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Abstract: *In this paper we assess the short- and mid-term effects of two cash transfer programmes in Uganda in terms of child underweight, school attainment, and the monetary returns to these indirect effects. Using a micro-simulation approach we test how the scale-up of these pilot interventions could affect human capital indicators and income growth. We first use panel data to estimate the links between income, child health, and school attainment. Thereafter we insert the estimates in a micro-simulation model to predict how cash transfer programmes could generate income returns through higher education attainment and compare programmes in terms of their rates of return.*

Keywords: Cash Transfer; Uganda; Education; Child Health; Simulation
JEL I25; I26; I15; H54; O15

Introduction

In developing countries a large array of experimental and non-experimental evidence shows that improved education and health outcomes can unleash positive long term developments (Glewwe & Kremer, 2006; Glewwe & Miguel, 2007; Psacharopoulos, 1985, 1994; Psacharopoulos & Patrinos, 2004; Strauss & Thomas, 2007). Thus, in addition to the important intrinsic values of health and education, there is a large and significant economic potential to be gained by encouraging investments in these human capital aspects. There is broad consensus on the importance of education and health for development among researchers, policymakers, and practitioners. Despite large returns, liquidity constraints can hinder the human capital investments of many poor households (Kremer, Brannen, & Glennerster, 2013). Social cash transfer programmes have become a widespread instrument to alleviate the financial burden that could constrain households in their decision to send their children to school. Spurred by positive findings in evaluations, a remarkable increase in the implementation of cash transfer programmes could be observed throughout the last decade. However, in spite of promising evidence on its impacts on a broad range of outcomes, there is still limited knowledge about the mid- and long-term impacts on the transformational capacity and the public returns to social protection investments.

In this paper we simulate the returns to social protection programmes in Uganda over a period of 10 years. More precisely, we examine ex-ante how the roll-out of social cash transfer programmes could generate returns to increased education attainment through household investments in education and child health. As investments in education require time to generate economic returns, we apply a micro-simulation model to assess the potential effects within a time frame of 10 years. Therefore, we estimate the relations between income, child health, and schooling decisions and quantify the returns to higher school attainments using nationally representative panel data. Subsequently, we use the estimates in the micro-simulation model to predict how investments in two social protection programmes could generate income returns through direct (transfers) and indirect (transfer induced human capital investments) benefits. As indicators of health and education we consider underweight at age 4, school enrolment, school continuation, and attainment. Finally, we simulate the aggregate benefits and rates of return in each period contrasting the discounted social protection programme benefits with the costs.

We consider two programmes of the social assistance grants for empowerment programme (SAGE) in the analysis: firstly, Uganda’s Senior Citizen Grant (SCG), a universal social pension targeted at older persons aged 65 and above. Secondly, the Vulnerable Family Grant (VFG) targeted at vulnerable households with restricted access to the labour market and high dependency ratios. Both programmes were tested in pilot regions as part of Uganda's Expanding Social Protection (ESP) initiative contributing to the broader objectives of the National Social Protection Policy which aims at reducing poverty and socio-economic inequalities for inclusive development. While the government of Uganda has recently announced that the VFG will be discontinued, the SCG will be scaled up reaching an additional five districts per year. This means that all 55 districts will be covered by the end of the fiscal year 2019/20. The transfers of both programmes are currently worth UGX 25,000 per month (about USD 8) and are paid bi-monthly using mobile money accounts.[1] In the analysis we explore the potential returns of both pilot programmes assuming a nationwide implementation.

The remainder of the paper is structured as follows: the Literature review section provides a (uncomplete) summary of the existing evidence; thereafter the background section describes the analysed interventions, followed by a description of the data and the conceptual framework. After the Data section, we present the estimation results on the semi-elasticities of education, child health, and income. In the Micro-Simulation section we outline the simulation procedures and present the results. In the last section we present concluding remarks.

Literature review

Social protection was conceived as a safety net with a main protective and preventive nature. Nonetheless, especially in recent years, attention has turned to the promotional and transformational effects that social protection programmes have. In this sense social protection can be seen as an investment, which can generate future returns and also enhance growth with consequent benefits for the national and local economy, including an increased tax base. In the next paragraphs, we provide a short overview of these promotional and transformational effects and their relation to the possible economic returns. Special attention is given to the effects at the household level and the current gaps in the literature that this paper seeks to address.

Social protection and human capital

It is argued, and empirically studied, that social protection can contribute to economic growth in different ways. The channels through which these effects take place can be grouped along the different economic levels. These pathways can, in fact, be represented by individuals and households, the local economy (such as multiplier and spill-over effects), and by the macro economy (including also political

[1] Note that the SCG is an individual transfer, while the VFG is a flat rate paid to eligible households.

effects) (Alderman & Yemtsov, 2012; Barrientos, 2012). In this study our focus is on the micro level (individuals and households), which is also recognised in the literature as the main channel.

At household and individual level the main focus in the literature has been on the effects of non-contributory cash transfers[2], both conditional and unconditional. These programmes can, through an income effect, allow recipients to invest more in human and physical capital, smooth consumption and allow them to engage in more risky but productive activities (Fiszbein et al., 2009).[3] The present evidence focuses on the positive impact of these programmes on human capital, especially of younger individuals. Numerous impact evaluation studies have shown that relatively small cash transfers to vulnerable households can have large effects on the education and health outcomes of children in beneficiary households (Haushofer & Shapiro, 2016; Kremer et al., 2013). Some of these effects have been found to be also robust over time (Behrman et al., 2011). The results of the evaluation of the VFG and SCG pilot programmes in Uganda seem to be no exception to this. A recent evaluation of SAGE indicated that the programme had positive effects on household welfare. Beneficiary households reported higher consumption expenditures, particularly with respect to food, which led to a decrease in food insecurity and hunger. However, households also used part of the transfers for health and education related expenditures and investments in productive assets (Merttens et al., 2016).

In summary, cash transfers have been found to have a positive and significant effect on human capital, as well as in productive assets, which results in higher living standards in the long term, even when the programme has stopped (Gertler, Martinez, & Rubio-Codina, 2012).

Returns to education and health

Besides the intrinsic value of education, individuals and households invest in human capital in expectations of higher earnings. The income effect of a cash transfer can help them investing in education. The strong sensitivity of schooling decisions to costs became already clearly visible after the introduction of free primary education in Uganda in 1997, when school enrolment rates nearly doubled as a consequence (Deininger, 2003; Glewwe & Kremer, 2006).

According to the human capital theory, expenditures on education and health are investments, which are expected to increase an individual's productivity. In a classical Mincerian model on the returns to education, log earnings are regressed on years of schooling (which measures the human capital acquired

[2] The focus has been much less on contributory social insurance benefits or non-contributory benefits in kind.

[3] Some programs, especially conditional cash transfers, work also through a substitution effect. Nonetheless the focus of this paper is on the income effect of these programs.

in formal education) and experience (which measures the human capital acquired in employment). Since the earnings-schooling relationship is concave, each additional year of schooling is expected to yield lower marginal returns. Studies which investigate returns to health estimate the wage equation with the left-hand side consisting of either wages of wage earners (Dercon, Hoddinott, & Woldehanna, 2005; Schultz & Tansel, 1997; Strauss & Thomas, 2007; Thomas & Strauss, 1997) or the self-employed (Thomas & Strauss, 1997), or the wage rate (Schultz & Tansel, 1997). Health status can be both an investment and consumption good. As an investment good it is acquired by individuals to improve their productivity and as a consumption good, it is demanded to increase utility.

An essential point to make is that many social protection programmes, especially conditional cash transfers, focus on the education and health of children. This is because theory and evidence suggests that interventions at an early stage of life have a long-lasting effect and are the most cost-effective (Campbell et al., 2014; Heckman, 2006). A potential drawback of focusing on the health of children, which is more a long-term investment, is that returns will be generated over a longer time period compared to increasing adult health and consequently their (immediate) productivity.

Gaps and potential long term returns

Despite this evidence, the literature on the long-term returns to social cash transfer programmes is still underdeveloped. Just few studies have considered these lasting human capital effects to predict long-term monetary returns of programmes. Glewwe and Kassouf (2012), by using the programme's impact on school enrolment, find that Bolsa Familia's benefits in terms of increased wages may not exceed its costs. McKee and Todd (2011) predict that Oportunidades will increase future mean earnings but with only modest effects on poverty rates and earnings inequality. Todd and Wolpin (2006) estimate the effects of the PROGRESA school subsidy programme on fertility and child schooling decisions. They also compare PROGRESA with alternative programmes. Mideros, Gassmann, and Mohnen (2016) simulate the potential returns to social protection investments in Cambodia including the benefits through increased education investments of beneficiaries finding positive returns after 12 periods. This paper builds on their approach by refining the simulation model and including returns through improved child health outcomes. Even though our estimation framework is essentially incomplete and only focuses on selected health and education indicators, it provides an exploratory estimate quantifying the link of social protection investments, human capital accumulation, and income growth.

Background

In Uganda, the Expanding Social Protection Programme (ESP) was set up to establish a national social protection system as a core element in the national planning and budgeting process. The ESP was approved by the Cabinet in 2010 on a pilot basis and initially funded by donors (DFID, Irish Aid and UNICEF). Its flagship programme is SAGE – Social Assistance Grants for Empowerment – consisting initially of two types of social transfers; the Senior Citizens Grant (SCG) and the Vulnerable Family Grant (VFG). The latter was discontinued at the end of SAGE I and phasing out started in November 2015 (Namuddu & Mayengo, 2016). Implementation is under the responsibility of the Ministry of Gender, Labour and Social Development (MGLSD). ESP is part of the National Development Plan and its core objective is to reduce vulnerability and enhance productivity. The SCG is targeted using a categorical approach: all people above the age of 64 are entitled to receive the SCG.[4] Enrolment in the programme takes place yearly. For the simulation the registration is modelled as an automated procedure in which all individuals above the age threshold are granted the SCG benefits.

According to ESP costing scenarios for a national scale-up of the SCG, the overall administrative cost to payments ratio for the SCG is around 9% over the 2014/15-2021/22 period (OPM Targeting Report, 2016). Direct costs of identifying beneficiaries are estimated to account for around 28% of total administrative costs and are expected to drop to 2.8% of administrative costs after scale-up. As a proportion of benefit payments, the direct targeting costs are low at just 10.3% and estimated to plunge to 0.2% after the scale-up. Based on these figures we expect the administrative programme costs for a national implementation to be at 7.1% of the programme payments. The VFG was designed to target poor and vulnerable households with restricted labour capacities and high dependency ratios. A set of indicators is used to develop an eligibility score that allows ranking households according to their approximated vulnerability. The proportion of elderly people and children, with special weights for orphans, people with disabilities and according to gender are considered in the score. Table 6 in the Appendix provides the weights of the VFG eligibility score.

The highest scoring 15% of households in each district are entitled to receive the cash transfer. The list of potential beneficiaries is then provided by the parish chief to the village council for validation and consent. If present in a beneficiary household, adult women are selected to be the actual recipients of the transfers. Re-targeting in VFG districts was planned to be conducted every two to three years when

[4] With the exception of Karamoja district where – due to extreme poverty and reduced life expectancy – the age criterion for enrolment is lowered to 60 years.

newly eligible beneficiaries would be enrolled. In the simulation model we compute the eligibility score in each period and assign VFG benefits to the top 15% of households at district level.[5] In the simulation we do not model targeting errors and assume that the allocation of benefits strictly follows the eligibility scores.

The overall administrative cost to payments ratio for the VFG is estimated to be around 32% (OPM Targeting Report, 2016). The direct targeting costs are estimated to decrease from 65% to around 57% of the administrative costs after a national scale-up. As a proportion of benefit payments the direct targeting costs are expected to decrease to 13%. Based on these figures we use administrative costs of 22.8% of the programme payments in the simulation model.

Analytical Framework

Our framework connects household decisions regarding child health, schooling and returns to schooling. For the relation of child health and schooling we follow a simple model developed by Glewwe and Miguel (2007): there are two time periods that refer to pre-school age and school age of a child. Thereby skills obtained in school at the end of the second period are a function of child health in the first and second period, parent's educational investments (monetary and time), child's innate ability, school characteristics/quality. In this (structural) schooling production function, all variables have a positive effect on school outcomes in period 2. Thus, child health in the first period has a positive effect on schooling outcomes in period 2 holding everything else fixed. Parents' utility is a function of consumption in period one and two; child's health in both periods; child's school attainment in period two. Parents maximise their utility function conditional to a budget constraint, the skills production function, and child health which is a function of medical inputs, the local health environment, and the innate health predisposition.

SAGE programmes increase the disposable income of households and thus relax the budget constraint. This is expected to increase the demand for child health inputs and the demand for schooling (directly and indirectly through improved child health). However, effects depend on whether the benefits are allocated in time period one or two. In period two, parents cannot go back and change their investment decisions in child health. In this case, the short term effect of SAGE on schooling works only through the education investments effect and the immediate effect of child health in period two on schooling decisions. Considering that SAGE beneficiaries in period one can internalise outcomes of period two in

[5] For the eligibility score we use the weights as presented in Table 6 except that we cannot differentiate between partial and severe disability (severe disability weights used).

their decisions, schooling increases through increased education and health investment in period two and through improved health in period one. Because of data constraints (discussed in the next section), we only consider the programme effects on child health before children enter school (period 1) and not during their time in school (period two). This implies that programmes require several years to unfold their full potential through child health in period one and the immediate education investments in period two. Therefore we simulate the SAGE effects over a period of 10 years to also account for more long term programme effects.

Increased school attainment induced by SAGE transfers further increase household incomes through higher earnings from improved education. The conventional return to education pathway suggests that more educated individuals earn higher wages as they become more productive. However, positive returns to education have also been reported for self-employed farm and non-farm earnings, which is important in a context of a large informal sector (Appleton, 2001c; Jolliffe, 2004). The returns to education further increase household's disposable income and improve child health and schooling. We refer to direct programme effects as those induced directly by SAGE cash transfers and indirect effects as those induced by increased programme induced investments in child health, schooling and returns to schooling. Figure 1 displays the analytical framework.

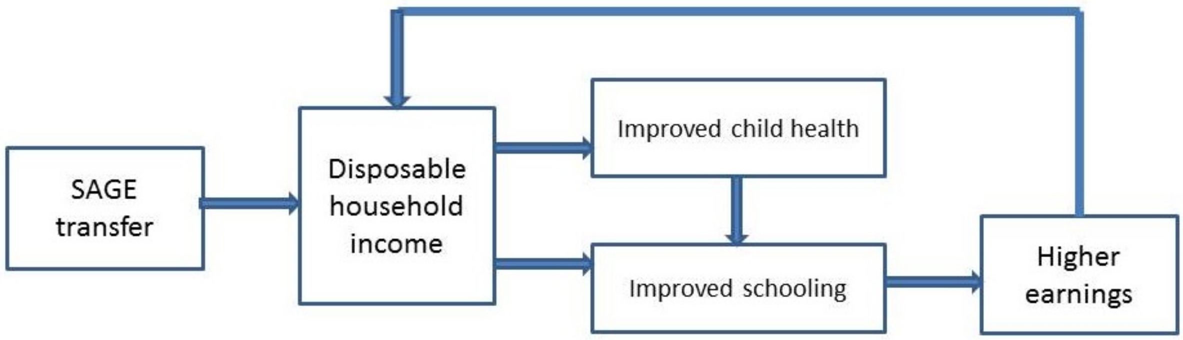

Figure 1: Analytical framework

Data

We use the Uganda National Panel Survey (UNPS), a nationally representative panel household survey that aims at producing empirical evidence for key policy areas. The sampling was based on the 2005 Socio-economic and Community survey. As the questionnaire design has changed markedly and several key variables were not collected in 2005, our analysis uses the four waves from 2009 to 2013. The UNPS is carried out annually over a twelve-month period covering a nationally representative sample of households. Each household is visited twice per year to account for seasonal fluctuations of expenses and income.[6] About 3,000 households were selected in 2009 out of which approximately 2,700 were interviewed in 2010, 2,800 in 2011 and 3,100 in 2013.[7] In total the sample includes observations of 82,718 individuals. For the analysis, we focus on households with at least two observations over time. Each wave includes a household, agricultural, and community module. Besides general household information we make use of the detailed education, health, expenditures, income, and agricultural sections. In addition we use the community data for health and education facility information.

Descriptive Statistics

Table 1 presents the descriptive statistics of the main outcome variables. The income variable is at the core of our analysis. We aggregated all household income sources including employed and non-employed work, farm incomes, non-farm enterprises, and other household incomes such as rents, interest rates, and inheritances. However, the income reports seemed incomplete, with a considerable number of negative incomes.[8] This is at least partly related to missing observations and changes in the questionnaire design across waves. Therefore we decided to use consumption to approximate household incomes).[9] Household consumption aggregates at 2005 prices are provided in the data set. The average monthly consumption per capita in 2005 prices summed up to around 37.000 UGS (approximately 47 US$). Crop farming was the main income source followed by incomes from non-agricultural enterprises, livestock and wage earnings and other household incomes (transfers, rents etc.). The data shows, that real household consumption was on average highest in 2009 and dropped markedly in 2010/11 and 2011/12.

As outlined in the framework we are interested in the programme effects on household's education investments. School enrolment is often erratic and the line between drop-outs and low attendance is

[6] The survey is conducted in two visits (approximately six months apart) in order to better capture agricultural outcomes associated with the two cropping seasons of the country (January – June and July – December). Approximately half of the households were randomly selected for the entire household questionnaire to be administered in the first visit, and a roster update in the second visit. The inverse happened for the other half of the sample.

[7] In 2013 1,800 new households were added to the sample.

[8] On average more than 15% reported negative or no incomes in all 4 waves.

[9] We estimated the models using an income aggregate. The main results hold, but we were not able to find instruments that explain the variation of incomes over time, which resulted in weak instrumental variables problems. Besides a long list of household assets and durables we used external rainfall data as described in Bengtsson (2010) as instrument for incomes.

blurred (Glewwe & Kremer, 2006). As the frequency of school participation is not covered in the data, we use a binary variable that describes whether household members are currently enrolled in school and the grade they are attending. However, the panel structure of the data allows us to analyse how changes in income affect school dropouts. School enrolment rates of school age children (6-24) remained relatively constant at about 77% in all waves with the lowest enrolment rates reported in 2013. Despite that, school attainment of adults above 16 with completed schooling was highest in 2013 with an average of 6 years of schooling, which increased by nearly half a year compared to 2009.

Besides education, we consider the indirect programme effects on child health. Trying to capture the full meaning of health seems impossible due to the multi-dimensional aspects and factors that make up health. The World Health Organization (WHO) mainstreamed several indicators to approximate the different dimensions of child health. Among those, anthropometric indicators have been the workhorse in the health economic literature and have been shown to be correlated with a large array of current and future health outcomes (Strauss & Thomas, 2007). As we are interested in the proximate effect of an income increase on child health, we use a binary variable for child underweight classified as a weight-for-age z-score below -2. Weight-for-age is a more contemporaneous measure of the nutritional status and better suited to capture short-term changes in incomes than height-for-age, which covers the aggregate of health investments over a longer period (Duflo, 2000, 2003; Haddad, Alderman, Appleton, Song, & Yohannes, 2003; Strauss & Thomas, 2007). We decided to regard the likelihood of underweight in the simulation to approximate severe health problems. The data set includes weight and height information for about 63% of all children up to age 4 in the sample. Following WHO growth standards and recommendations we construct age and gender specific z-scores out of which observations below -2 standard deviations from the reference values given by WHO are classified as underweight. In the analysis we disregard about 6.5% of children -mostly toddlers below one year of age- that have been measured in a lying position to avoid measurement error. Table 1 shows that child underweight at age 4 was about 12% on average and fell from 14% in 2009 to 10% in 2013. Descriptive statistics and definitions of the control variables used in the analysis can be found in the Appendix Table 7.

Table 1 Descriptive Statistics of the main Outcome Variables

	Total	2009	2010	2011	2013
Consumption per capita in 2005/6 prices (UGS), per month					
Mean	38,921	52,042	38,705	28,589	33,104
S.D.	46,676	53,747	51,406	37,587	28,022
N	69,129	19,962	19,069	19,924	10,174
Current School Enrolment (age 6-24)					

Mean	0.76	0.76	0.76	0.77	0.75
S.D.	0.43	0.43	0.43	0.42	0.43
N	27,511	7,947	7,081	7,371	5,112
School Attainment (Completed years of schooling, age>16)					
Mean	5.83	5.57	5.95	5.79	6.13
S.D.	4.20	4.19	4.19	4.19	4.24
N	21,513	6,176	5,508	5,762	4,067
Underweight at age 4 (binary variable if weight-for-age z-score below -2)					
Mean	0.12	0.14	0.09	0.14	0.10
S.D.	0.33	0.35	0.29	0.34	0.29
N	1,162	452	248	355	193

Note: own calculations based on UNPS data using nationally representative sampling weights. The number of observations varies because of the age filters and because of missing observations in the underweight and consumption variables.

Elasticities

In order to generate the coefficients for the micro-simulation model, the relations between income, child health and education need to be quantified. Therefore we estimate the effect of an increase in income on child health, school enrolment and school continuation. Thereafter we quantify the returns to education on incomes. The estimated coefficients are then used in the micro-simulation model to analyse how social transfers could generate human capital and benefits through higher levels of education. As explained above we use household consumption per capita in the whole analysis to approximate incomes.

Indirect Effects: Child Health

To quantify the effect of income on child health, we regress a binary variable underweight H_{it} on the logarithm of consumption $\ln(I_{it})$ and a set of additional regressors N_{it}.[10] The selection of control variables mainly follows a study by Haddad et al. (2003) in which the authors analyse income effects on pre-school Weight-for-Age z-scores in 12 developing countries. As we are interested in the short-run effect of incomes on child health, we control for the local health infrastructure and the household specific sanitation endowment.[11] In addition we control for household characteristics including the level of education of the household head, size and composition of the household and individual characteristics including age, sex, and orphan-hood status and include regional and time fixed effects, which can be presented in a simplified form as follows:

[10] We use the natural logarithm of consumption to regard the log-normal distribution of the consumption variable in the data. For the simulations we apply a Duan's smearing factor to retransform log consumption predictions to level values (Duan, 1983).

[11] In the long run households with higher incomes can choose to invest in the health environment through own investments (sanitation or drinking water) or investments are made on behalf of them on the community level.

Equation (1) $$H_{it} = \beta + \gamma \ln(I_{it}) + \theta N_{it} + u_i + u_{it}$$

As baseline model we estimate a linear random effects model. In the second step, we estimate individual fixed effects models that avoid unobserved heterogeneity bias through genetic predisposition and other time invariant factors. Lastly, we estimate two stage least square (2SLS) models to account for potential measurement error of consumption reports and the potential simultaneity of time allocated to income generating activities and child care. Therefore, we instrument household consumption using various assets and durable goods including land ownership, prevalence of cell phones, and ownership of non-housing buildings as instrument for household consumption. Similar instruments have been used in the literature as their prevalence is correlated with household consumption, but they have no direct bearing on child health (Haddad et al., 2003; Mideros et al., 2016). It could be argued that cell phones give access to information that improve health, however, in the case of Uganda there were -to our knowledge- no large scale mobile based information programmes in the analysed period that could have had a direct impact on the likelihood of child underweight making it a valid instrument. The complete estimation tables including all control variables and the first stage of the 2SLS can be found in the Appendix Table 8.

Table 2 Consumption Effect on Child Underweight (age 1-4)

	(1) Underweight (OLS RE)	(2) Underweight (OLS FE)	(3) Underweight (2SLS RE)	(4) Underweight (2SLS FE)
Ln Consumption	-0.05**	0.02	-0.11*	0.10
	(-3.71)	(0.74)	(-2.19)	(0.75)
Observations	2175	2175	2172	1663
R^2		0.06		0.04
p-value of Hausman test [1]	0.00		0.55	
First stage F- Statistic[2]			162.27	7.33
Sargan score p-value[3]			0.11	0.25
p-value of Wald test of exogeneity[4]			0.01	0.52

t statistics in parentheses. Complete regression table in the Appendix Table 8. Cell phone, land ownership, and ownership of non-housing buildings used as instrument for consumption. Linear probability models estimated and two stage least squares estimations in models 3 and 4.
[1] test of orthogonality of regressors and individual effects
[2] F-statistic of the first stage estimation to be compared with Stock-Yogo critical values
[3] test if the over-identifying restrictions are valid
[4] test of non-significance of the residuals from the first-stage OLS regression in the second stage
* $p < 0.05$, ** $p < 0.01$

The estimated consumption semi-elasticities are displayed in Table 2. The results show a negative effect of consumption on the likelihood of underweight of children between age 1 and 4 in the random effects models. The consumption coefficient of the fixed effects model is not significant and changes sign. Based on the applied instrumental variables the exogeneity of consumption is rejected by the Wald test of exogeneity, and based on the model the 2SLS approach is appropriate. As with the OLS models estimating fixed effects leads to a change in coefficient signs and a non-significant consumption coefficient. Despite the OLS models, a Hausman test does not reject the absence of correlation between the regressors and the individual effect. There could be a couple of reasons why the random and fixed effects estimates of the consumption coefficient differ despite a non-significant Hausman test. First, dropping time-invariant covariates in the fixed effects estimations could affect the consumption coefficients without undermining the test results on the correlation between the regressors and the individual effect. Secondly, the variation of the instrumental variables over time is low and explains only a small share of the variation in consumption over time. The F-test of the first stage estimation is slightly below the 10% critical Stock-Yogo value, which could lead to a poor performance of the estimator.[12] Therefore we use the specification of column 3 for the micro-simulation model.

The coefficient suggests that a 10% increase in consumption decreases the likelihood of child underweight by 1%.[13] Our estimate seems to be in line with the mean coefficients of all 12 countries analysed in Haddad et al. (2003). Their results for Sub Saharan Africa include Kenya, South Africa, and Mozambique indicating a (large) income elasticity range of 0.08 in South Africa to 0.41 in Kenya estimating 2SLS models, however, using weight-for-age z-scores instead of underweight. Similarly, Bengtsson (2010) finds in Tanzania that child weight is sensitive to income changes particularly of female children. The authors find that a 10% decrease in income resulted in a 0.5 kg decrease in the body weight of females up to age 4.

Indirect Effects: Schooling

Following our research framework we measure the quantity of education as completed years of schooling using two steps: first, we estimate school enrolment for children between age 4 and 8 as a function of household's income and children's underweight status at age 4; thereafter we regress subsequent school continuation for children up to age 24 on household incomes.

In the first step we estimate the effect of household consumption $\ln(I_{it})$ and underweight at age 4 (CH_i) on the likelihood of school enrolment (E_{it}). Therefore we explore the panel data to test how underweight at age 4 affected the school enrolment in the following data waves. Given that our data covers a time span from 2009 to 2013, we estimate the likelihood of school enrolment up to age 8. However, modelling the link between health and enrolment is complex and there are many confounders that affect education and child health investments. As underweight at age 4 is determined before school enrolment decisions are taken, there is less of an identification problem here (Glewwe and Jacoby

[12] Using different sets of instrumental variables further weakened explanation power.
[13] Marginal effects of probit models instead of linear probability models show similar coefficients.

(1994)). We use proxy variables to control for confounders of school enrolment N_{it} as far as the data allows. Therefore we include the education level of the household head, access to schools in the community, as well as household composition, time and regional fixed effects and other household characteristics. As underweight at age 4 is time invariant, we are not able to estimate the effects of underweight at age 4 with a fixed effects model.[14] As in the previous models we furthermore present 2SLS models instrumenting household consumption using land ownership and household's durables.

Equation (3) $$E_{it} = \beta + \gamma \ln(I_{it}) + \delta CH_i + \theta N_{it} + u_i + u_{it}$$

After estimating the income and child health effects on school enrolment we estimate how income affects school continuation. That means we test how changes in income affect the likelihood of school drop-outs. Other than the estimation of school enrolment, we do not account for child health effects as information on underweight at age 4 is not available for older children and the panel structure is not longitudinal enough to capture the health effects on higher education levels. Yet, in the simulations child health is implicitly –though only partially- incorporated through the effect on first time school enrolment, which affects subsequent schooling decisions. For the estimations we use a similar approach as outlined in equation (3) separately for primary, secondary, and tertiary education ages. However, estimating the likelihood of school continuation is subject to a number of challenges. Most importantly, simultaneity and unobserved heterogeneity could bias the estimated coefficients. Simultaneity arises if school enrolment is a substitute for child work, which could lead to a downward bias of the estimated coefficient (Grimm, 2011). Typical concerns with unobserved heterogeneity include child's ability and a time variant correlation of household incomes and opportunities to obtain a job that requires a certain degree of education. Therefore we additionally estimate individual fixed effects models and 2SLS models using household assets and durables as instrument for consumption as described in the previous section.

Table 3 Consumption and Underweight Effect on School Enrolment (age 5-8)

	(1) Enrolment (OLS RE)	(2) Enrolment (2SLS RE)
Ln Consumption	0.01	-0.01
	(0.53)	(-0.16)
Underweight at age 4	-0.14**	-0.14**
	(-3.83)	(-3.87)
Observations	1307	1304
p-value of Hausman test [1]	0.09	
First stage F- Statistic[2]		53.36

[14] As robustness check we explored the variation within households estimating family fixed effects as suggested in. Nonetheless the allocation of investments within households remains unobserved. The estimation results were similar in size, but the child health effect not significant.

Sargan score p-value[3]	0.87
p-value of Wald test of exogeneity[4]	0.68

t statistics in parentheses. Cell phone, land ownership, vehicle, and ownership of non-housing buildings used as instrument for consumption. Linear models estimated in 1 and 3 and probit model in 2. Complete regression in Table 9 in the Appendix.
[1] test of orthogonality of regressors and individual effects
[2] F-statistic of the first stage estimation to be compared with Stock-Yogo critical values
[3] test of the over-identifying restrictions
[4] test of non-significance of the residuals from the first-stage OLS regression in the second stage
* $p < 0.05$, ** $p < 0.01$

The estimated semi-elasticities of income and underweight are displayed in Table 3. The coefficients suggest a negative and significant effect of underweight at age 4 on school enrolment. Being underweight at age 4 was associated with a 14 percentage point decrease in the likelihood of school enrolment between age 5 and 8.[15] At the same time, we find no effect of consumption on the likelihood of school enrolment. Based on the applied instrumental variables the exogeneity of consumption is not rejected by the Wald test of exogeneity . We thus use specification 1 for the simulation model. These results are in line with a study on the effect of child health on delayed enrolment in Ghana. Glewwe and Jacoby (1994) find that lower Height-for-Age z-scores increased delayed enrolment significantly whereas household income had no effect on delayed enrolment when treated as endogenous.

In the next step we present the consumption effects on school continuation of previously enrolled children (displayed in Table 4). The baseline random effects model shows a positive and significant effect of consumption on school continuation. The results hold when estimating individual fixed effects models and for the sub-samples of primary, secondary, and tertiary age individuals. 2SLS models do not indicate any significant consumption effects on school continuation; Wald tests of exogeneity do not reject the exogeneity of consumption based on the applied instrumental variables (see column 5-7), which is why we use the OLS specifications of columns 2 to 4 for the simulations.

The relatively small effect of consumption on school continuation could be related to the introduction of free primary education in Uganda in 1997. Deininger (2003) showed that free primary education reduced the effect of household incomes on enrolment decisions significantly and balanced the strong gender bias towards male enrolment rates. The success of public education policies could explain why the consumption coefficients are small compared to findings in other countries (Grimm, 2011; Kremer et al., 2013; Mideros et al., 2016). However, this would also imply that there is less scope for the cash transfer programmes to increase education outcomes in Uganda.

[15] Marginal effects of probit models instead of linear probability models show similar coefficients. Including the inverse Mills ratio in the estimations to regard the selection of children into school enrolment results in very similar coefficients (probit random effects models; not presented).

Table 4 Consumption Effect on School Continuation (age 6-24)

	(1) School Continuation (OLS RE) (5-24)	(2) School Continuation (OLS FE) (5-12)	(3) School Continuation (OLS FE) (13-18)	(4) School Continuation (OLS FE) (19-24)	(5) School Continuation (2SLS FE) (5-12)	(6) School Continuation (2SLS FE) (13-18)	(7) School Continuation (2SLS FE) (19-24)
Ln Consumption	0.04**	0.01*	0.02*	0.06**	0.01	-0.03	-0.11
	(12.14)	(2.13)	(2.21)	(3.78)	(0.44)	(-0.33)	(-0.80)
Observations	25945	12467	8264	5214	9582	6062	3454
R^2		0.01	0.10	0.13	0.01	0.09	0.08
p-value of Hausman test [1]	0.00						
First stage F- Statistic[2]					37.47	13.77	10.26
Sargan score p-value[3]					0.51	0.22	0.09
p-value of Wald test of exogeneity[4]					0.88	0.57	0.21

t statistics in parentheses. Cell phone, land ownership, vehicle, and ownership of non-housing buildings used as instrument for consumption. Linear models estimated. Complete regression table in Table 10 in the Appendix.

[1] test of orthogonality of regressors and individual effects

[2] F-statistic of the first stage estimation to be compared with Stock-Yogo critical values

[3] test if the over-identifying restrictions are valid

[4] test of non-significance of the residuals from the first-stage OLS regression in the second stage

.$^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Returns to Education

Increased school enrolment and improved child health leads to higher educational attainment, which eventually generates returns to education. The conventional pathway suggests that more educated individuals earn higher wages as they become more productive. Non-experimental studies which have analysed returns to education typically use the Mincerian framework (Appleton, 2001a; Card, 2001; Girma & Kedir, 2005; Kingdon & Soderbom, 2007; Psacharopoulos & Patrinos, 2004). In the Mincerian model, log wages are regressed on years of schooling (S_i) and work experience ($A_{it}\ and\ A_{it}^2$):

Equation (4) $$\ln\left(Y_{it}\right) = \beta + \delta S_i + \varepsilon A_{it} + \epsilon A_{it}^2 + u_{it}$$

However, there are several problems encountered in estimating returns to education in Uganda; firstly, only a relatively small fraction of households receives a wage salary (about 14% of working age adults reported wages from employed work). However, positive returns to education have also been reported for self-employed farm and non-farm earnings (Appleton, 2001c; Jolliffe, 2004). We use consumption as approximation for income and thus consider all forms of household incomes. Therefore we regard the allocative effect of education on consumption and estimate the effect of the highest school attainment in the household on consumption.[16]

Secondly, endogeneity problems could lead to biased coefficients. This could for example come from workers' unobserved ability systematically correlating with both years of education and the dependent

[16] As robustness check we estimated the returns to education using the mean years of schooling, which led to very similar results.

earnings, or systematic measurement error in consumption reports. Several scholars have dealt with endogeneity problems by estimating returns to education using two stage least squares models (Card, 2001; Kerr & Quinn, 2010; Leyaro, Morrissey, & Owens, 2010; Rankin, Sandefur, & Teal, 2010). We follow this approach using access to primary and secondary schools on the community level as instrument for educational attainment as has been suggested in the literature (Glewwe & Miguel, 2007). Restricted access to schools increases the cost of schooling, which is expected to be negatively related to school attainments. On the other hand, the accessibility of schools is expected to have no direct effect on incomes, qualifying it as instrument for the maximum and mean level of schooling in the household. In Table 5 we show the estimated coefficients of the max school attainment in households on log consumption.

Table 5 Effect of School Attainment on HH Consumption

	(1) Ln Consumption (OLS RE)	(2) Ln Consumption (2SLS RE)	(3) Ln Consumption (OLS FE)	(4) Ln Consumption (2SLS FE)	(5) Ln Wage (hourly) (Heckman Selection)
Max. School attainment in HH	0.05^{**}	0.11^{**}	0.00	0.06	
	(30.84)	(6.60)	(1.30)	(0.24)	
School attainment (individual)					0.17^{**}
					(7.69)
Observations	11098	9339	11098	9339	25059
p-value of Hausman test [1]	0.00			0.00	
First stage F- Statistic[2]		75.09		2.19	
Sargan score p-value[3]		0.17		0.25	

t statistics in parentheses Access to primary and secondary school used as instrument for school attainment in columns (2) and (4). Linear models estimated. Estimations in column 5 based on individual wages and Heckman selection model. Complete estimation table in Table 11 in the Appendix.
[1] F-statistic of the first stage estimation to be compared with Stock-Yogo critical values
[2] test of the over-identifying restrictions
[3] test of non-significance of the residuals from the first-stage OLS regression in the second stage
* $p < 0.05$, ** $p < 0.01$

The results of the random effects models indicate a positive and significant effect of maximum school attainment on household consumption. An additional year of the maximum level of schooling is associated with a 5% increase in consumption. The effect more than doubles if we estimate 2SLS models with access to primary and secondary schools in the community as instruments for school attainment.[17] Wald tests of exogeneity results suggest that school attainment should be treated as endogenous in our specification. In the fixed effects estimations the coefficient are still positive but drop markedly. As in previous estimations our instruments vary little over time. The F-statistic of the first stage estimation is

[17] Note that the number of observations drop markedly in the 2SLS model as the community information on access to schools has many missing observations.

very low and the estimation suffers from weak identification. Therefore we prefer the specification of column 2. As robustness check, we estimate the effect of school attainment on individual wages (column 5) with a Heckman selection model, which suggests an increase of 17% in hourly wages for an additional year of education, which is larger compared to our preferred model. This is not surprising as returns to education have been found to be lower for farm earnings than for employed work (Appleton, 2001c; Jolliffe, 2004). Earlier estimates on the returns to education in Uganda find that four years of primary education increase the agricultural production by about 7% (Appleton & Balihuta, 1996) and increase wages by about 7%-8% for each additional year of schooling (Appleton, 2001c). Psacharopoulos and Patrinos (2004) report an average return of 12% in wages of an additional year of schooling in Sub Saharan Africa, which corresponds to our findings.

Micro-Simulation

In order to assess the short and mid-term effects of the programmes, we construct a micro-simulation model. We simulate the programme effects over a 10 years' time range on the national level. That means that we simulate the effects not only in the pilot regions where the SCG and VFG are or have been implemented, but for the hypothetical case of a country-wide implementation. The dynamic simulation model incorporates the child health and education responses and returns to education as estimated in Table 2 to Table 5. The income level approximated by household consumption is calibrated using the UNPS 2011 data.[18] Based on the VFG and SCG eligibility criteria, the programme transfers are assigned either to individuals above age 64 (SCG) or to the top 15% in each district in terms of the eligibility score (VFG). That means, we assume that the allocation of programme benefits strictly follow the targeting formula and that benefit take-up is 100%. As households do not necessarily consume the complete transfers, we apply a propensity to consume of 80% following Angelucci and Attanasio (2009). Hence, we assume that each UGS transferred, increases consumption by 0.8 UGS. The programme transfers are equally distributed among household members. This means that individual grants are equally shared within the household.[19]

The simulation procedures are the same in each period as outlined in Figure 5 in the Appendix. First, eligible households are allocated the programme transfers, which increases their consumption level by 0.8 times the transfers. Based on the new consumption level, the model predicts children's health, the

[18] We use 2011 as it offers most information on child underweight at age 4 and current school enrolment. We do not use 2013 as the number of household with at least two observations over time is relatively low.
[19] Existing evidence advocates against the alternative assumption that pensions are not shared within households (e.g. Woolard and Klasen (2005)).

likelihood of school enrolment, and the likelihood of school continuation (separately for primary, secondary, and tertiary school age) according to the preferred models of Table 2 to Table 4. Subsequently, the educational attainment is updated if individuals completed an additional year of schooling. This allows us to assess how an increase in income could affect our education and child health indicators. In the third step we simulate the returns to higher education attainments using the coefficients as presented in Table 5. Therefore, programme induced changes in educational outcomes are compared to a control scenario without the programme transfers. In that regard the indirect benefits can be formulated as follows:

Equation (5) $$B = E_{t=1} - E_{t=0}$$

Where $E_{t=1}$ refers to the expected outcomes including the indirect effects and $E_{t=0}$ to the expected outcomes in the absence of the programmes. The new income levels are calculated as the sum of the previous income level plus the direct effect (transfers) and the indirect benefits (returns to education). The difference in income in a scenario with and without the programmes reflects the overall benefits B of the programmes in our model.

In the last step, the micro-simulation includes a demographic module accounting for demographic changes over time. We incorporate WHO mortality rate projections by age and sex to probabilistically determine deaths and newborns of women age 15-49 in each period. The simulated population increases at an average rate of 2.8% per period, which is close to the observed annual population growth of around 3% in the last 5 years. The demographic development in the model is the same for control and programme scenarios as the data does not allow estimating mortality and fertility rate changes with higher incomes. The demographic module ensures that individual eligibility is adjusted within the simulation horizon. For example, individuals that turn 65 during the simulation period become eligible for the SCG. Similarly, the VFG eligibility score is estimated in each period. At the end of each period, the demographic changes are realised. In the next period households need to qualify again for the programme transfers and only the educational benefits are carried over to the next period's income. This procedure is performed for 10 periods. As it is too complex to model the formation of new households such as for example children moving out to build new families, we only simulate the mid-term effects over 10 periods in order to avoid excessively large households over time.

Similar to the programme benefits, the costs can also be separated into direct and indirect sources. The direct costs refer to programme transfers and operational costs. The costs of sending children to school (fees, uniforms etc.) are implicitly incorporated in increased household expenditures. From a policymaker's perspective there could be indirect costs associated with the public provision of education, or, given a fixed education budget, a decrease in the quality of (and returns to) education for example due to increasing class sizes. In addition, the distortionary cost of raising money to finance the provision of additional schooling could further increase the costs for the public. These indirect costs are important, but difficult to quantify. We only consider the programme related operational and administrative costs, something that needs to be born in mind in the interpretation of the results.

Micro-Simulation Results

We present the simulation results as relative changes of implementing the VFG and SCG compared with the control scenario without any transfers (see equation 5). Therefore we fit the simulated data of the programme effects per period using local mean smoothing techniques. We use Nadaraya–Watson Epanechnikov kernel estimators with a rule of thumb bandwidth of 1.5 to fit the outcome variables per period. As we only observe outcomes once per period (discrete variable), we selected a bandwidth larger than the optimal bandwidth minimising the mean integrated squared error (MISE) using least square cross validation.[20] Furthermore, we present confidence intervals for the individual or household level variation in outcomes.[21]

Child Health

Figure 1 shows the simulated programme effects on child underweight at age 4. For the VFG, the likelihood of child underweight decreases along the 10 periods with the programmes compared to the control scenario without transfers. The SCG also reduces the likelihood of child underweight, but the effect diminishes over time. After 10 periods the effects of both programmes converge to an annual reduction in child underweight of 0.2 percentage points. The initial differences between SCG and VFG are mainly driven by different programme sizes. While about 60% of households have at least one member above the age of 65 and would thus receive SCG, by definition only 15% of households would be assigned VFG transfers. The diminishing effect of SCG over time can be explained with demographic changes. In the simulations, the share of households with individuals over 65 and children of age 4 is decreasing over time. Disregarding the demographic module leads to a slightly decreasing likelihood of child underweight over time.

[20] Findings do not change markedly using bandwidths between 1-2 in steps of 0.25 as robustness check (not presented).

[21] In addition, several probabilistic elements (mortality, fertility, propensity of school enrolment etc.) in the simulation model can lead to a variation in the simulated outcomes. Figure 7 in the Annex displays the variation in outcomes due to probabilistic elements in the simulation after iterating the simulation model for25 times.

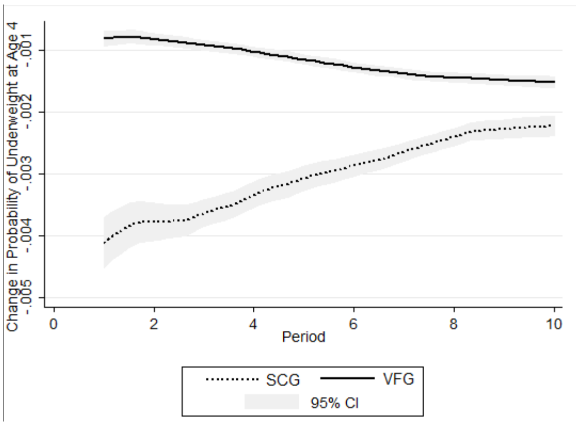

Figure 1 Programme effects on child underweight at age 4 (local mean smoothing with bandwidth of 1.5)

Education

Figure 2 shows the simulated programme effects on school enrolment of children between age 5 and 8 and the subsequent likelihood of school continuation for the age bracket between 6 and 24. The simulation results indicate very small programme effects on school enrolment. The effect is largest for the SCG and increases over time. However, after 10 periods the likelihood of first time school enrolment only increases by slightly less than 0.02% compared with the control scenario. As Uganda has introduced free primary education for many years now, the results could reflect that there is little scope for the programmes to further increase school enrolment rates.

The effects on school continuation of all previously enrolled children between age 6 and 24 range between 0.5% (SCG) and 0.1% (VFG) after 10 periods. The effects only marginally increase over time (SCG) or remain stable (VFG) throughout the 10 periods of the simulation.

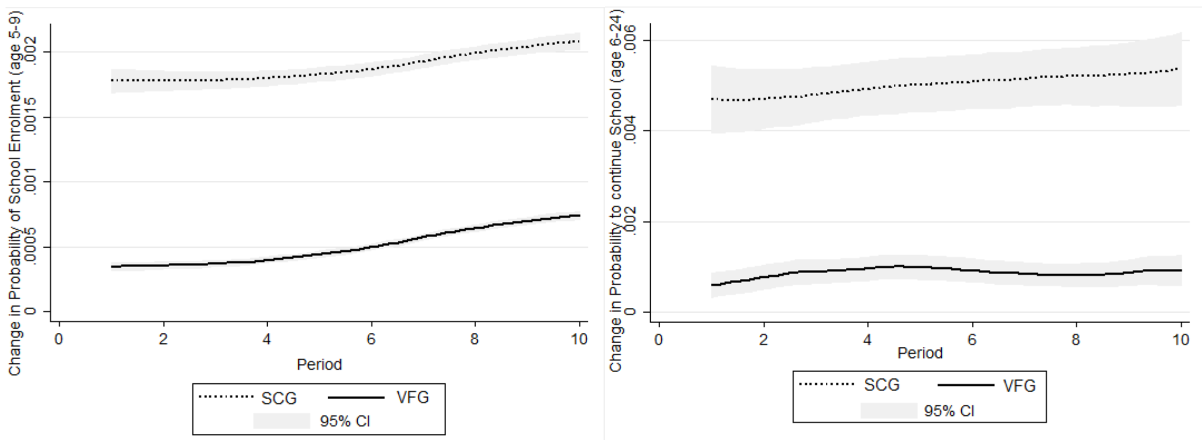

Figure 2 Programme Effects on School Enrolment (6-9; left) and School Continuation (age 6-24; right) (local mean smoothing with bandwidth of 1.5)

The combined effects on school enrolment and continuation increase school attainment measured as completed years of schooling. The effect is relatively low, but increases over time resulting in a difference of slightly more than 0.01 years of schooling in the SCG scenario after 10 periods. The figure seems relatively small, but it has to be noted that it refers to all individuals with completed schooling, which reflects about one third of the population of roughly 39 million Ugandans, which translates into a very large absolute number of additional years of schooling that the programmes could generate. As with the previous results, the effect is significantly larger for SCG compared with VFG due to the larger number of programme beneficiaries and higher average transfers.

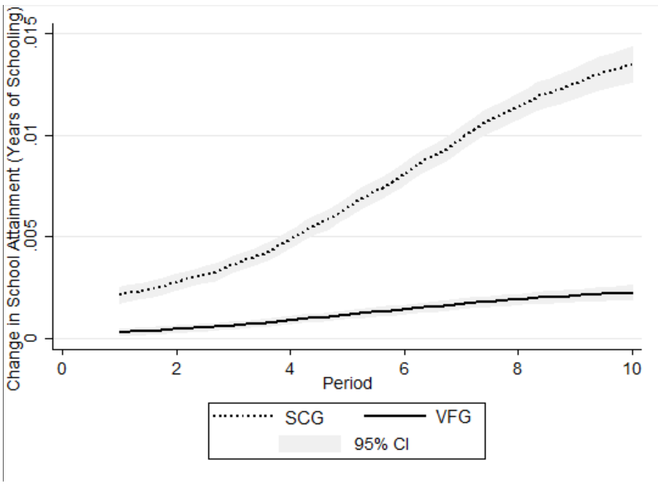

Figure 3 Programme Effects on School Attainment
(Years of Schooling; local mean smoothing with bandwidth of 1.5)

Returns to Education

In the last step we examine the monetary returns to increased school attainment. The monetary returns to education per year are close to zero in the beginning but increase steadily to about 100 UGS (SCG) and 20 UGS (VFG) per capita in period 10. The results underpin that investments in education require time to unfold their potential. However, comparing the education returns to the programme transfers still shows a negative balance after 10 periods. On average each individual received around 5.000 UGS in the SCG scenario and 650 UGS in the VFG scenario per period. To account for the different cost structures, Figure 4 presents the rate of return (RoR) of both programmes. Therefore the sum of direct and indirect benefits generated through education returns are compared to the sum of the operational costs of the programme. Benefits and costs are discounted with a discount rate of 10%.[22] The results show that both

[22] The discount rate was set based on the inflation rate of 6.5% in 2012-2013 plus a net interest rate of 3.5%.

programmes do not generate positive returns through education. However, we see an increase of around 3% of both programmes over time due to the returns to education. The results suggest that the SCG performs better in terms of the RoR, which is due to the lower operational costs of the programme.

The negative RoR's could be related to the fact that only 80% of the programme transfers are used for consumption and thus 20% of the transfers are regarded as unproductive costs in the analysis. Using a propensity to consume of 100% instead, the RoR turns positive after 13 periods for the SCG but still remain negative after 20 periods for the VFG.

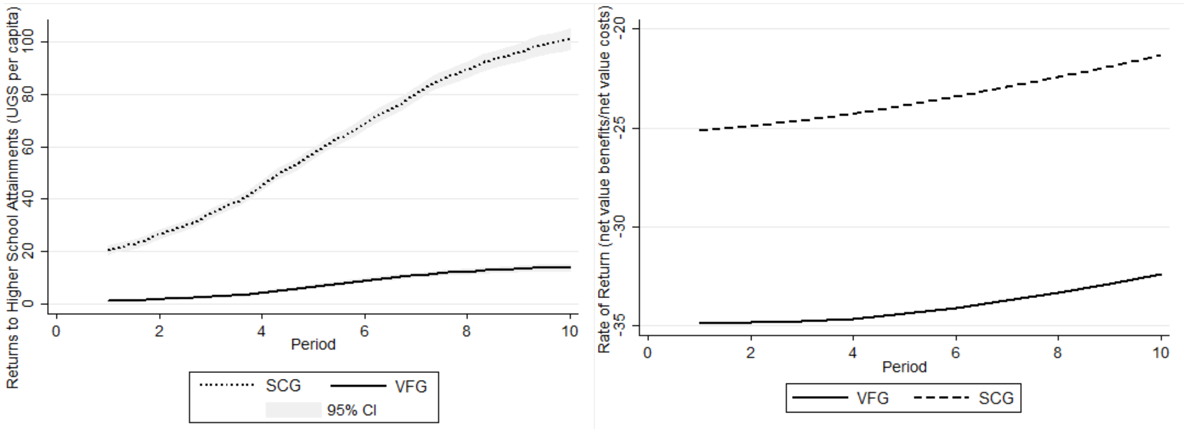

Figure 4 Monetary Returns to Education (local mean smoothing with bandwidth of 1.5) and Rates of Return (line graph)

Discussion

Our simulation model is a simplification of real life that is certainly flawed to some degree. Still, we want the model to be a good enough approximation to shed light on the programmes effects on child health and school attainment. It is important to realise that this ex-ante assessment only considers monetary returns through higher education. Other indirect effects such as for example returns to improved adult health, increased agricultural investments, and improved risk management are missing and could change the estimated rates of return significantly. Even for education we cannot take into account important aspects such as for example the quality of schooling or the effect of improved education on better health, or the effects of improved health on mortality rates and thus programme costs. The list of missing transmission channels could easily be extended. Therefore, these estimated rates of return must not be seen as an overall evaluation of the programmes, but as an ex-ante comparison of the returns of both programmes through child underweight, increased enrolment and school continuation.

Besides that, we have to rely on non-experimental methods to quantify the coefficients to be applied in the simulation model and the selection of instrumental variables is always debatable. However, compared to other studies, our estimation results seem to be in line with previous evidence. As robustness check we furthermore used the lower and upper bound predictions of the estimations in the simulations. To illustrate this, Figure 6 in the Annex displays the results for the RoR using the lower and upper bound coefficients of the returns to education (Table 5) in the simulation model. After ten periods, the results of the upper and lower bounds differ by around one percentage point compared with the average predictions of the returns to education, but the overall implications of the findings still hold.

Conclusions

In this paper we performed an ex ante assessment of the potential short- and mid-term effects of two cash transfer programmes in Uganda in terms of child health, educational attainment, and the monetary returns to these indirect programme effects. Using a micro-simulation approach we are able to examine how the scale-up of these pilot interventions on the national level could affect human capital indicators and income growth.

The results suggest positive income effects on child underweight at age 4 and school continuation that increase over time. After 10 years the simulation predicts a decrease of 1.5 percentage points in child underweight and an increase in school attainments of 0.01 years of schooling of all adults compared with a scenario without the cash transfer programmes. Despite positive returns to education, the programme costs still exceed these indirect benefits after 10 periods leading to negative rates of return. Comparing the SCG, which is universally targeted at people above 64, with the proxy-means tested VFG programme shows that the universal programme leads to larger effects. This is mainly due to the higher payouts for the SCG programme, but even after considering the administrative costs the rates of return of the SCG are larger than of the VFG in our framework. This seems to be driven by the large administrative costs of the VFG, which are about three times the estimated SCG costs.

Despite the multiple promotional and transformational effects not being included and the estimation issues, this study helps to understand the dimensions of the effects within a limited framework. The study shows how effects add up over time and how indirect programme effects can further fuel promotional and transformational effects. Given Uganda's significant efforts in promoting education for all, the results could indicate that there is little additional scope for the analysed programmes to increase school enrolments. One aspect that seems of great importance for future work is to regard the effect of social cash transfers on the quality of learning and the acquired skills of children. For example if social cash transfer programmes improve child health and increase the time available for learning, children might acquire more skills within the same amount of years of schooling with the financial support of cash transfer programmes.

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	1. Direct Effect		2. Indirect Effects				3. Outcome	4. Demographics
Period	**Non-Eligible**	**Eligible**	**Child Health**	**Schooling**	**Attainment**	**Indirect Benefit**	**Consumption**	**Demographic changes**
1	Consumption according to UNPS 2011	Consumption + Transfers*prop. to Consume (targeting according to Table 6)	Predict prob. of child based on adapted consumption	Predict prob. of school enrollment, and school continuation based on adapted consumption, child health, and previous enrolment	Adapt highest education attainment in the household	Predict consumption with and without change in education. Behavioral benefit: $Benefit = \widehat{C_1^{SP_i,1}}\left(\widehat{E\left(C_1^{SP_i,1}\right)}\right) - \widehat{C_1^{SP_i,0}}\left(\widehat{E\left(C_1^{SP_i,0}\right)}\right)$	Direct + Behavioral effects (consumption level next period is consumption – transfer* prop. to consume)	New-borns and deaths according to official fertility and mortality rates. Everyone ages one year and household size is adapted accordingly.
⋮								
10	Income level of end of period 9	Income + Transfer (targeting according to Table 6)	Predict prob. of child based on adapted consumption	Predict prob. of school enrollment, and school continuation based on adapted consumption, child health, and previous enrolment	Adapt highest education attainment in the household	Predict consumption with and without change in education. Behavioral benefit: $Benefit = \widehat{C_{10}^{SP_i,1}}\left(\widehat{E\left(C_{10}^{SP_i,1}\right)}\right) - \widehat{C_{10}^{SP_i,0}}\left(\widehat{E\left(C_{10}^{SP_i,0}\right)}\right)$	Direct + Behavioral effects (consumption level next period is consumption – transfer* prop. to consume)	New-borns and deaths according to official fertility and mortality rates. Everyone ages one year and household size is adapted accordingly.

Figure 5 Simulation Procedures per Period

Table 6 VFG Eligibility Score Weights

	Single orphan	Double orphan	Not Orphan	Partial Disability	Severe Disability	No Disability
Child 0-2	5	10	2	0	0	0
Child 3-5	5	10	2	5	5	2
Child 6-10	5	10	2	5	5	2
Child 11-15	5	10	2	5	5	2
Female 66+				15	35	15
Male 66+				15	35	15
Female 16-65				15	35	-10
Male 16 - 65				15	35	-10

Source: OPM Targeting Report

Table 7 Descriptive Statistics of Control Variables

Control Variable	Mean	Standard Deviation
Education HH Head (years)	24.82	16.32
Age HH Head (years)	46.82	14.57
Individual is Head of the HH (d.)	0.15	0.36
HH Size	8.54	4.15
Share of HH Member >65	0.18	0.26
Share of HH Member <16	0.48	0.23
Female (d.)	0.52	0.50
Polygamous HH (d.)	0.04	0.19
Double Orphan (d.)	0.01	0.10
Single Orphan (d.)	0.05	0.21
HH migrated in the past (d.)	0.53	0.50
Main Source of Drinking Water? (d.)	0.47	0.50
HH has private Latrine (d.)	0.37	0.48
Farming main HH Income (d.)	0.14	0.35
Mobile phone	0.65	0.48
Land ownership (d.)	0.67	0.47
Ownership Buildings (non-housing) (d.)	0.27	0.45
Prevalence of Vehicle in HH	0.04	0.19
House ownership (d.)	0.88	0.32
Access to Primary Education in the Community 1 yes, 2 outside community, 3 no	1.42	0.,50
Access to Secondary Education in the Community 1 yes, 2 outside community, 3 no	1.85	0.40

Source: UNPS 2009/10 – 2013/14

Table 8 Consumption Effect on Child Underweight (age 1-4)

	(1) Underweight (OLS RE)	(2) Underweight (OLS FE)	(3) Underweight (2SLS RE)	(4) Underweight (2SLS FE)
Ln Consumption	-0.05**	0.02	-0.11*	0.10
	(-3.71)	(0.74)	(-2.19)	(0.75)
Age	-0.15**	-0.11*	-0.16**	-0.10+
	(-3.80)	(-2.28)	(-3.89)	(-1.76)
Age squared	0.02**	0.03**	0.03**	0.03**
	(3.51)	(3.76)	(3.60)	(3.13)
Clean Drinking Water	0.01	0.01	-0.00	0.02
	(0.40)	(0.54)	(-0.02)	(0.66)
HH has private latrine	-0.00	0.00	-0.00	0.00
	(-0.08)	(0.17)	(-0.03)	(0.20)
Education HH head	-0.00+	-0.00	-0.00	-0.00
	(-1.76)	(-0.33)	(-0.20)	(-0.53)
HH size	0.00	0.01	-0.00	0.02
	(0.48)	(1.32)	(-0.11)	(1.38)
Female	-0.00	0.00	-0.00	
	(-0.15)	(.)	(-0.16)	
HH polygamy	-0.05	-0.12	-0.06	-0.10
	(-1.31)	(-1.63)	(-1.39)	(-1.26)
HH migrated	-0.02	-0.07*	-0.01	-0.08*
	(-0.66)	(-2.00)	(-0.58)	(-2.10)
Single orphan	0.02	0.11	0.01	0.12+
	(0.47)	(1.64)	(0.30)	(1.73)
Double orphan	0.13	0.15	0.13	0.14
	(0.88)	(0.80)	(0.92)	(0.73)
region==Kampala	0.01	0.00	0.06	-0.01
	(0.09)	(0.05)	(0.77)	(-0.11)
region==Central	0.00	0.00	0.02	
	(0.01)	(.)	(0.57)	
region==Eastern	0.00	0.00	-0.01	
	(0.10)	(.)	(-0.34)	
region==Northern	0.01	0.00	-0.01	
	(0.51)	(.)	(-0.25)	
year== 2010	-0.02	-0.09**	-0.04+	-0.07
	(-1.21)	(-3.37)	(-1.76)	(-1.63)
year== 2011	-0.05**	-0.19**	-0.09**	-0.15*
	(-2.69)	(-4.25)	(-2.72)	(-2.11)
year== 2013	-0.05+	-0.30**	-0.07*	-0.28**
	(-1.72)	(-3.74)	(-2.14)	(-3.03)
Observations	2175	2175	2172	1663
R^2		0.06		0.04
p-value of Hausman test	0.00		0.55	
First stage F- Statistic			162.27	7.33
Sargan score p-value			0.11	0.25
p-value of Wald test of exogeneity			0.01	0.52

t statistics in parentheses. Cell phone, land ownership, and ownership of non-housing buildings used as instrument for consumption. Linear models estimated. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 9 Consumption and Underweight Effects on first time School Enrolment (age 5-9)

	(1) Enrolment (RE)	(2) Enrolment (RE)
Ln Consumption	0.01	-0.01
	(0.53)	(-0.16)
Underweight at age 4	-0.14^{**}	-0.14^{**}
	(-3.83)	(-3.87)
Education HH head	0.00	0.00
	(0.63)	(0.76)
Age	0.41^{*}	0.43^{*}
	(2.38)	(2.48)
Age squared	-0.02	-0.02
	(-1.33)	(-1.43)
Farm HH	-0.26	-0.29
	(-0.41)	(-0.46)
Age HH head	0.00	0.00
	(0.21)	(0.26)
HH size	-0.00	-0.00
	(-1.02)	(-1.25)
Share of old HH member	0.06	0.04
	(0.41)	(0.26)
Share of young HH member	0.01	-0.03
	(0.08)	(-0.25)
Female	0.05^{*}	0.05^{+}
	(1.97)	(1.92)
HH polygamy	-0.06	-0.06
	(-0.91)	(-0.97)
Double orphan	0.19	0.19
	(1.16)	(1.15)
Single orphan	0.06	0.06
	(1.15)	(1.11)
HH migrated	0.08^{*}	0.09^{*}
	(2.23)	(2.40)
region== Kampala	-0.22	-0.22
	(-1.55)	(-1.52)
region==Central	-0.03	-0.02
	(-0.61)	(-0.52)
region==Eastern	0.04	0.03
	(0.94)	(0.78)
region==Northern	-0.10^{**}	-0.11^{**}
	(-2.63)	(-2.59)
year== 2010	-0.08	-0.11
	(-0.19)	(-0.25)
year== 2011	0.01	-0.02
	(0.03)	(-0.04)
year== 2013	-0.02	-0.05
	(-0.04)	(-0.12)
Observations	1307	1304
p-value of Hausman test	0.09	
First stage F- Statistic		53.36
Sargan score p-value		0.87
p-value of Wald test of exogeneity		0.68

t statistics in parentheses. Cell phone, land ownership, vehicle, and ownership of non-housing buildings used as instrument for consumption. Linear models estimated. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 10 Consumption Effect on School Continuation (Age 5-24)

	(1) School Continuation (OLS RE) (5-24)	(2) School Continuation (OLS FE) (5-12)	(3) School Continuation (OLS FE) (13-18)	(4) School Continuation (OLS FE) (19-24)	(5) School Continuation (2SLS FE) (5-12)	(6) School Continuation (2SLS FE) (13-18)	(7) School Continuation (2SLS FE) (19-24)
Ln Consumption	0.04**	0.01*	0.02*	0.06**	0.01	-0.03	-0.11
	(12.14)	(2.13)	(2.21)	(3.78)	(0.44)	(-0.33)	(-0.80)
Education HH head	0.00**	0.00	0.00	-0.00	0.00	0.00	0.00
	(8.65)	(0.51)	(0.84)	(-0.18)	(0.47)	(1.01)	(0.02)
Age HH head	0.00**	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
	(7.95)	(2.46)	(2.41)	(2.34)	(2.30)	(2.25)	(2.50)
HH size	0.00**	0.00	0.00	0.01*	0.00	-0.00	0.01
	(6.90)	(0.40)	(0.25)	(2.29)	(0.42)	(-0.33)	(0.67)
Farm HH	0.00	0.00	0.03*	-0.02	0.00	0.03*	-0.02
	(0.78)	(0.65)	(2.16)	(-0.95)	(0.55)	(2.26)	(-0.84)
Share of old HH member	-0.02	0.01	0.03	0.07	0.02	0.01	-0.03
	(-1.43)	(0.62)	(0.57)	(0.94)	(0.57)	(0.10)	(-0.28)
Share of young HH member	0.02	0.01	-0.06	0.14^{+}	0.01	-0.08	0.08
	(1.41)	(0.29)	(-1.07)	(1.68)	(0.31)	(-1.24)	(0.84)
Female	-0.03**	0.00	0.00	0.00			
	(-5.52)	(.)	(.)	(.)			
HH polygamy	-0.05**	-0.02	-0.05	0.04	-0.02	-0.05	0.04
	(-4.21)	(-1.03)	(-1.01)	(0.59)	(-1.04)	(-1.07)	(0.54)
Double orphan	-0.03*	-0.03	-0.04	0.00	-0.03	-0.04	
	(-2.29)	(-1.41)	(-1.21)	(.)	(-1.37)	(-1.23)	
Single orphan	0.01	-0.00	-0.01	0.00	-0.00	-0.01	
	(0.83)	(-0.07)	(-0.45)	(.)	(-0.03)	(-0.44)	
HH migrated	-0.03**	-0.01	0.01	0.01	-0.01	0.02	0.01
	(-7.49)	(-1.22)	(1.12)	(0.52)	(-1.23)	(1.21)	(0.68)
Age	0.10**	-0.02	0.86	-2.01	-0.02	0.75	-1.49
	(12.27)	(-0.41)	(0.63)	(-0.77)	(-0.41)	(0.55)	(-0.55)
Age squared	-0.01**	0.00	-0.05	0.09	0.00	-0.04	0.07
	(-10.97)	(0.74)	(-0.52)	(0.75)	(0.74)	(-0.44)	(0.53)
Age cubic	0.00**	-0.00	0.00	-0.00	-0.00	0.00	-0.00
	(4.93)	(-0.90)	(0.40)	(-0.73)	(-0.90)	(0.32)	(-0.51)
region==Kampala	-0.03*	0.01	-0.19	-0.53	0.01	-0.18	-0.30
	(-2.50)	(0.08)	(-0.57)	(-1.49)	(0.09)	(-0.54)	(-0.73)
region==Central	-0.01	-0.00	-0.10	-0.54	-0.00	-0.10	-0.32
	(-0.88)	(-0.03)	(-0.32)	(-1.54)	(-0.02)	(-0.30)	(-0.80)
region==Eastern	0.04**	0.01	-0.28	0.00	0.01	-0.31	
	(5.83)	(0.06)	(-0.77)	(.)	(0.09)	(-0.83)	
region==Northern	0.01	0.01	-0.15	0.00	0.01	-0.21	
	(1.01)	(0.04)	(-0.33)	(.)	(0.08)	(-0.44)	
year== 2010	0.01^{+}	-0.00	-0.02	-0.06*	-0.00	-0.03	-0.10*
	(1.68)	(-0.93)	(-1.39)	(-2.53)	(-0.44)	(-1.10)	(-2.38)
year== 2011	0.03**	-0.00	-0.06**	-0.12**	0.00	-0.08^{+}	-0.20**
	(5.03)	(-0.19)	(-3.09)	(-3.72)	(0.04)	(-1.67)	(-2.73)
year== 2013	0.01	-0.02*	-0.16**	-0.30**	-0.02	-0.18**	-0.38**
	(0.86)	(-2.08)	(-5.22)	(-5.87)	(-1.42)	(-3.48)	(-4.78)
Observations	25945	12467	8264	5214	9582	6062	3454
R^2		0.01	0.10	0.13	0.01	0.09	0.08
p-value of Hausman test	0.00						
First stage F- Statistic					37.47	13.77	10.26
Sargan score p-value					0.51	0.22	0.09
p-value of Wald test of exogeneity					0.88	0.57	0.21

t statistics in parentheses. Cell phone, land ownership, vehicle, and ownership of non-housing buildings used as instrument for consumption. Linear models estimated. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 11 Household Consumption Returns to Education

	(1) Ln Consumption (OLS RE)	(2) Ln Consumption (2SLS RE)	(3) Ln Consumption (OLS FE)	(4) Ln Consumption (2SLS FE)	(5) Ln Wage (hourly) (Heckman Selection)
Max. School attainment in HH	0.05**	0.11**	0.00	0.16	
	(30.84)	(6.60)	(1.30)	(1.12)	
School attainment (individual)				0.02*	0.17**
				(1.98)	(7.69)
Mean HH Age	0.03**	0.03**	0.01**	-0.00^{+}	
	(9.53)	(7.72)	(3.12)	(-1.74)	
Mean HH Age squared	-0.00**	-0.00**	-0.00	-0.08**	
	(-6.73)	(-4.35)	(-1.49)	(-5.09)	
HH size	-0.04**	-0.06**	-0.06**		0.00
	(-18.92)	(-10.32)	(-13.51)		(.)
Female HH head	-0.03^{+}	0.06^{+}	0.00	-0.08	-0.09
	(-1.74)	(1.86)	(.)	(-1.08)	(-0.60)
HH polygamy	-0.04	-0.01	-0.01	0.02	0.01
	(-0.93)	(-0.29)	(-0.28)	(0.67)	(0.01)
HH migrated	0.08**	0.04**	0.02	-0.29	0.36**
	(6.16)	(2.59)	(1.29)	(-0.80)	(2.77)
Share of old HH Member	-0.73**	-0.57**	-0.67**	0.20	
	(-17.81)	(-7.13)	(-12.87)	(0.44)	
Share of young HH Member	-0.38**	-0.11	-0.19**	0.52	
	(-8.01)	(-0.86)	(-2.69)	(1.14)	
region==Kampala	0.53**	0.47**	0.48^{+}	0.47	0.48**
	(14.83)	(8.38)	(1.89)	(1.05)	(2.91)
region==Central	0.33**	0.28**	0.45^{+}	0.15	0.24^{+}
	(15.76)	(10.30)	(1.82)	(0.23)	(1.77)
region==Eastern	-0.13**	-0.09**	0.04		0.33*
	(-5.85)	(-4.14)	(0.13)		(2.29)
region==Northern	-0.19**	-0.12**	0.38	-0.38**	0.34^{+}
	(-8.72)	(-4.83)	(0.93)	(-7.70)	(1.69)
year== 2010	-0.33**	-0.38**	-0.30**	-0.55**	0.00
	(-27.53)	(-23.91)	(-24.87)	(-13.58)	(.)
year== 2011	-0.51**	-0.55**	-0.49**	-0.52**	0.00
	(-41.60)	(-35.47)	(-38.26)	(-5.59)	(.)
year== 2013	-0.42**	-0.49**	-0.42**	0.16	0.00
	(-31.15)	(-19.60)	(-27.02)	(1.12)	(.)
Age					0.07**
					(3.22)
Age squared					-0.00**
					(-2.80)
HH head					0.34*
					(2.48)
Observations	11098	9339	11098	9339	25059
p-value of Hausman test	0.00			0.00	
First stage F- Statistic		75.09		2.19	
Sargan score p-value		0.17		0.25	
p-value of Wald test of exogeneity		0.00		0.28	

t statistics in parentheses Access to primary and secondary school used as instrument for school attainment. Linear models estimated and selection model results of Heckman Selection model not presented.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 12 Number of observations and attrition for the original 2009 households

Number of observations	Number of original hh in 2009 (total = 2,975)	Percentage
1	157	5.28%
2	239	8.03%
3	1,050	35.29%
4	1,529	51.39%
Total	2,975	100%
BGLW test for attrition?		

Table 13 First stage of preferred 2SLS Models

	(1)	(2)	(3)	(4)
	Ln Consumption (RE(	Ln Consumption (RE)	Ln Consumption (FE)	Max School Attainment (RE)
Mobile phone	0.28**	0.30**	0.12**	
	(16.54)	(21.50)	(11.63)	
Land ownership	0.04*	0.05**	0.06**	
	(2.16)	(3.37)	(6.23)	
Ownership Buildings (non-housing)	0.09**	0.06**		
	(5.17)	(4.13)		
Prevalence of Vehicle in HH		0.74**		
		(18.16)		
House ownership			0.09**	
			(4.98)	
Primary school in community				-0.24**
				(-3.15)
Secondary school in community				-0.54**
				(-5.75)
Observations	5251	7785	25259	9416
Control Variables included	Yes	Yes	Yes	Yes

t statistics in parentheses.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

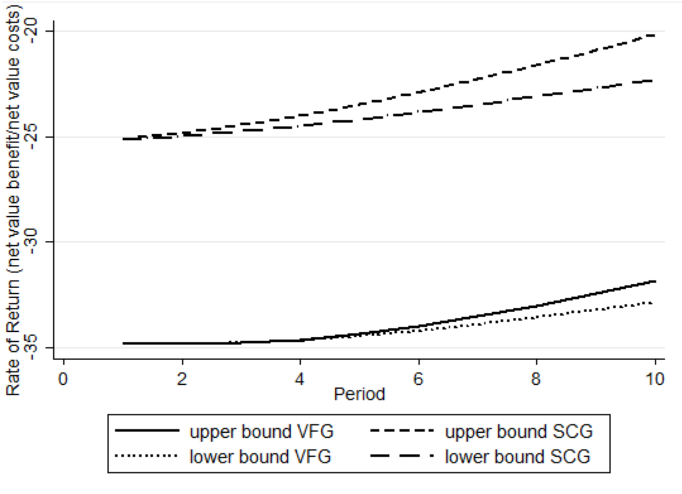

Figure 6 Rates of Return using lower and upper bound predictions of returns to education (Table 5; line graph)

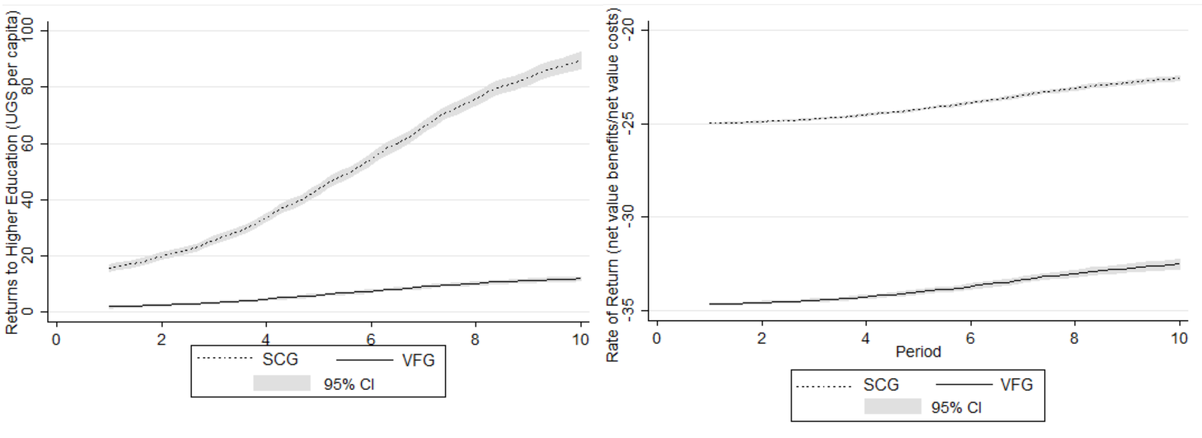

Figure 7 Mean Monetary Returns to Education (left) and Rates of Return (right) pooled after 25 Iterations of the Micro-Simulation (local mean smoothing with bandwidth of 1.5)

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