$

where A_i represents Uwezo test scores in English and math of pupil i, and $\boldsymbol{X}_i$ is a vector of observable individual and household characteristics, which include age, age squared, gender, disability status, whether the pupil attended preschool or not, current grade dummies, household size, household head's age, squared household head's age, household head's gender and education, and wealth index, which is created by applying the procedure described in the previous section. For the refugee model, $\boldsymbol{X}_i$ also includes the number of years the household has lived in Uganda, and the main source of income. A vector on school characteristics is divided into a variable for the percentage of refugee pupils in the school S_i^{REF}, a binary variable on the type of school S_i^{GOV}, taking the value of 1 if it is a government school and 0 if it is non-government school, and other

[17] As stated in the previous sub-section, the data showed that there are almost no refugees in non-refugee EAs, as expected, and almost all children in refugee settlements are refugees. Despite this, a substantial number of refugees in the data set attend government schools that are located outside the refugee settlement where few refugees should live. This can happen because refugee children and living in a refugee settlement, commonly go to government schools near refugee settlements in Uganda as reviewed in Section 3, and Uwezo 2017 covers these refugee pupils.

school characteristics S_i^0, which include total number of pupils in the school, PTR, and whether untrained teachers are hired by parents/NGOs. Then D_i is a vector of district dummies. Last, ε_i is an error term. Since all Ugandan native pupils in the final sample attend government schools, $S_i^{GOV}$is dropped from the model in the analysis for them. Consistent OLS estimates are only obtained under the assumption that the explanatory variables are uncorrelated with the error term.

Distribution of refugees is often seen as random especially under a strict refugee placement policy. In fact, many studies have been conducted in developed countries to analyze the ethnic enclave effect on socio-economic outcomes among immigrants utilizing the exogenous nature of the distribution of resettled refugees under dispersal policy (Beaman, 2012; Damm, 2014). There can be no self-selection in refugees' housing in those developing countries where strict encampment policy is implemented. In Uganda's context, it is also true that refugees have almost no choice in their initial placement. In general, South Sudanese refugees who crossed the border into Uganda arrived at border collection points and were registered as refugees by Uganda's government. Usually, refugees are first transferred to reception/transit centres, temporally stay there, and then are allocated a specific plot in the refugee settlement (Hovil and Kigozi, 2015).

However, in Uganda, refugees even have freedom of movement and the right to seek employment in principle, as reviewed in Section 3; thus, refugee concentration in school is most likely endogenous among both refugees and Ugandan natives in West Nile. In fact, Tables 2 and 3 show statistically significant differences in the means of some covariates between government and non-government school attendees among refugees. These differences are potentially explained by the fact that refugee parents/guardians who are more exposed to non-refugee settings can send their children to local government schools with a lower PTR and more host-community peers. It can also happen that refugee parents/guardians who were educated in their home country send their children to donor-funded non-government schools with a higher PTR but more refugee peers.[18]

Refugee concentration may also be endogenous in the model using native pupil data because school transfer is very common at the primary education level in Uganda (JICA, 2012). Parents or guardians in the host community may send their high-ability children to schools with no or low refugee concentration, considering the decreased quality of education among schools which host refugee pupils. It is also possible that low-performing government schools are more likely to host refugee pupils to receive donor support. This issue of simultaneity can be also another major source of endogeneity.

It is unrealistic to undertake an experiment which randomly assigns refugee/native pupils to schools with different refugee concentration. To assess the impact of refugee concentration on socio-economic outcomes of host communities, one standard approach is to apply difference-in-difference (DD) method, taking the massive refugee influx as a natural experiment (Fallah et al., 2019; Kreibaum, 2016). However, using DD method may not be possible in this study with some technical difficulties in construct required pooled or panel data.[19] Moreover, previous studies generally use immigrant concentration and/or distance to the refugee settlement as the instruments to the refugee concentration (Fallah et al., 2019). Conducting community-level analysis employing these instruments may not be workable in this study due to the extremely small number of sample EAs selected in Uwezo 2017. Another possible strategy is to use school fixed-effects model to explore the variation in refugee or Ugandan native peer concentration across adjacent cohorts within the same school, applying a similar method to that used in the many previous studies of immigrant concentration (Ballatore et al., 2018; Hoxby, 2000). However, the lack of class-level refugee concentration information in Uwezo 2017 data does not allow us to use this method. Applying household fixed effect model used in Wamalwa and Burns (2018) does not work as well due to the low within-household variation in school choice among the final sample.

Despite these conditions, to answer the research question regarding refugee pupils, matching methods can be employed to partly address the endogeneity of treatment variable, borrowing the framework used in Cortes (2006). To begin with, the study applied an inverse probability weighting (IPW) estimator using the surveyed household sample. Let Y_i be our outcome of interest, namely Uwezo test scores of English and math, and Z_i be our treatment indicator. If the refugee pupil i attends a local government school ($Z_i = 1$), his or her test score is $Y_i\,(1)$, while $Y_i\,(0)$ is the test score of a refugee pupil attending a non-government school ($Z_i = 0$). Following Imbens (2004), the average treatment effect (ATE) of attending a local government school can be defined as $E\,[Y_i\,(1) - Y_i\,(0)]$. A related treatment effect, called the average treatment effect for the treated (ATT), is defined as $E\,[Y_i\,(1) - Y_i\,(0) \mid Z_i = 1]$. Identifying ATT within this framework requires the following two assumptions to be met: (a) conditional independence, denoted as $Y_i\,(1), Y_i\,(0) \perp Z_i \mid \boldsymbol{X}_i$; and (b) the common support, denoted as $0 < \Pr\,(Z_i = 1 \mid \boldsymbol{X}_i) < 1$. Moreover, it is known that extreme propensities, which is close to 0 or 1, result in bias in the estimate (Kang and Schafer, 2007). To mitigate this issue, the study simply dropped the sample pupils whose propensity score is outside of the range [0.1, 0.9] following Crump et al. (2009).

In implementing matching methods, we first need to calibrate the propensity score, which is defined as the probability of attending local government school by refugees conditional observed covariates. The equation can be written as follows:

$$e_i = \Pr(Z_i = 1|\boldsymbol{X}_i) \tag{2}$$

where $\boldsymbol{X}_i$ represents a vector of the same set of observable individual and household characteristics included in Eq. 1.[20] The IPW estimator, proposed in Rubin (1985), applies the classic approach developed for adjusting the bias we face when we restrict a sample to individuals with complete data on the treatment evaluation study and interpret the matching procedure as a process of imputing missing values on counterfactual outcomes. In practice, a linear model to the English and math test scores is fitted, with no independent variable, using weighted least squares regression. To obtain the IPW estimate of the average treatment effect for the refugee pupils attending local government school, the study uses the weights given by $w_i = Z_i + \frac{(1-Z_i)e_i}{1-e_i}$ (Austin, 2011, p. 409).

Secondary, using the surveyed school sample with some school-level covariates, the study calculates the doubly robust (DR) estimators, developed to maintain the validity of either the propensity score model

[18] The study assumes that school choice between government and non-government schools is available for all refugees in refugee settlements considering the generally high degree of refugee mobility in the West Nile context (Vancluysen, 2021). However, refugees' school choice can also be attributed to the proximity to each type of school, and the study does not account for this factor. With more geographic information, a future study may be able to account for this factor in combination with a map of all types of schools in both refugee settlements and host communities.

[19] Although the Uwezo conducted learning assessment before the influx started in 2016, the key explanatory variable, refugee concentration at school, is only available in the data collected in 2017. In addition, since Uwezo randomly selects different EAs in each selected district in each wave, panel data can only be constructed at the district level.

[20] The set of variables for individual and household characteristics is made up of those that simultaneously affect school choice and test score, as guided by the theories and empirical findings from the previous studies. Wamalwa and Burns (2018), who applied the matching method to identify the differential impact of school choice between government and regular private schools on test scores in Kenya using the Uwezo data, is primarily used to come up with an initial set of variables for all pupils. Cortes (2006), who applied the matching method to identify the impact of school choice on test scores among immigrant children in the United States, is also referenced to add some variables relevant to refugee pupils.

Table 4
OLS estimation results for refugee pupils in surveyed school sample.

Dependent variable: test scores	English		Math	
	(1)	(2)	(3)	(4)
School characteristics				
Government school		0.153		–0.298*
		(0.132)		(0.166)
Percentage of refugees	–0.00162	0.000578	0.00416*	–0.0000977
	(0.00167)	(0.00266)	(0.00224)	(0.0036)
School size	–0.0000216	–0.000006	0.0000352	0.000005
	(0.0000297)	(0.0000282)	(0.0000306)	(0.0000425)
Pupil–teacher ratio	–0.000191	0.000302	0.000150	–0.000806
	(0.000713)	(0.000849)	(0.00101)	(0.00117)
Unqualified teachers are hired	0.187***	0.200***	0.184	0.159
	(0.0616)	(0.0600)	(0.112)	(0.121)
Individual characteristics				
Age	0.0206	0.0284	0.0752	0.0599
	(0.0921)	(0.0941)	(0.0959)	(0.0966)
Age squared	0.000280	–0.0000363	–0.00140	–0.000783
	(0.00421)	(0.00427)	(0.00414)	(0.00420)
Female	–0.156**	–0.155**	–0.117**	–0.119**
	(0.0614)	(0.0612)	(0.0503)	(0.0503)
Some disability	–0.0396	–0.0386	–0.126**	–0.128**
	(0.0813)	(0.0813)	(0.0590)	(0.0620)
Attended preschool	–0.0583	–0.0568	0.0895	0.0865
	(0.0776)	(0.0773)	(0.0641)	(0.0637)
Household characteristics				
Number of years in Uganda (Base: 0–1 years)				
2–7 years	0.169	0.173	–0.259	–0.266
	(0.142)	(0.140)	(0.182)	(0.172)
8 or more years	0.156**	0.159**	–0.0427	–0.0481
	(0.0714)	(0.0717)	(0.0851)	(0.0870)
Household size	0.00565	0.00605	0.0116	0.0109
	(0.00735)	(0.00733)	(0.0158)	(0.0164)
Wealth index (refugees)	-0.0712*	–0.04914	–0.0712*	–0.0652
	(0.0378)	(0.0368)	(0.0378)	(0.0400)
Main source of income (Base: UNHCR stipends)				
Farming/fishing	0.266***	0.273***	0.0215	0.00707
	(0.0775)	(0.0798)	(0.0896)	(0.0832)
Trading/business/other	0.304***	0.318***	0.159	0.132
	(0.103)	(0.105)	(0.137)	(0.130)
Age of the household head	0.00364	0.00406	–0.00198	–0.00278
	(0.0101)	(0.0102)	(0.0135)	(0.0137)
Squared age of the household head	–0.000063	–0.0000738	–0.0000192	–0.00000165
	(0.000120)	(0.000123)	(0.000151)	(0.000154)
Household head is female	0.0205	0.0215	0.153**	0.151**
	(0.0896)	(0.0902)	(0.0726)	(0.0726)
Education of the household head (Base: none)				
Primary education	0.0613	0.0585	0.0947	0.100
	(0.0756)	(0.0755)	(0.0849)	(0.0846)
Post-primary education	–0.0195	–0.0132	0.348***	0.335***
	(0.100)	(0.0981)	(0.106)	(0.108)
District dummies (Base category: Adjumani)				
Arua	–0.0801	–0.182	–0.298**	–0.100
	(0.0913)	(0.116)	(0.140)	(0.193)
Yumbe	0.00224	–0.0117	–0.268*	–0.241*
	(0.0620)	(0.0607)	0.137	0.135
Constant	–0.959*	–1.318	–2.029***	–1.332*
	(0.500)	(0.677)	(0.602)	(0.721)
R-squared	0.586	0.587	0.555	0.558
Number of observations	581	581	581	581

Notes: Refugee sample is restricted to those in refugee settlement and further restricted to those attending sample schools. Numbers in parentheses are robust standard errors clustered at the school level. Grade dummies are included in all models. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

or the outcome model, but not necessarily both of them, is specified correctly (Hoshino, 2007; Seaman and Vansteelandt, 2018). The study uses a DR estimator, named the inverse-probability-weighted regression adjustment (IPWRA) estimator proposed by Wooldridge (2007). Using the propensity score calculated using the surveyed school sample as a weight, a linear model to the English and math test score is fitted, this time with independent variables, $\boldsymbol{X}_i$, S_i^{REF}, and S_i^0, using weighted least squares regression separately for refugee pupils attending local government school (treatment group) and those attending non-government school (control group). The IPWRA estimate of the ATT can be obtained by calculating the average difference between predicted test score, resting the computation of the mean test score for the subset of sample pupils in local government school. The regression adjustment (RA) estimator of the ATT, obtained by using the test score predicted by unweighted least squares regression, is also presented.

Table 5
OLS estimation results for native pupils in surveyed school sample.

Dependent variable: test scores	English		Math	
	(1)	(2)	(3)	(4)
School characteristics				
Percentage of refugees	–0.0116***		–0.00852***	
	(0.00275)		(0.00292)	
Refugee concentration level (Base: 0–5%)				
5–20%		–0.232***		–0.179*
		0.0841		(0.0989)
20–50%		–0.430**		–0.411**
		(0.197)		(0.192)
50–100%		–0.704***		–0.370**
		(0.132)		(0.170)
School size	0.000337***	0.000352**	0.000322***	0.000369***
	(0.000113)	(0.000136)	(0.000108)	(0.000123)
Pupil–teacher ratio	–0.00987***	–0.00911***	–0.000943	–0.000560
	(0.00256)	0.00292	(0.00209)	(0.00222)
Unqualified teachers are hired	–0.0584	–0.0426	0.116	0.122
	(0.0988)	(0.106)	(0.0962)	(0.0982)
Individual characteristics				
Age	0.0591	0.0509	0.180**	0.172**
	(0.0677)	(0.0701)	(0.0674)	(0.0702)
Age squared	–0.00208	–0.00185	–0.00753**	–0.00732**
	(0.00333)	(0.00342)	(0.00314)	(0.00324)
Female	–0.0160	–0.0128	–0.0163	–0.0119
	(0.0510)	(0.0510)	(0.0549)	(0.0548)
Some disability	–0.0271	0.0382	–0.0560	–0.0617
	(0.0838)	(0.0816)	(0.0693)	0.0716
Attended preschool	0.156*	0.140*	0.0614	0.0340
	(0.0797)	(0.0789)	(0.0767)	(0.0796)
Household characteristics				
Household size	–0.00255	–0.00165	–0.00708	–0.00606
	(0.0115)	(0.0118)	(0.00737)	(0.00711)
Wealth index (natives)	0.0606	–0.0491	0.0180	0.0283
	(0.0554)	(0.0532)	(0.0458)	(0.0440)
Age of the household head	–0.000733	0.00111	0.0188	0.0205
	(0.0115)	(0.0119)	(0.0142)	(0.0138)
Squared age of the household head	0.0000428	0.0000217	–0.000151	–0.000171
	(0.000115)	(0.000118)	(0.000158)	(0.000153)
Household head is female	0.138**	0.152**	0.0270	0.0409
	(0.0628)	(0.0651)	(0.0648)	(0.0669)
Education of the household head (Base: none)				
Primary education	0.0395	0.0489	–0.0426	–0.0341
	(0.0910)	(0.0938)	(0.0827)	(0.0846)
Post-primary education	0.111	0.105	0.146	0.144
	(0.118)	(0.114)	(0.0895)	(0.0886)
District dummies (Base: Adjumani)				
Arua	–0.0549	–0.126	–0.226*	–0.283**
	(0.133)	(0.137)	(0.127)	(0.129)
Yumbe	–0.0939	–0.107	–0.150	–0.149
	(0.114)	(0.116)	(0.0883)	(0.0891)
Constant	–0.837***	–0.822**	–2.464***	–2.492***
	(0.339)	(0.339)	(0.412)	(0.403)
R-squared	0.704	0.706	0.650	0.651
Number of observations	544	544	544	544

Notes: Refugee sample is restricted to those in refugee settlement and further restricted to those attending sample schools. Numbers in parentheses are robust standard errors clustered at the school level. Grade dummies are included in all models. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

6. Results and discussion

6.1. OLS estimates: Effects of school type and/or refugee concentration on learning achievement of refugee and native pupils

To answer the research questions, the study first conducted OLS regression analysis using the surveyed school sample. As shown in Table 4, there is no statistically significant difference in English score between refugee pupils who attend local government schools and those who attend non-government schools, after controlling all the standard individual/household factors and other school factors. Comparing this result with *t*-test result in Table 2, average difference was reduced from 0.221 to 0.153 test score standard deviations. The coefficient for the percentage of refugees in model 1 is negative, which suggests that refugee pupils perform better in English if they learn in a school with more Ugandan native students. Although the result of the simple regression shows a statistically significant negative effect, it again turns insignificant after holding observables constant.

On the other hand, Table 4 shows that refugee pupils in local government schools perform worse than their counterparts by 0.298 score standard deviations after controlling all observable factors although this is not statistically significant at the 5% level. The result in model 3 shows that refugee pupils perform better if they learn in schools with a higher proportion of refugees. This positive effect disappears in model 4 potentially because it is absorbed by the school type variable, which motivates us to further investigate the school type effect on refugees' performance, applying a matching/weighting approach, in the other sub-section.

Table 6
Probit estimation result of the determinants of attending government schools among refugee pupils.

Dependent variable = 0 if a pupil attends non-government school, 1 if he or she attends government school	(1)		(2)	
	Coefficient	Average marginal effects	Coefficient	Average marginal effects
Individual characteristics				
Age	0.253*	–0.0117	0.0536	–0.0202
	(0.129)	(0.00811)	(0.153)	(0.0126)
Age squared	–0.0126**		–0.00503	
	(0.00565)		(0.00693)	
Female	–0.0175	–0.00550	0.0161	0.00514
	0.0867	(0.0273)	(0.0772)	(0.0247)
Some disability	–0.344***	–0.109***	–0.103	–0.0329
	(0.130)	(0.0410)	(0.216)	(0.0687)
Attended preschool	0.383***	0.121***	0.355*	0.113*
	(0.118)	(0.0364)	(0.188)	(0.0581)
Household characteristics				
Number of years in Uganda (Base: 0–1 years)				
2–7 years	0.0792	0.0244	0.356	0.115
	(0.195)	(0.0607)	(0.597)	(0.194)
8 or more years	0.324**	0.105*	0.0296	0.00938
	(0.164)	(0.0536)	(0.565)	(0.179)
Household size	–0.0136	–0.00429	0.00187	0.000594
	(0.0196)	(0.00617)	(0.0326)	(0.0104)
Wealth index (refugees)	0.1600**	0.0505**	0.339	0.108
	(0.0729)	(0.0227)	(0.244)	(0.0720)
Main source of income (Base: UNHCR stipends)				
Farming/fishing	0.0686	0.0221	0.269	0.0868
	(0.246)	(0.0799)	(0.513)	(0.166)
Trading/business/other	–0.154	–0.0472	–0.261	–0.0801
	(0.238)	(0.0709)	(0.513)	(0.153)
Age of the household head	0.0307	0.00278	–0.00977	0.000702
	(0.0290)	(0.00201)	(0.0316)	(0.00303)
Squared age of the household head	–0.000301		0.000172	
	(0.000344)		(0.000381)	
Household head is female	0.109	0.0345	0.367	0.117
	(0.177)	(0.0557)	(0.288)	(0.0925)
Education of the household head (Base: none)				
Primary education level	–0.470***	–0.157***	–0.490	–0.171
	(0.178)	(0.0605)	(0.356)	(0.125)
Post-primary education level	–0.507**	–0.168**	–1.001***	–0.330***
	(0.226)	(0.0740)	(0.334)	(0.120)
Constant	–2.526***		–0.465	
	(0.922)		(1.400)	
Pseudo R-squared	0.114		0.172	
Log likelihood	–610.45967		–326.91507	
Number of observations	1096		581	

Notes: Numbers in parentheses for coefficients are robust standard errors clustered at the household level and EA level for surveyed household sample and surveyed school sample, respectively. Numbers in parentheses for average marginal effects are delta method standard errors. Grade dummies are included in all models. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 5 presents results from our OLS regression analyses using Ugandan native data from the surveyed school sample. The results generally show that higher refugee concentration is significantly related to lower test scores of Ugandan native pupils in both English and math. In the final models, a one percentage point increase in refugee concentration is associated with 0.012 and 0.009 score standard deviation decrease in English and math test scores of native pupils, respectively, which is statistically significant at the 1% level. This estimated effect size is fairly stable across models which include different controls. The estimates from the models using a categorical variable as an explanatory variable (models 2 and 4) reveal a nonlinear effect of refugee concentration. Overall, the effect size gets bigger as the percentage of refugees gets higher.

Although many previous studies on non-refugee migrants in developed countries find no significant effect of immigrant concentration on natives' performance as reviewed in Section 2 (Bossavie, 2020; Brandén et al., 2016; Geay et al., 2013; Ohinata and van Ours, 2013), the finding of this study is consistent with those that have found a negative effect in non-refugee migrant studies (Ballatore et al., 2018; Jensen and Rasmussen, 2011). Since few empirical studies to assess the effects of refugee concentration on natives' test scores have been conducted, this study at least provides important baseline evidence showing that the performance of native pupils in local government schools is worse among pupils in schools hosting more refugees.

However, this evidence should be interpreted with the highest caution. First, due to the limitation of the data set explained in Section 5, this study only produces naive estimates, which are not comparable with the estimates from the above studies. Second, it is worth noting that the evidence was obtained using the data collected during the massive refugee influx. The evidence should not be interpreted out of the context where the government and donors had little room for providing sufficient support to refugee-hosting local government schools as described in Section 3.

6.2. *OLS estimates: Determinants of learning achievement of refugee and native pupils*

Although the present estimates are not strictly causal, Tables 4 and 5 show some interesting differences in the determinants of test scores between refugees and Ugandan natives. The results generally indicate that more demand-side characteristics are significantly correlated with learning achievement among refugee pupils than among native pupils. Starting with individual characteristics, female pupils perform worse than males only among refugees, at 5% significance level. A statistically significant negative effect of some disabilities on math test score is also

Table 7
Matching/weighting estimation results for refugee pupils.

	Surveyed household sample	Surveyed school sample		
	IPW	IPW	IPWRA	RA
	(1)	(2)	(3)	(4)
Panel A: Untrimmed sample				
Dependent variables				
English	–0.018(0.0694)	0.0877(0.127)	–0.0457(0.111)	0.0311(0.0908)
Math	–0.245***(0.0589)	–0.175*(0.0945)	–0.305**(0.103)	–0.258***(0.0820)
Number of observations				
Treatment (attending government school)	353	242		
Control (attending non-government school)	743	339		
Total	1096	581		
Panel B: Trimmed sample				
Dependent variables				
English	–0.0117(0.0694)	0.0688(0.122)	–0.0481(0.105)	0.0228(0.0806)
Math	–0.249 *** (0.0581)	–0.184 **(0.0839)	–0.295 **(0.0959)	–0.289 ***(0.0997)
Number of observations				
Treatment (attending government school)	348	229		
Control (attending non-government school)	674	299		
Total	1022	528		

Notes: Numbers in parentheses are robust standard errors clustered at the household level and EA level for surveyed household sample and surveyed school sample, respectively. IPW = inverse probability weighting. IPWRA = inverse-probability-weighted regression adjustment. RA = regression adjustment. Average treatment effect on treated (ATT) was estimated in all models. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

found only among South Sudanese refugees.

Looking at the household characteristics, there seems to be no major predictor of learning achievement in Ugandan pupils, though as an exception having a female household head is positively correlated with English test score. Household size and wealth index have no statistically significant effect. On the other hand, learning achievement of refugees is determined by several household-level factors. For instance, among refugees, a positive effect of household head's education on math test score is found significant at a 1% level, although the same effect is not observed for English test score. Among the refugee sample, the household head's education and English test score do not even show a positive correlation. In contrast, refugees' English test score is strongly correlated with variables related to their life in the host country. Having a source of income other than UNHCR stipends is strongly correlated with pupils' English test score. The results also show that the effect size of trading/doing business/other is larger than the one for farming and fishing. Moreover, pupils who have stayed longer in Uganda perform significantly better in English, while years lived in Uganda had no significant effect on math test score.

Turning back to the school characteristics, the result shows that PTR is negatively correlated with English test score among Ugandan native pupils. On the other hand, the results do not show any statistically significant correlation between PTR and refugee pupils' learning achievement. Instead, Table 4 shows that hiring untrained teachers is positively correlated with refugees' test scores in English.

The finding for native pupils, showing few significant demand-side factors, may be attributed to the fact that native sample is restricted to those in government-funded schools under UPE policy. Even under Uganda's progressive refugee education policy, refugee pupils' learning achievement is significantly determined by some demand-side factors. English and math scores are predicted by different factors among refugees and natives potentially due to the unique context of this study. For instance, finding significant coefficient for the gender dummy only among refugees may be explained by the fact that gender inequality is still a persistent issue in education in South Sudan, as confirmed in the recent EGRA study by Raza et al. (2019). Besides, insignificant coefficient for the household head's education is only found among refugees may be because refugee parents who have primary-school-aged children in 2017 were educated when their country was not yet independent and had not yet switched the national language from Arabic to English. Moreover, unique significant household characteristics for the English test score among refugees may suggest that, in the context of West Nile, Uganda, economic and social inclusion in the host community seems to have a positive correlation with refugee pupils' language acquisition.

With regard to the correlation with PTR, only the finding for English test score among natives show a trend which is similarly found in previous studies in developing countries such as Jones (2016). It was insignificant among refugees although previous studies constantly highlight the issue of overcrowded classrooms in refugee education (Richardson et al., 2018). As mentioned in Section 4, in the context explained in detail in Section 3, the finding on significant correlation between hiring untrained teachers and English test score among refugees may be interpreted as showing a positive effect of the presence of a refugee teaching assistant on refugee pupils' learning. The study offers baseline evidence on the role of refugee instructors, which has been widely recognized in the previous qualitative studies such as Culbertson and Constant (2015) and Mendenhall et al. (2015), although it requires richer data compared to migrant studies in developed countries such as Seah (2018) assessing the impact of having immigrant teachers on students' test scores in the United States.

6.3. Matching/weighting estimates: Effects of attending local government school on learning achievement of refugee pupils

The effects of being included in local government school on refugees' English and math test scores are further examined by applying matching/weighting techniques. As a first step, probit regression analysis was conducted to produce a propensity score. The results, presented in Table 6, eventually reveal the determinants of attending government schools among refugee pupils. In line with descriptive statistics presented in Tables 2 and 3 and discussed in Section 4, probit regression finds that refugees' experience of attending preschool and their household heads' education are significant predictors of the type of school refugees in refugee settlements attend. In model 1, using the surveyed household sample, refugee pupils who attended preschool are 12% more likely to attend government school compared with those who did not attend preschool and 17% less likely to attend government school if their household head completed post-primary education as compared with no education.

While main source of income is not found to be a significant predictor of attending government schools, the results of model 1 show that refugee pupils who have been exposed to non-refugee conditions are more likely than other refugee pupils to attend government schools. Model 1 also reveals that refugee pupils with a disability are 11% less likely to attend government school and that this average marginal effect is statistically significant at the 1% level.

Using the surveyed household sample, a density distribution of propensity scores for pupils in government and non-government schools is generated; it shows a considerable overlap between the two groups (see Fig. A3). Therefore, the common support assumption for propensity score matching is satisfied. Although the overlap assumption basically holds in the distribution of propensity scores produced using the surveyed school sample, there seems to be no sample in non-government schools whose propensity score is less than 0.1 that can be matched with the sample in government schools (see Fig. A4). Showing estimates from trimmed data is also required to partly address this issue for the school surveyed data analysis.[21]

Before implementing matching methods using the estimated propensity scores as inverse-probability weights, a balancing test, proposed by Imai and Ratkovic (2014), was conducted by looking at the restrictions imposed by balance as overidentifying conditions. The results of the balancing test using the weighted surveyed household and weighted surveyed school data show that we cannot reject the null hypothesis, that covariates are balanced. Tables B2 and B3 show the standardized difference in covariates and variance ratio between raw and weighted data for the surveyed household sample and the surveyed school sample, respectively. Although matching quality meets the aforementioned standards, it should be noted that matching is based on the conditional independence assumption, which is intrinsically irrefutable (Masten and Poirier, 2018). The results should be interpreted within the limits of this assumption.[22]

Overall, matching/weighting estimation results confirm the insignificant effect of local government school attendance on English test scores as well as the significant negative effect on math test scores although the IPW estimate using the untrimmed surveyed school sample shows insignificant effect as an exception. As shown in Table 7, both the IPW estimate using the surveyed household sample and the IPWRA estimate using the surveyed school sample show statistically significant negative effects while the OLS estimates presented in Table 4 show that the effect is not statistically significant at the 5% level. The IPWRA estimate from the trimmed surveyed school sample shows that pupils in government schools scored lower by 0.295 score standard deviations than their counterparts; in contrast, all matching/weighting estimates on the effect on English score are insignificant.

In studies from developed countries, especially in Europe, where migrants tend to study a language which is different from that in home countries, rigorous empirical studies tend to show a negative effect of migrant concentration on migrant students' educational outcome (Jensen and Rasmussen, 2011; Schneeweis, 2015). The insignificant effect of being included in local government schools on refugees' English scores may be attributed to the fact that refugees have been at least exposed to education in English in their home countries in this context, as reviewed in Section 3, although Piper et al. (2020) found the South Sudanese refugees score lower in English than those from other countries potentially due to their relatively low exposure level to education in English. However, the matching/weighting estimates shows a negative effect on math test score. These findings are to some extent in line with Delprato et al. (2019), although their findings rely fully on descriptive analysis. In a context where refugees and hosts share the same national language, namely Arabic, Delprato et al. (2019) found that refugees in local government schools perform worse in math, but no gap was observed in Arabic between regular schools and camp schools.

7. Conclusion

The study gave special focus to assessing the effects of attending local government schools instead of non-government schools on refugee pupils' performance as well as the effects of refugee concentration on native pupils' performance in government schools. According to the results from the analyses controlling observable factors among refugee pupils, the effects of being included in a local government school is insignificant for their English performance. These insignificant effects on refugee pupils' English score are fairly robust across different estimation methods, holding observable characteristics constant. In contrast to this, while OLS estimate shows insignificant effect, matching/weighing estimates consistently show significantly negative effects on refugee pupils' math score with an exception of the insignificant effect obtained in IPW estimate using the untrimmed surveyed schools sample.

Although not strictly causal, OLS estimates imply a negative effect of refugee concentration in government schools on native pupils' performance in both English and math. OLS estimates also show that a unique school-level factor, hiring of refugee teaching assistants, has significant positive effects on the English test scores of refugee pupils, while conventional school-level factors, such as PTR, have no significant effect.

Including refugees in the national education system has already been mainstreamed in many developing countries. Overall, the evidence from Uganda, which is known as a showcase country in implementing this scheme, suggests that there is little evidence showing that simply promoting the inclusion of refugees in national education has had a positive effect on refugee or native pupils' learning achievement during the massive refugee influx. Although in including refugees in the national education system, lots of attention is paid to the issue of language education, the results could be interpreted to show that inclusion in local government schools has no significant negative effect on refugee pupils' English scores in a context where the national language of refugees and that of natives are the same. Rather than taking standard measures, resource should be allocated to context-specific and cost-effective measures to ensure quality of learning for both refugees and natives. In the context of West Nile, targeted support may be needed for natives learning with refugees in government schools as well as for teaching subjects other than language to refugees in mixed classrooms. Utilizing motivated refugee teachers, many of whom potentially have qualification in their home country that is unrecognized in the host country, as teaching assistants, or by offering flexible retraining opportunity for them to be credentialed in Uganda, could be a cost-effective measure to enhance the quality of language learning for refugees, although further study is required to obtain more conclusive evidence to support this measure.

Last, as is often the case with observational cross-sectional data, scope for bias remains, and the results should be interpreted with due caution. Although this study makes a notable contribution as one of the pioneering quantitative studies in this areas, limited methods can be applied for overcoming the endogeneity of refugee concentration in school due to the shortage of data in general. The study thus re-emphasizes the need for learning assessment of both refugees and natives to evaluate the effects of refugee inclusive policies. It will be important to accumulate more evidence in different contexts as a similar policy is introduced in more contexts, especially in developing countries. Specifically, in addition to sampling children from more schools, it

[21] Meeting a common support assumption is certainly necessary to obtain an unbiased estimate of ATT for applying methods that relate to the propensity score (Austin, 2011). However, the IPW estimator is at least implementable even where this assumption is violated (Bishop et al., 2018). As mentioned in Section 5, this study adopted the trimming method primarily for mitigating bias caused by the extreme propensities. However, it is certainly true that trimming the sample in this way is just one among many approaches that can be used to mitigate common support issues. This study exhibits the limitation that not all possible approaches developed for addressing common support problems in using propensity score for weighting are adopted here (Lechner and Strittmatter, 2019).

[22] This study applied the methods that make an assumption of conditional independence, also known as confoundedness (Imbens and Rubin, 2015). However, it is generally understood that it is difficult to make this assumption hold in practice, especially because we need to be confident that there is no observable confounder, which is unrealistic (Cunningham, 2021). As noted in Section 5, this study investigates the possibility of applying other causal inference methods that can be used when the conditional independence assumption is questionable. Nevertheless, this ends by relying on OLS and matching/weighting methods,mainly due to data shortage.

will be important to collect data from both refugee and native children within the same school. Conducting a longitudinal study, which enables us to take unobservable fixed effects into account, is essential as well. Collecting longitudinal educational data from refugees could also be important, as more and more refugees are in protracted situations.

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CRediT authorship contribution statement

Katsuki Sakaue: Conceptualization, Methodology, Software, Formal analysis, Writing-Original Draft: **James Wokadala**: Resources, Writing-Reviewing and Editing.

Conflicts of interest statement

None.

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Appendix A. Additional figures

see Figs. A1-A4.

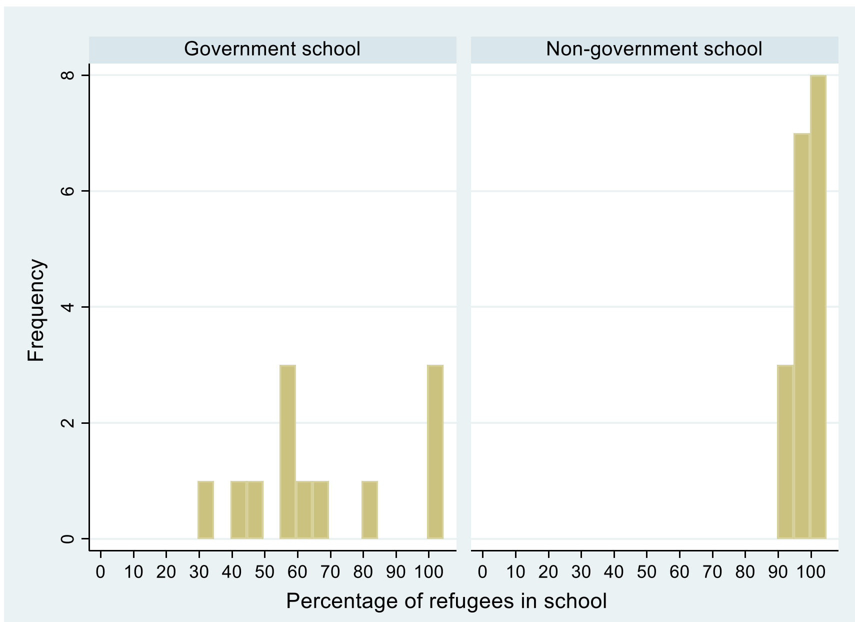

Fig. A1. Percentage of refugees in school by school type in refugee settlements.

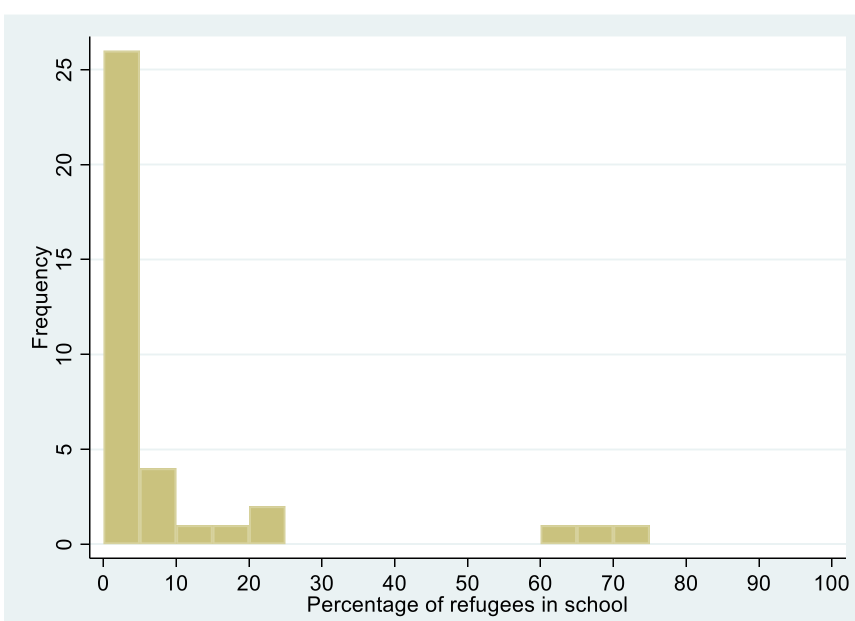

Fig. A2. Percentage of refugees in school in government schools in non-refugee EAs.

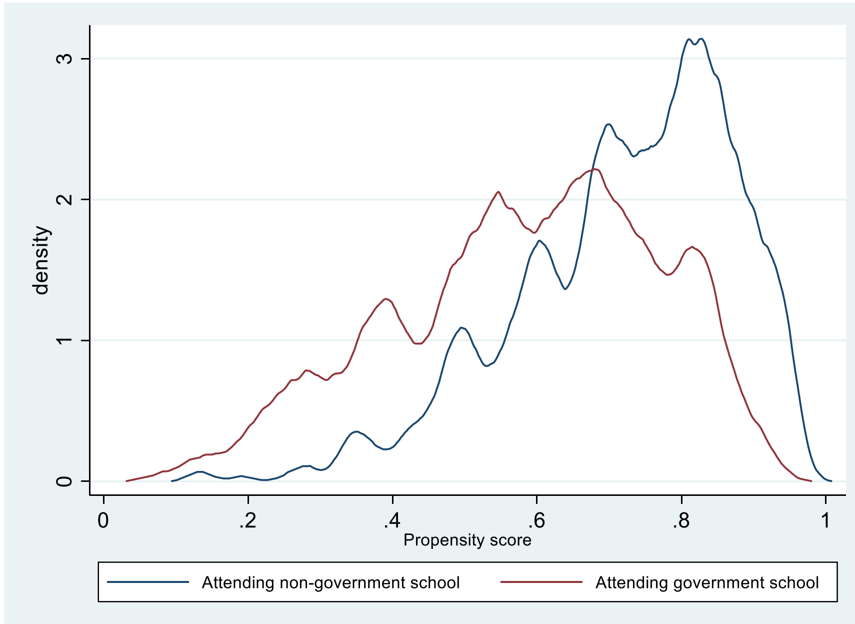

Fig. A3. Histogram of propensity score using surveyed household sample.

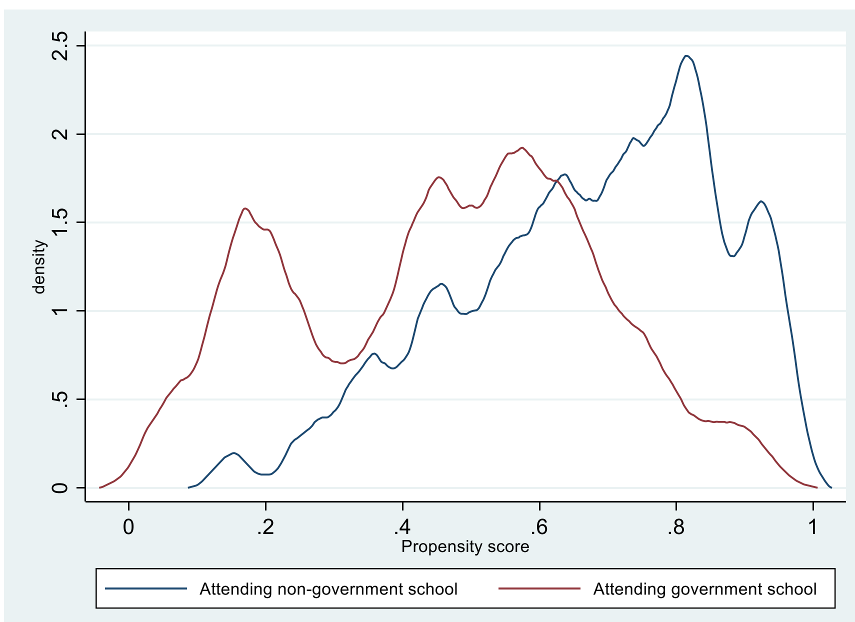

Fig. A4. Histogram of propensity score using surveyed school sample.

Appendix B. Appendix tables

see Tables B1-B3.

Table B1
Scoring factors and summary statistics for variables entering the computation of the first principal component.

	Refugees (n = 670)				Natives (n = 691)			
	M	*SD*	Scoring Factors	Factor loadings	*M*	*SD*	Scoring Factors	Factor loadings
Main source of water								
Borehole	0.529	0.499	0.315	0.494	0.670	0.468	–0.138	–0.241
Piped	0.224	0.417	–0.209	–0.329	0.085	0.277	0.252	0.439
Covered well/spring	0.011	0.011	–0.019	–0.030	0.061	0.239	–0.001	–0.001
Open well/spring	0.002	0.039	0.004	0.006	0.036	0.187	–0.055	–0.096
Rainwater/river/lake/dam/other	0.235	0.424	–0.160	0.251	0.147	0.352	0.015	0.026
Ownership of toilet/latrine	0.796	0.402	–0.058	0.091	0.895	0.306	0.160	0.279
Main source of lighting								
Electricity	0.005	0.067	0.118	0.185	0.046	0.207	0.287	0.500
Solar	0.701	0.450	–0.351	–0.550	0.456	0.493	0.198	0.345
Gas/paraffin	0.163	0.363	0.303	0.476	0.419	0.488	–0.296	–0.517
Other	0.132	0.332	0.120	0.189	0.079	0.266	–0.046	–0.080
Ownership of consumer goods and livestock								
Television	0.006	0.077	0.094	0.147	0.051	0.219	0.362	0.631
Radio	0.152	0.360	–0.112	–0.175	0.359	0.480	0.308	0.537
Computer	0.012	0.109	–0.025	–0.039	0.038	0.190	0.307	0.535
Mobile telephone	0.429	0.495	0.047	0.074	0.485	0.500	0.286	0.499
Vehicle	0.013	0.115	–0.070	–0.110	0.012	0.107	0.245	0.427
Motor cycle	0.052	0.052	–0.083	–0.130	0.116	0.320	0.246	0.428
Bicycle	0.052	0.335	–0.053	–0.084	0.424	0.495	0.149	0.259
Cattle	0.013	0.115	–0.002	–0.003	0.306	0.461	0.116	0.202
Sheep/goats	0.120	0.325	0.010	0.016	0.570	0.495	0.091	0.158
Wall materials of the main house								
Mud/stick/polythene	0.753	0.753	–0.523	–0.821	0.358	0.475	–0.217	–0.379
Iron sheet	0.003	0.055	0.096	0.151	0.022	0.146	0.204	0.356
Stone/bricks/timber	0.244	0.428	0.513	0.805	0.619	0.481	0.153	0.266

Notes: Principal Component Analysis was conducted separately using refugee and native data, which were collapsed to household-level before making any restrictions. Each variable takes the value of 1 if true, 0 otherwise. The scoring factor is the weight assigned to each variable (normalized by its mean and standard deviation) in the linear combination of the variables that constitute the first principal component. The factor loadings are calculated by multiplying the scoring factors by the square root of the eigenvalues.

Table B2
Covariate balance summary before and after propensity score weighting using surveyed household sample.

	Standardized difference		Variance ratio	
	Raw	Weighted	Raw	Weighted
Individual characteristics				
Age	0.160	–0.0458	0.854	1.009
Age squared	0.142	–0.0458	0.910	1.027
Female	–0.0555	0.0111	0.992	1.003
Some disability	–0.158	0.00465	0.748	1.010
Attended preschool	0.387	0.00578	0.962	0.997
Current grade (Base: Grade 1)				
Grade 2	–0.000480	0.0358	1.001	1.072
Grade 3	–0.0228	0.00504	0.964	1.009
Grade 4	–0.0188	0.00281	0.971	1.005
Grade 5	0.167	0.0199	1.479	1.041
Grade 6	0.243	–0.0670	1.864	0.884
Grade 7	0.00815	–0.0127	1.053	0.928
Household characteristics				
Household size	–0.00751	0.0497	1.152	1.319
Wealth index (refugee settlements)	0.355	0.0257	1.030	0.940
Main source of income (Base: UNHCR stipends)				
Farming/fishing	–0.0399	–0.0186	0.875	0.938
Trading/business/others	–0.152	–0.0352	0.635	0.888
Number of years in Uganda (Base: 0–1 years)				
2–7 years	0.0196	–0.0958	1.036	0.862
8 years or more	0.167	–0.0449	1.179	0.968
Age of the household head	0.250	–0.0137	0.986	1.021
Squared age of the household head	0.207	–0.00873	1.115	1.045
Household head is female	0.250	0.0366	0.712	0.940
Education of the household head (Base: none)				
Has primary education	–0.230	–0.0214	0.995	0.995
Has post-primary education	–0.174	–0.0316	0.754	0.943

Table B3
Covariate balance summary before and after propensity score weighting using surveyed school sample.

	Standardized difference		Variance ratio	
	Raw	Weighted	Raw	Weighted
Individual characteristics				
Age	0.0434	0.0362	0.931	0.973
Age squared	0.0350	0.0334	0.955	0.995
Female	–0.0399	0.0190	0.991	1.006
Some disability	–0.0645	–0.00745	0.875	0.984
Attended preschool	0.344	0.0955	1.004	0.977
Current grade				
Grade 2	0.00534	–0.0213	1.012	0.958
Grade 3	0.00651	0.0296	1.013	1.054
Grade 4	–0.0550	0.0348	0.919	1.061
Grade 5	0.0923	–0.00555	1.242	0.988
Grade 6	0.182	0.0114	1.492	1.021
Grade 7	–0.0111	–0.0394	0.937	0.797
Household characteristics				
Household size	0.0426	0.256	1.346	1.790
Wealth index (refugee settlements)	0.652	0.0227	1.494	0.871
Main source of income (Base: UNHCR stipends)				
Farming/fishing	–0.0326	–0.0151	0.920	0.961
Trading/business/others	–0.0795	–0.0426	0.768	0.863
Number of years in Uganda (Base: 0–1 years)				
2–7 years	0.131	–0.0932	1.297	0.864
8 years or more	–0.170	–0.0955	0.837	0.896
Age of the household head	0.307	0.0680	1.138	1.067
Squared age of the household head	0.0680	0.0656	1.415	1.200
Household head is female	0.478	0.0944	0.539	0.837
Education of the household head (Base: none)				
Has primary education	–0.110	–0.146	0.999	1.002
Has post-primary education	–0.500	–0.0215	0.443	0.946

References

Assad, R.A., 2019. Impact of Syrian Refugees on Education Outcomes in Jordan. Centre for Economic Policy Research, London, UK. CEPR Discussion Pap. No. DP14056.

Austin, P.C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivariate Behav. Res. 46 (3), 399–424.

Ballatore, R.M., Fort, M., Ichino, A., 2018. Tower of Babel in the classroom: Immigrants and natives in Italian schools. J. Lab. Econ. 36 (4), 885–921.

Beaman, L.A., 2012. Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the U.S. Rev. Econ. Stud 79 (1), 128–161.

Betts, A., Bloom, L., Kaplan, J., Omata, N., 2017. Refugee Economies: Forced Displacement and Displacement and Development. Oxford University Press, Oxford, UK.

Bilgili, Ö., Loschmann, C., Fransen, S., Siegel, M., 2019. Is the education of local children influenced by living near a refugee camp? Evidence from host communities in Rwanda. Int. Migr. 57 (4), 291–309.

Bishop, C.D., Leite, W.L., Snyder, P.A., 2018. Using propensity score weighting to reduce selection bias in large-scaler data sets. J. Early Interv. 40 (4), 347–362.

Bossavie, L., 2020. The effect of immigration on natives' school achievement: Does length of stay in the host country matter? J. Hum. Resour. 55 (2), 733–766.

Brandén, M., Birkelund, G.E., Szulkin, R., 2016. Does School Segregation Lead to Poor Educational Outcomes? Evidence from Fifteen Cohorts of Swedish Ninth Graders. Institute for Analytical Sociology, Department of Management and Engineering, Linköping University, Linköping, Sweden. IAS Working Paper Series no. 2016:4.

Cortes, K.E., 2006. The effects of age at arrival and enclave schools on the academic performance of immigrant children. Econ. Educ. Rev. 25 (2), 121–132.

Crump, R.K., Hotz, V.J., Imbens, G.W., Mitnik, O.A., 2009. Dealing with limited overlap in estimation of average treatment effects. Biometrika 96 (1), 187–199.

Culbertson, S., Constant, L., 2015. Education of Syrian Refugee Children: Managing the Crisis in Turkey, Lebanon, and Jordan. Rand Coop., Santa Monica, CA.

Cunningham, S., 2021. Causal Inference: The Mixed Tape. Yele University Press, New Haven, CT.

Damm, A.P., 2014. Neighborhood quality and labor market outcomes: evidence from quasi-random neighborhood assignment of immigrants. J. Urban Econ. 79, 139–166.

Delprato, M., Morrice, M., Al-Nahi, S., 2019. A Summary of Key Patterns in the Jordanian Education System by School Type, Gender and Region. University of Sussex, Brighton, UK. Project Report.

Dryden-Peterson, S., 2003. Education of Refugees in Uganda: Relationships between Setting and Access. Refugee Law Project, Kampala, Uganda. Working Paper Series.

Dryden-Peterson, S., 2006. Livelihoods in the region: The present is local, the future is global? Reconciling current and future livelihood strategies in the education of Congolese refugees in Uganda. Refugee Surv. Q. 25 (2), 81–92.

Dryden-Peterson, S., 2016. Refugee education: the crossroads of globalization. Educ. Res. 45 (9), 473–482.

Fallah, B., Krafft, C., Wahba, J., 2019. The impact of refugees on employment and wages in Jordan. J. Dev. Econ. 139, 203–216.

Filmer, D., Pritchett, L.H., 2001. Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. Demography 38 (1), 115–132.

Geay, C., McNally, S., Telhaj, S., 2013. Non-native speakers of English in the classroom: what are the effects of pupil performance? Econ. J 123 (570), F281–F307.

Hair, J.F., Anderson, R.E., Tatham, R.L., Black, W.C., 1998. Multivariate Data Analysis, 5th ed. Prentice Hall, Upper Saddle River, NJ.

Hicks, R., Maina, L., 2018. The Impact of Refugees on Schools in Uganda. British Council, London, UK.

Hoshino, T., 2007. Doubly robust-type estimation for covariate adjustment in latent variable modeling. Psychometrika 72 (4), 535–549.

Hovil, L., Kigozi, D., 2015. South Sudanese Refugees in Adjumani District, Uganda: Telling a New Story? The International Refugee Rights Initiative, New York, NY.

Hoxby, C., 2000. Peer Effects in the Classroom: Learning from Gender and Race Variation. National Bureau of Economic Research, Cambridge, MA. NBER Working Paper no. 7867.

Imai, K., Ratkovic, M., 2014. Covariate balancing propensity score. J. R. Stat. Soc. B 76 (1), 243–263.

Imbens, G.W., 2004. Nonparametric estimation of average treatment effects under exogeneity: a review. Rev. Econ. Stat. 86 (1), 4–29.

Imbens, G.W., Rubin, D.B., 2015. Causal Inference for Statistics, Social, and Biomedical, Sciences: An Introduction. Cambridge University Press, New York, NY.

Jallow, Tijan, Tournée, J., Mwesigye, A., Schierbeck, H., Kasahura, F., Mayanja, R., Mwange, G., 2004. Self-Reliance Strategy (1999–2003) for Refugee Hosting Areas in Moyo, Arua and Adjumani Districts, Uganda: Report of the Mid-Term Review. UNHCR, Geneva, Switzerland. RLSS Mission Report (03).

Jensen, P., Rasmussen, A.W., 2011. The effect of immigrant concentration in schools on native and immigrant children's reading and math skills. Econ. Educ. Rev. 30 (6), 1503–1515.

JICA, 2012. Basic Education Sector Analysis Report: Uganda. JICA, Tokyo, Japan.

JICA, 2018. Data Collection Survey on Social Infrastructure Needs of Refugee-Hosting Communities in Northern Uganda Final Report. JICA, Tokyo, Japan.

Jones, S., 2016. How does classroom composition affect learning outcomes in Ugandan primary schools? Int. J. Educ. Dev. 48, 66–78.

Kang, J.D.Y., Schafer, J.L., 2007. Demystifying double robustness: a comparison of alternative strategies for estimating a population mean from incomplete data. Stat. Sci. 22 (4), 523–539.

Kaplan, I., Stolk, Y., Valibhoy, M., Tucker, A., Baker, J., 2016. Cognitive assessment of refugee children: effects of trauma and new language acquisition. Transcult. Psychiatry 53 (1), 81–109.

Kayabwe, S., Nabacwa, R., 2014. The Use and Usefulness of School Grants: Lessons from Uganda. IIEP-UNESCO, Paris, France.

Kisira, S., 2008. Uganda. In: Phillipson, B. (Ed.), Low-Cost Private Education: Impacts on Achieving Universal Primary Education. Commonwealth Secretariat, London, U.K., pp. 131–172

Krause, U., 2016. Limitations of development-oriented assistance in Uganda. Forced Migr. Rev. 52, 51–53.

Kreibaum, M., 2016. Their suffering, our burden? How Congolese refugees affect the Ugandan population. World Dev. 78, 262–287.

Lechner, M., Strittmatter, A., 2019. Practical procedures to deal with common support problems in matching estimation. Econ. Rev. 38 (2), 193–207.

Magoola, J.Y., 2015. Uwezo Uganda Sample Design for 2015 Annual Learning Assessment. UBOS, Kampala, Uganda.

Masten, M.A., Poirier, A., 2018. Identification of treatment effects under conditional partial independence. Econometrica 86 (1), 317–351.

Mendenhall, M., Cha, J., Falk, D., Bergin, C., Bowden, L., 2021. Teachers as agents of change: positive discipline for inclusive classrooms in Kakuma refugee camp. Int. J. Inclus. Educ. 25 (2), 147–165.

Mendenhall, M., Dryden-Peterson, S., Bartlett, L., Ndirangu, C., Imonje, R., Gakunga, D., Gichuhi, L., Nyagah, G., Okoth, U., Tangelder, M., 2015. Quality education for refugees in Kenya: pedagogy in urban Nairobi and Kakuma refugee camp settings. J. Educ. Emerg. 1 (1), 92–130.

Mendenhall, M., Gomez, S., Varni, E., 2018. Teaching amidst Conflict and Displacement: Persistent Challenges and Promising Practices for Refugee, Internally Displaced and National Teachers. Background Paper for Global Education Monitoring Report 2019. UNESCO, Paris, France.

Miller, E., Ziaian, T., Esterman, A., 2018. Australian school practices and the education experiences of students with a refugee background: a review of the literature. Int. J. Inclus. Educ. 22 (4), 339–359.

Miyamoto, K., 2020. Migrants and comparative education: call to re/engagement. In: Gross, Z. (Ed.), World Council of Comparative Education Societies, vol. 17. Bill, Leiden, Netherlands, pp. 205–224.

MoES, 2018. Education Response Plan for Refugees and Host Communities in Uganda. MoES, Kampala, Uganda.

Mulkeen, A., 2010. Teachers in Anglophone Africa: Issues in teacher supply, training, and management. World Bank, Washington, DC.

National Planning Authority, 2015. Pre-primary and Primary Education in Uganda: Access, Cost, Quality and Relevance. National Planning Authority, Kampala, Uganda.

Ndijuye, L.G., Rao, N., 2019. Early reading and mathematics attainments of children of self-settled recently naturalized refugees in Tanzania. Int. J. Educ. Dev. 65, 183–193.

Ohinata, A., van Ours, J.C., 2013. How immigrant children affect the academic achievement of native Dutch children. Econ. J 123 (570), F308–F331.

Orach, C.G., De Brouwere, V., 2006. Integrating refugee and host health services in West Nile districts, Uganda. Health Policy Plan. 21 (1), 53–64.

Piper, B., Dryden-Peterson, S., Chopra, V., Reddick, C., Oyanga, A., 2020. Are refugee children learning? Early grade literacy in a refugee camp in Kenya. J. Educ. Emerg. 5 (2), 71–107.

Raza, W.A., Kabir, M.M., Rashid, R., 2019. Factors affecting early grade educational attainment: Evidence from South Sudan. Int. J. Educ. Dev. 65, 92–97.

Richardson, E., Macewen, L., Naylor, R., 2018. Teachers of Refugees: A Review of Literature. Education Development Trust, Highbridge House, UK.

Rubin, D.B., 1985. The use of propensity scores in applied Bayesian inference. In: Bernardo, J.M., De Groot, M.H., Lindley, D.V., Smith, A.F.M. (Eds.), Bayesian Statistics. Elesevier Science Publishers BV, Amsterdam, Netherlands, pp. 463–472.

Schneeweis, N., 2015. Immigrant concentration in schools: consequences for native and migrant students. Lab. Econ. 35, 63–76.

Seah, K.K., 2018. Immigrant educators and students' academic achievement. Lab. Econ. 51, 152–169.

Seaman, S.R., Vansteelandt, S., 2018. Introduction to double robust methods for incomplete data. Stat. Sci. 33 (2), 184–197.

Sesnan, B., Allemano, E., Ndugga, H., Said, S., 2013. Educators in Exile: The Role and Status of Refugee Teachers. Commonwealth Secretariat, London, UK.

Todd, P.E., Wolpin, K.I., 2003. On the specification and estimation of the production function for cognitive achievement. Econ. J 113 (485), F3–F33.

Tumen, S., 2021. The effect of refugees on native adolescents' test scores: Quasi-experimental evidence from PISA. J. Dev. Econ. 150.

UBOS, ICF, International, 2018. Uganda Demographic and Health Survey 2016. UBOS, Kampala, Uganda.

UNESCO, 2011. Building a Better Future: Education for an Independent South Sudan. Education for All Global Monitoring Report Policy Paper. UNESCO, Paris, France.

UNESCO, 2016. Education 2030: Incheon Declaration and Framework for Action for the Implementation of Sustainable Development Goal 4: Ensure Inclusive and Equitable Quality Education and Promote Lifelong Learning Opportunities for All. UNESCO, Paris, France.

UNESCO, 2018a. Global Education Monitoring Report 2019: Migration, Displacement and Education – Building Bridges, Not Walls. UNESCO, Paris, France.

UNESCO, 2018b. Global Initiative on Out-of-School Children: South Sudan Country Study. UNESCO, Paris, France.

UN-HABITAT, UNHCR, 2020. Nakivale Settlement Profile: Isingiro District, Uganda. UNHCR,, Geneva, Switzerland.

UNHCR, 2017. Regional Update: South Sudan Situation: 16–31 October 2017. (Accessed 23 March 2021). Available online: 〈https://reporting.unhcr.org/sites/default/files/UNHCR%20South%20Sudan%20Situation%20Regional%20Updat%20-%2031OCT17.pdf〉.

UNHCR, 2018a. Global Trends: Forced Displacement in 2017. UNHCR, Geneva, Switzerland.

UNHCR, 2018b. Turn the Tide: Refugee Education in Crisis. UNHCR, Geneva, Switzerland.

UNHCR, 2019. Refugee Education 2030: A Strategy for Refugee Inclusion. UNHCR, Geneva, Switzerland.

UNHCR, 2020. Global Trends: Forced Displacement in 2019. UNHCR, Geneva, Switzerland.

UNHCR Representation in Uganda, 2017. Uganda Refugee Response – Monthly Snapshot: October 2017. (Accessed 23 March 2021). Available online: 〈https://reliefweb.int/sites/reliefweb.int/files/resources/Uganda%20Snapshot%20October%202017.pdf〉.

Uwezo, 2016. Are Our Children Learning? Uwezo Uganda 6th Learning Assessment Report. Twaweza East Africa, Kampala, Uganda.

Uwezo, 2018. Are Our Children Learning? Uwezo Learning Assessment in Refugee Contexts in Uganda. Twaweza East Africa, Kampala, Uganda.

Vancluysen, S., 2021. Deconstructing borders: mobility strategies of South Sudanese refugees in northern Uganda. Glob. Netw. 1–16. https://doi.org/10.1111/glob.12322.

Vyas, S., Kumaranayake, L., 2006. Constructing socio-economic status indices: How to use principal components analysis. Health Policy Plan. 21 (6), 459–468.

Wakano, A., 2016. The Effect of Ratio between PTA Teachers and Government Employed Teachers on Education Outcomes in Kenya Primary Schools. Graduate School of Economics and Osaka School of International Public Policy, Osaka, Japan. Discussion Paper 16-14.

Wamalwa, F.M., Burns, J., 2018. Private schools and student learning achievements in Kenya. Econ. Educ. Rev. 66, 114–124.

Wooldridge, J.M., 2007. Inverse probability weighted estimation for general missing data problems. J. Econ. 141 (2), 1281–1301.

World Bank, 2016a. An Assessment of Uganda's Progressive Approach to Refugee Management. World Bank, Washington, DC.

World Bank, 2016b. The Uganda Poverty Assessment Report 2016-Farms, Cities and Good Fortune: Assessing Poverty Reduction in Uganda from 2006 to 2013. World Bank, Washington, DC.