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Public transfers and crowding-in and -out of private transfers: Experimental evidence from Kenya

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ABSTRACT

In rural areas of developing countries, private transfers are shared for altruistic reasons, to mitigate negative shocks (insurance motive) and in exchange for services. However, when public and private transfers provide similar benefits, an overlap exists, potentially crowding-out informal mechanisms. In this paper, we test whether an exogenous increase in household income, due to transfers by the Hunger Safety Net Program (HSNP) to pastoralist households in Northern Kenya, reinforces or dampens the redistributive dynamics associated with private transfers. We exploit the experimental implementation of HSNP to control for endogeneity with the randomly provided unconditional cash transfer. We show that an HSNP-induced rise in household income by 2,000 Kenyan Shillings is associated with a non-negligible decline in the total value of private transfers equivalent to 12% of the income increase. For transfers given, we show that the HSNP transfer leads to increased sharing equivalent to 11% of the income increase. Testing for non-linearities, we identify a significant reduction in the value of private transfers received at low levels of the income distribution. Concomitantly, we identify a positive relationship between income and transfers given that is most pronounced among poorer households. We further show that we possibly observe altruistic, insurance and exchange related sharing motives coexisting among Northern Kenyan pastoralists. The identified crowding-in and -out effects have implications for the design and efficacy of social programs beyond Kenya, demonstrating that traditional transfer dynamics are altered due to public programs.

1. Introduction

In developing countries, the transfer of wealth is a complex process that involves family members near and far, friends as well as neighbors. Sharing motives range from altruism of the relatively better off towards the poor to insurance mechanisms to mitigate the effects of negative shocks and the exchange of informal services. The pressure to share and mitigate risk is heavily affected by shocks such as extreme weather events and diseases and upheld by social norms (Lane, 1994; Merttens et al., 2013). Private transfers also serve as health insurance when farmers fall ill (Krishnan & Sciubba, 2009). In addition, such transfers foster child support between relatives that are motivated by the exchange of services (Akresh, 2005). The roles for private transfers are further reinforced by the non-functioning of credit markets (Adams & Page, 2005; Cox, Hansen & Jimenez, 2004; Townsend, 1994).

Private or informal transfers are a mix of cash transfers and in-kind donations/non-cash transfers made by friends, members of the extended family, and development partners/religious organizations. Transfers are received and given within the local community but depending on individual household perceptions involve family members who are away from home. In this paper, we assess whether transfers from all these sources change in response to an unconditional cash transfer program provided by the government. We consider the unconditional cash transfer as an income shock and assess to what extent private transfer dynamics are altered. Notably, we look at both, transfers received by and/or given to other households.

While the history of private transfers dates back several centuries, public social transfers are comparably new and aim at poverty alleviation, income redistribution, and the support of vulnerable members of society. In Germany, and The United States, public transfer systems were initiated around 1880, and 1931, respectively. In developing countries, they were initiated in the 1990s after Mexico's success with the PROGRESA program (Flora & Heidenheimer, 1981; Haque, 2001; Mesa-Lago, 2002; Williamson & Pampel, 1993). At least initially, public

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transfers tend to be implemented in parallel with pre-existing private transfer arrangements. However, when public and private transfers provide similar social benefits, an overlap exists, and this has the potential to cause crowding-in and -out effects between the different mechanisms of support and protection. Existing estimates suggest that the expansion of public social transfers has the potential to replace between 20 and 91% of private transfers in developing countries (Haque, 2001; Cox & Jimenez, 1998; Jensen, 2004; Maitra & Ray, 2003).

Despite such projections, empirical evidence remains ambiguous in predicting the magnitude and direction of the transfer derivative (Altonji et al., 1997; Gibson et al., 2011). A transfer derivative measures how the receipt of private transfer changes in response to an increase in household resources (Albarran & Attanasio, 2003; Attanasio & Ríos-Rull, 2000; Nikolov & Bonci, 2020). To date, there is no unanimous conclusion from developing country studies about the magnitude of transfer derivatives as effects depend on an individual's position within the income distribution, the level of precision in the measurement, and the type of social assistance (conditional or unconditional). Identified effects range from strong crowding-out effects (Brown & Jimenez, 2011; La & Xu, 2017) to weak substitution effects (Gibson et al., 2011; Kazianga, 2006) including a mix of transfer derivatives (Cox et al., 2004; Nikolov & Bonci, 2020).

To shed further light on the existence and magnitude of transfer derivatives, this paper provides new evidence from pastoralist societies in Northern Kenya. The rural setting of pastoralist communities offers excellent ground for testing crowding-in and -out effects in private transfers as a response to a newly introduced public transfer as the majority of the households rely on rain-fed agriculture for livelihood support and is consistently exposed to shocks while being credit-constraint and poverty-prone. In 2010, only about 12.9% of the households reported having received credit from formal financial institutions, and over 80% of the households were classified as income-poor (Merttens et al., 2013). Consequently, households are dependent on private transfers in the presence of shocks to smoothen consumption. Moreover, these pastoralist households are known for their long history of livestock sharing which rests on cultural and religious norms (Lane, 1994), and provide thus an interesting case study.

In our analysis, we take advantage of the random implementation of the Hunger Safety Net Program (HSNP) that was launched in Northern Kenya in 2010 targeting 60,000 households (Merttens et al., 2013). HSNP randomly selected households from 24 treatment and 24 control sub-locations with beneficiary households being entitled to an unconditional cash transfer of about 20 USD every other month. In our empirical analysis, we analyze the baseline and first follow-up surveys –conducted in 2010 and 2011, respectively. First, we quantify the effect of the exogenous increase in household pre-transfer income, stemming from HSNP. Next, we assess to what extent the value of private transfers received or given changes in response to the income shock triggered by the receipt of the HSNP transfer. Our preferred model is the IV Tobit model which accounts for both the left censoring in our transfer data and the endogeneity in income which we instrument with the randomly introduced HSNP shock.

Five results stand out: First, we show that benefitting from HSNP increases the value of household pre-transfer income. Receipt of the HSNP transfer increases household income by almost KES 2,000 (~USD 25.2).[1] Second, there is a negative relationship between household pre-transfer income and the value of private transfers received. Specifically, we identify with our preferred IV Tobit model that a rise in household pre-transfer income by KES 2,000 is associated with a reduction in the value of non-cash, cash, and total transfers received by KES 140, 170 and 230 (~USD 1.8–2.9), respectively. Third, for private transfers given, we demonstrate that a rise in household pre-transfer income by KES 2,000 is associated with a rise in the value of total transfers and cash transfers given to other households by KES 220 and 374 (~USD 2.8 and 4.7), respectively. Fourth, we also tested for non-linearity in the income-private transfer relationship. For households in the first quartile of the income distribution, we show that an HSNP-induced rise in household pre-transfer income by KES 2,000 is associated with a reduction in the value of cash and total transfers received by KES 2,114 and 2,314 (~USD 26.7 and 29.2), respectively. At the upper end of the income distribution, we identify statistically insignificant impacts. These findings provide evidence that crowding-out disproportionally impacts lower income households. In addition, we show that the sub-sample of households that experience an asset shock is even more affected by the HSNP-induced decline in the receipt of private transfers, suggesting that the other households in the community consider them as state-insured and pointing to insurance as one possible motive for sharing. Concomitantly, the sub-sample of households with comparably larger dependency ratios tends to experience a smaller reduction in the receipt of private transfers when being an HSNP recipient, indicating the presence of exchange-related motives. Lastly, we show for households in the first quartile of the income spectrum that an HSNP-induced rise in household pre-transfer income by KES 2,000 is associated with a rise in the value of total transfers given to other households by KES 2,586. Interestingly, households in the first income quartile tend to give higher amounts than those in the higher income quartiles. This is akin to insurance against future shocks but is against traditional norms that dictate that it is the high-net-worth household's role to give to the poor households, in particular when the latter experience shocks. Overall, these findings show non-negligible impacts from HSNP and have implications for the design and efficacy of social programs since they demonstrate that traditional, informal transfer patterns are altered and partly crowded out when government social programs are put in place.

With these findings, we contribute to the existing literature along two dimensions. First, our study further helps nuancing the growing number of analyses about crowding-in and -out effects due to public transfers. We explore pastoralist households in Northern Kenya who are highly dependent on transfers to smoothen the impacts of (weather) shocks and identify crowding-out of private transfers received due to a rise in household income. Importantly, we show that the HSNP cash transfer mainly affected the receipt of *cash* transfers but not non-cash transfers suggesting that existing financial dependencies are loosened. Moreover, we observe increases in transfers given across all scenarios that likely reflect a mix of insurance but also altruistic motives in the context of strong sharing norms. We contribute to the academic debate, especially with the identification of these latter effects as the giving of private transfers has received considerably less attention compared to the receipt of private transfers. Our analysis thus complements the findings of previous studies conducted in South Africa (Jensen, 2004; Maitra & Ray, 2003), Burkina Faso (Grimm et al., 2021; Kazianga, 2006), and Ghana (Strupat & Klohn, 2018). Second, we contribute to the literature on informal risk-sharing in poor village economies (Fafchamps & Gubert, 2007; Kazianga & Udry, 2006; Townsend, 1994). This existing literature has demonstrated that risk-sharing in developing countries is related to kinship relationships and geographical proximity. What has been studied less is the impact of an exogenous rise in household income among poor households on the value of private transfers received and given. We assess different mechanisms through which impacts could differ and show that depending on the situation of the own household and the other households in the community a mix of sharing motives of altruism, insurance, and exchange co-exist.

The rest of this paper is organized as follows. In section 2 we introduce the HSNP program. The conceptual framework underlying our analysis is presented in section 3. Sections 4 and 5 introduce the data and the empirical strategy, respectively. Section 6 discusses our findings and section 7 provides heterogeneity and robustness analyses. Section 8 concludes the paper.

[1] Applying the 2010 official USD-KES exchange rate of 79.23 retrieved from the World Development Indicators, available at: https://data.worldbank.org/indicator/PA.NUS.FCRF?locations=KE. [Last accessed: 29th August 2022].

2. Introduction to HSNP

HSNP is an unconditional, social cash transfer program implemented in four rural, predominantly pastoralist districts (Wajir, Turkana, Marsabit, and Mandera) in Northern Kenya. The program is implemented by Oxford Policy Management with support from the Government of Kenya and was initiated as a randomized controlled trial.

The program started in August 2009 and is still running, benefiting over 243,734 households as of May 2019, about 60% of whom are female-headed households. Its main objective is to improve the welfare of poor households. HSNP started off with a staggered implementation. Of all eligible target households, those residing in 24 randomly chosen sub-locations identified for treatment received the program step-wise over the course of one year; those randomized into the control group –another 24 sub-locations– only received HSNP after 2 years. Program eligibility involved two stages: In the first stage, the HSNP districts were selected based on the poverty index of the 2005/06 Kenya Integrated Household Budget Survey (KIHBS). According to KIHBS 2005/06, approximately 85% of the households in HSNP districts were income poor, i.e., they lived below the national poverty line of <2 USD per day, and about 54% were in the bottom national decile (Merttens et al., 2013). In a second step, in each district, the identification of treatment and control sub-locations was done in a public lottery that was attended by both the local administration and HSNP officials. On a month-by-month basis, one treated and one similar control sub-location was selected for program inclusion. Sub-locations included in the study were sorted within each district by population density and paired into treatment–control matches to ensure similarity across random units.

The baseline surveys took place immediately after the selection of the sub-location pairs and before treated sub-locations started receiving HSNP transfers. This staggered roll-out was designed to take place over 12 months to also capture seasonal variation. The sequence in which the sub-locations were targeted and surveyed was randomly determined. For the household survey, 66 eventual HSNP target households were selected per location using a simple random sampling procedure without replacement. The random sampling took place in three types of settlements (permanent, non-permanent, and main) in every sub-location.[2]

De facto, the baseline survey was undertaken from August 2009 to November 2010 (thereafter 2010). Households in treated sub-locations started receiving the transfer immediately after the baseline survey. The first follow-up survey took place between November 2010 and November 2011 while the second follow-up took place between February and November 2012, two years after the start of the program. Fig. 1 provides a graphical representation of the study set-up. In this phase of HSNP, i.e., from 2010 to 2012, only HSNP beneficiary households in treated sub-locations received the transfers while control households did not benefit from HSNP until the end of 2012. Our identification strategy relies on this staggered rollout and randomized allocation of treatment and control sub-locations into the program.

Concerning the support provided by HSNP, the program has two components: A bi-monthly cash transfer and a contingency fund. Initially, the cash transfer was fixed at about 20 USD per household, which is equivalent to about 12% of household consumption expenditure in 2010. The amount was increased to 30 USD in September 2011 and to 35 USD in March 2012 (Merttens et al., 2013). Over the first 24 months of program implementation, i.e., between 2010 and 2012, most households had received 12 transfers. The second program component –the contingency fund– provides additional financial support to households when they experience severe drought conditions. This contingency fund made its first payment in 2011.

In addition to the matched, staggered, randomized design identifying the HSNP locations and allowing for the impact assessment, the program relies on a trifold targeting mechanism: community-based targeting (CBT), social pension receipt (SP), or dependency ratio targeting (DRT). One of the three was randomly applied across similar pairs of sub-locations. The goal of this approach was to allow for a comparison of the relative performance of the three mechanisms.

The study sample consists of an equal share of CBT, SP, and DRT sub-locations. Where CBT targeting is used, *community members identified poor households* that would benefit from the program. Under dependency ratio targeting, households were selected if the *proportion of their dependents*, i.e., members under the age of 18 or above the age of 55 years or those being disabled or critically ill, *exceeded a set threshold*. Wherever the social pension mechanism was applied, *all individuals above 55 years were eligible* to receive the transfer. Under CBT and DRT, about 82 and 73.7% of registered beneficiaries, respectively, were women while an equal share of men and women were granted the transfer under the social pension targeting.[3]

The HSNP data have already been analyzed in the final impact evaluation report by Merttens et al. (2013) highlighting that HSNP resulted in increased consumption expenditure and a reduction of extreme poverty despite a very severe drought that hit HSNP districts in 2011. Poverty impacts are shown to be driven by poorer and smaller households. Dietrich and Schmerzeck (2019) further assessed the role of the 2011 drought showing that market isolation mediates the impact of the cash transfer on nutrition with impacts disappearing in the more isolated communities. In addition, Dietrich and Schmerzeck (2020) analyze the effects of rising food prices on food demand, highlighting that the impact on nominal food expenditures overstates the impact measured at constant prices. Aizawa (2020) assesses the effect of HSNP on household nutritional intake showing that expenditure for milk and milk products went up, as did expenditures for sugar, roots and tubers, yet in terms of nutritional intake only the amount of sugar consumed went up. Concomitantly, HSNP improved the nutritional intake of vitamin B12 by 36.6% and calcium by 34.9% after 12 months and of fat by 25.2% after 24 months.

However, these previous studies have not analyzed the effect of changes in household pre-transfer income on private transfers received by or given to other households. In fact, Merttens et al. (2013) call for a study about private transfers. Importantly, the HSNP dataset contains detailed household-level information on the amount of private transfers received and given, disaggregated by types (either as cash or non-cash transfers), along with the usual household survey information about household head characteristics, asset holdings, and household consumption expenditures. The fine disaggregation allows for the analysis of private transfers received and given by types –a feature that is missing in most empirical studies present in the current literature.

3. Conceptual framework

Our conceptual considerations rest on the idea of a private transfer response function as modelled by Cox et al.'s (2004) private transfer model. Receipt of HSNP is expected to impact private transfers received/given by a household and the direction of this impact depends on the motive of the informal transfer. Based on the existing theory of household transfers (Barro, 1974; Becker, 1974; Cox, 1987; Cox et al., 2004),

[2] A permanent settlement is a collection of dwellings where at least some households are always residing and/or there is at least one permanent housing or compound structure. A non-permanent settlement does not have permanent structures and people are only temporarily residing there. The term main settlement refers to the primary permanent settlement in each sub-location and is usually where the local administration is based.

[3] This mix of targeting mechanisms results in two important outcomes. First, CBT and DRT increased the bargaining power of women in household decision-making processes while SP may have increased the bargaining power of elderly household members. Second, some households received multiple payments per cycle since about 25% of the households selected through SP had two members above 55 years of age in the 2010 survey.

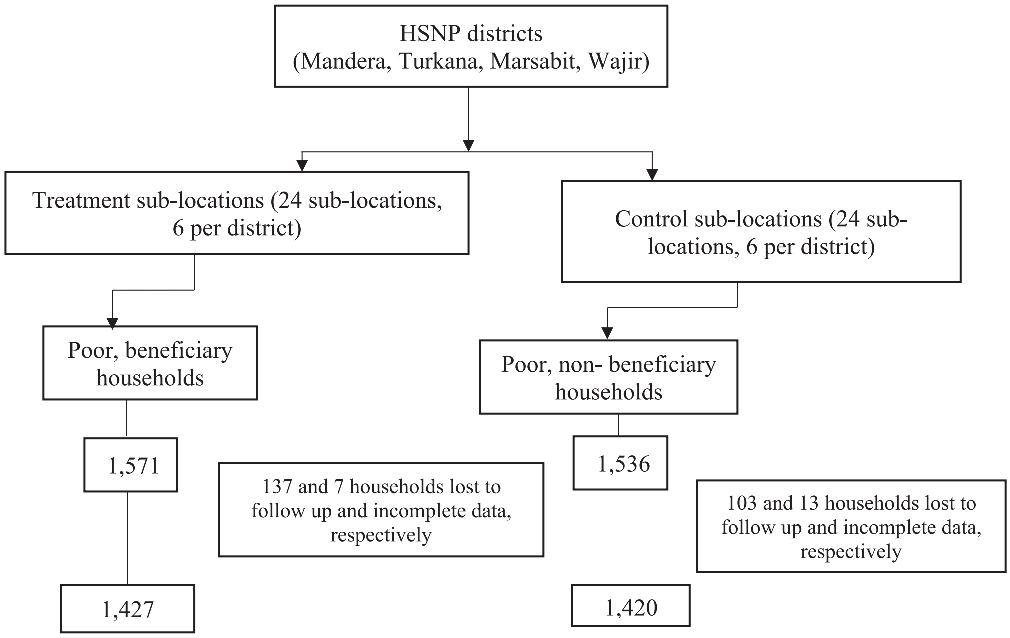

Fig. 1. Study set-up.

it can be argued that households make private transfers for three reasons: (i) altruism, (ii) mutual insurance and (iii) exchange. An altruistic motive of private transfers is driven by the donor's concern about the recipient's utility. The main thrust of the altruism model is the idea that donors tend to adjust their transfer behaviour based on the recipients' earnings. This implies that a donor ensures that her transfer behavior is consistent with the recipient's income level and that a rise in recipient income will lead to a decline in the value of private transfers received (Barro, 1974; Becker, 1974). The altruism motive predicts complete crowding-out of private transfers received, which can be empirically identified by the negative coefficient associated with household income in the private transfer-income relationship. Similarly, the altruism motive models the dependency between better off and poorer households implying that donors increase private transfers given in response to a positive shock on their own income (Becker, 1993; Becker, 1974). Empirically this results in a positive coefficient associated with household income in the relationship between giving private transfers and income. In short, recipients of social support are expected to receive fewer private transfers while in turn they should be providing more to others when mainly motivated by the altruism motive (Secondi, 1997).

Under mutual insurance, transfers act as insurance and thus cushion households against negative shocks (Townsend, 1994). These shocks can take many forms such as extreme weather events, crop pests, sudden illness, death, and education spending. Thus, poor, risk-prone households tend to rely on private transfers as insurance, whereas better off households can turn to formal insurance or savings. Thus, in contrast to the altruism motive for sharing, the insurance mechanism requires the prevalence of shocks or at least the credible risk of shocks. Poor households experiencing a shock are expected to receive a transfer from other households (Townsend, 1994). Yet, receipt of HSNP transfers provides poor households with a new source of income and therefore reduces reliance on seasonal income sources (Strupat & Klohn, 2018). This is expected to strengthen resilience against shocks and lessens the need to join informal risk-sharing schemes. At the same time, if poor households receive sufficient extra income from social welfare to boost their total household income the likelihood of private transfers from the recipient household to other household increases when the latter experience a shock (Strupat & Klohn, 2018). Empirically, the insurance mechanism implies a negative (positive) coefficient associated with household income in the private transfer receipt (provision)-income relationship. Thus, empirically we have similar predictions as for the altruism motive.

In turn, when the exchange motive prevails, private transfers are considered payments for services provided by the recipient to the donor (Secondi, 1997; Bernheim et al., 1985; Cox, 1987). This means that the number of services (e.g., visits, contacts) provided by, say a child to her parents, are partly motivated by the expected monetary compensation (Bernheim et al., 1985; Cox, 1987). Consequently, the amount of transfer received could either be a positive or negative function of a child's income. For instance, when a child's income rises, the opportunity cost of providing services to her parents also rises. Under such circumstances, the expected compensation will rise and the relationship between a child's income and the value of transfers received from parents is positive as long as parents' demand for services is inelastic as it implies that they have to increase the value of transfers to the child to maintain the same level of services. If such a scenario holds, the receipt of a government subsidy will increase the amount of transfer received and there would be no crowding-out. Yet, in a setting where demand for services is highly elastic, parents' demand for services would fall in line with the compensation level and this would lead to crowding-out. If the recipient of social welfare is also the recipient of the service, we are equally faced with two scenarios. For inelastic services received, the provided transfers are likely to go up, but for elastically supplied services, transfers might be crowded-out by social welfare. Thus, the postulation of an exchange motive does not allow us to unambiguously sign the coefficient associated with household income in the private transfer-income relationship.

Detailed analytical derivations of the private transfer response function are provided by Cox et al. (2004). Empirically, we cannot unambiguously distinguish the three transfer motives. Yet, in our heterogeneity analyses we test for non-linearities in the relationship between income and private transfers allowing us to infer which motive is most likely to prevail. In addition, we conduct a sample split zooming in on households affected by an asset shock and on households with a high dependency ratio to address whether there we see different dynamics. By comparing results from the full model with the sub-sample analyses we derive which motives are most likely to be most prevailing.

4. Data

This study employs the HSNP dataset[4] that is longitudinal, starting with a baseline in 2010 and having follow-ups in 2011 and 2012, respectively. Our final sample of 5,698 households is drawn from the HSNP 2010 and 2011 survey waves. We do not use the data from the 2012 follow-up survey because 8 sub-locations (2 per district) were dropped non-randomly. According to Merttens et al. (2013), this process undermined the study design thereby making it hard to detect the impact of the program. Moreover, it would erode baseline balance if we work with the additional survey round but fewer households. Therefore, we only include 2010 and 2011 data.

The data were collected by Research Solutions Limited and it took about one year to complete each survey round (Merttens et al., 2013). The survey instrument collected information about the household head, consumption, transfers, shocks, and asset ownership among others. The instrument was directed at the household head or the intended program beneficiary in the case of social pension targeting. To capture private transfers, respondents were asked to report the value of private transfers received by the household or given to other households residing in the neighboring sub-locations, during the 3 months preceding the survey. The sample attrition rate was low –about 8%.

We present descriptive statistics for the outcome of interest, i.e., the participation in the exchange of private transfer and their size at baseline in Table 1: before even assessing participation in private transfers, we study pre-transfer household income. In our set-up, pre-transfer income corresponds to the quarterly consumption expenditure including rent (in nominal terms) net of transfers received and sent by households (compare Grimm et al., 2021). According to Deaton and Zaidi (2002), in agricultural-based economies like the pastoralist communities in Northern Kenya that we study, using income to rank households has been shown to introduce more instability compared to consumption-based rankings. Moreover, using a consumption-based dataset has several merits. First, consumption survey modules have clear concepts and protocols which are more readily understood by households. At the same time, there are fewer imputation challenges compared to income (Deaton & Zaidi, 2002), implying that consumption is a good measure of living standards in developing countries where data sources are limited and income cannot be simply collected from printed or electronic monthly income statements. In the rest of the paper, we refer to our consumption measure as household income. Household quarterly, pre-transfer income in the sample amounts to KES 21,781.54 on average. Applying the 2010 official USD-KES exchange rate of 79.23, this amounts to roughly USD 275. Treatment households report a baseline pre-transfer income of KES 22,449.23 (~USD 283), which is KES 1,338.70 (~USD 17) higher compared to the household income reported by the control households. Yet, this difference is not statistically significant.

Turning to participation in transfers we observe that less than one-third of the households do not participate independent of whether they are located in treated or control sub-locations. Approximately 38% of households were exclusive recipients of private transfers while 25% were simultaneous recipients and donors of private transfers with 6% being only donors; such low participation of households as donors of private transfers only are consistently reported across rural areas of developing countries and highlight that sharing tends to be reciprocal and potentially contains an insurance motive (Kazianga, 2006). Over time, i.e., between 2010 and 2011, there is a roughly 10 pp increase in the share of households who do not engage in sharing. This can be observed across treatment and control locations without any statistically significant difference. This is mirrored in a 4.5 pp decline in the share of households who receive transfers and an almost 8 pp decline among those households who simultaneously give and receive transfers. One observation that stands out is that we observe significantly more only donors in the treatment group in 2011. Their share is twice as big compared to the control sample and it is the only group that increases in share over time (Table 1, Panel D). This also marks the only statistically significant difference in sharing, and it only occurs in 2011, i.e., after the treatment, and is thus a possible outcome of HSNP, which has also been identified in the surveys (Merttens et al., 2013). In Panel B of Table 1, we further zoom into the value of private transfers received (intensive margin). The households under study received about KES 1,718 (~USD 22) of total transfers on average at baseline. When we disaggregate private transfers received by type (cash or non-cash),[5] we observe that 75% of the total value of all private transfers received is in the form of cash transfers. Treatment households report a higher level of all types of transfers at baseline but in statistical terms, the amounts are similar to the ones observed for the control households.

The non-cash transfers are smaller in value. In total, they amount to KES 429 (~USD 5.4) which is comparably small relative to the amount of cash transfers. The difference with control households amounts to roughly USD 1 and is statistically insignificant (Table 1, Panel C). Next, we turn to transfers given at baseline. In terms of value, the total amount of transfers given amounts to KES 522 (~USD 6.6) at baseline and is similar to the composition of transfers received. Cash transfers given to other households represent 85% of the total value of transfers given with the remaining 15% representing non-cash transfers. Importantly, there is no statistically discernable difference in transfers given between treatment and control households. Similar to the observed drop in the incidence of transfers, we observe a decline in the value of transfers between 2010 and 2011 for both transfers received and transfers given (Table 1, Panels E, F). Across transfers, we do not identify statistically significant differences between the amounts received or given by treatment and control households at follow-up. Thus, at first glance, we see a decline in transfers over time at the extensive as well as the intensive margin which seems to take place across both treatment and control locations.

Last but not least we turn to treatment by HSNP. As reported at the bottom of Table 1, 52% of the sampled households were treated by the program and the average value of HSNP received was KES 9,686 (~USD 122) for those benefitting from the program in the first year. Note that the bi-monthly payment amounted to KES 2,150 (~USD 27). Thus, it implies that the average beneficiary household has received between four and five installments in 2011.

Concerning the baseline socio-economic status, we present descriptive statistics in Panel A of Table 2: The only difference that we identify between treatment and control households is in terms of household size. Treatment households are bigger by 0.3 members. Note that we apply the OECD calculation of household size. Since the OECD scale assigns a value of 1 to household heads, 0.5 to any other adult household member, and 0.3 to every child (Hagenaars et al., 1994), the findings imply that on average control households have one child less. This can partly be explained by the fact that participation in the program was based on household size. For instance, a household was selected if the proportion of their dependents exceeded a set threshold or whenever there were any individuals above 55 years. Furthermore, the households have a high average dependency ratio of 67% where dependents are children younger than 18 years, elderly people of 55 years and above, and chronically ill or disabled individuals. We do not identify any significant differences between treated and control households for the dependency ratio. Similarly, the treatment and control households do not differ with respect to the average age of the household head, the gender and marital status of the head. As a reflection of the pension targeting mechanism

[4] The HSNP dataset is available at: https://microdata.worldbank.org/index.php/catalog/1917. [Last accessed: 1st May 2019].

[5] Monetary values are assigned to non-cash/in-kind transfers. To the best of our knowledge, monetary values were imposed by the survey team based on their local knowledge.

Table 1
Participation in the exchange of private transfers and their value at baseline and follow-up for the treatment and control group.

	Full sample	Treatment	Control	Difference in means
	Mean (SD)	Mean (SD)	Mean (SD)	
Baseline data (Year = 2010)				
Household pre-transfer income	21,781.54	22,449.23	21,110.55	1,338.68
	(1,152.69)	(1,883.12)	(1,354.71)	
Part A: Household participation				
Non-participation in private transfers	0.31	0.31	0.31	−0.01
Recipient of private transfers only	0.38	0.37	0.39	−0.02
Donors of private transfers only	0.06	0.06	0.06	0.00
Both donor and recipient of transfers	0.25	0.27	0.24	0.03
Part B: Private transfer received				
Total transfer (KES)	1,718.25	1,996.43	1,438.69	557.75
	(276.65)	(507.17)	(221.14)	
Cash (KES)	1,289.42	1,528.80	1,048.86	479.94
	(280.21)	(507.09)	(241.98)	
Non-cash (KES)	428.83	467.64	389.83	77.81
	(42.64)	(45.83)	(72.39)	
Part C: Private transfer given				
Total transfer (KES)	521.82	584.91	458.42	126.49
	(169.57)	(271.39)	(208.20)	
Cash (KES)	444.09	493.69	394.26	99.43
	(170.99)	(273.06)	(211.08)	
Non-cash (KES)	77.72	91.22	64.16	27.06
	(14.58)	(25.36)	(14.45)	
Follow-up data (Year = 2011)				
Household pre-transfer income	26,482.08	28,032.82	24,923.70	3,109.12
	(1,453.83)	(2,412.38)	(1,608.06)	
Panel D: Households participating in private transfer				
Non-participation in transfers	0.41	0.41	0.42	−0.01
Recipient of transfers only	0.34	0.32	0.35	−0.03
Donors of transfers only	0.08	0.11	0.05	0.05**
Both donor and recipient of transfers	0.17	0.16	0.18	−0.02
Panel E: Value of private transfer received				
Total transfer received	1,223.55	1,173.83	1,273.52	−99.70
	(145.36)	(191.38)	(222.71)	
Cash transfer received	905.03	850.49	959.84	−109.35
	(142.62)	(188.23)	(217.94)	
Non-cash transfer received	318.52	323.34	313.68	9.65
	(35.58)	(54.96)	(46.31)	
Panel F: Value of private transfer given				
Total transfer given	199.73	238.90	160.36	78.54
	(29.79)	(45.45)	(37.80)	
Cash transfer given	135.76	169.09	102.26	66.83
	(24.70)	(38.41)	(30.39)	
Non-cash transfer given	63.97	69.81	58.11	11.71
	(12.23)	(18.33)	(16.48)	
Treatment	0.52			
Value of the treatment	4,855.06 (719.53)	9,686.30 (198.901)	0.00	
	9,686.30***			
Observations	**2,847**	**1,427**	**1,420**	

Notes: For variable definitions see appendix 1; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Quarterly nominal values of income, cash, non-cash, and the total of private transfers are presented; all monetary values are in Kenyan Shillings (KES). Non-cash transfer received refers to the sum of in-kind donations (gifts or aid received from non-governmental organizations, religious organizations or the private sector. Note that the combined in-kind donations are not private transfers in a strict sense but we treat them as private transfers as private contributions form part of it and the state transfer might similarly crowd out transfers from non-governmental and religious organizations) and the items classified as non-cash transfers received (mainly food support); SD is the standard deviation derived with clustering at the sublocation level. The mean difference captures the difference in means between households in control and treated sub-locations.

and local Kenyan reality of the senior person being the household head, we observe that the average age of the head is almost 56 years. More than two thirds of the households are headed by a man and only about 3% are divorced.[6]

Next, we turn to household asset holdings, which represent information assets such as mobile phones, TVs, and computers as well as jewelry and other items of value (for details see Appendix 1). They are presented as basket and in terms of their monetary value. While treated household only have assets of an average total value of KES 2,853, control households' own assets worth KES 3,591. Yet, the difference is not statistically significant due to the large variations in the sample. In addition, we account for productive assets as captured by Tropical Livestock Units (TLU). In the TLU calculation a value of one is assigned for every cattle owned, 0.1 for donkey/ass/mule, 0.1 for sheep/goat 0.01 for poultry, and 1.4 for a camel. Households in treated sub-locations had 8 TLU compared to 7 TLU for those in control sub-locations, yet there is a considerable variation in TLUs across sub-samples implying that the found difference is statistically insignificant. The fairly high TLU is representing the fact that many households in our sample are herders. This is also reflected in their mobility. We observe that 7% of the surveyed households are fully mobile and 10% are partly mobile indicating the nomadic lifestyle prevalent in the region.

[6] We consider this variable as our marital status variable as it was directly provided in the survey data.

Table 2
Balancing of household characteristics at baseline.

	Full sample	Treatment	Control	Difference in means
	Mean (SD)	Mean (SD)	Mean (SD)	
Household size (OECD)	4.51 (0.08)	4.65 (0.11)	4.36 (0.10)	0.29**
Dependency ratio	0.67 (0.01)	0.68 (0.01)	0.67 (0.01)	0.00
Age of the household head	55.66 (0.99)	55.21 (1.39)	56.11 (1.44)	0.90
Household head is male (=1)	0.68	0.69	0.67	−0.02
Household head is divorced (=1)	0.03	0.03	0.02	0.01
Household assets (KES)	3221.30 (1071.82)	2853.42 (989.85)	3591.00 (1927.99)	−737.58
Tropical Livestock Units (TLU)	7.54 (0.97)	8.03 (1.58)	7.06 (1.15)	0.97
Fully mobile (1 = Yes)	0.07	0.07	0.07	−0.01
Partly mobile (1 = Yes)	0.10	0.09	0.11	−0.02
Disabled household member (=1)	0.06	0.05	0.06	0.00
Chronically ill household member (=1)	0.28	0.29	0.27	0.02
Death of productive member or injury (=1)	0.12	0.12	0.12	0.00
Reduction in income (=1)	0.14	0.15	0.14	0.01
Asset shock (=1)	0.54	0.52	0.56	−0.04
Drought (=1)	0.53	0.53	0.52	0.01
Observations	**2,847**	**1,427**	**1,420**	

Notes: For variable definitions see appendix 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All monetary values are in Kenyan Shillings (KES); SD is the standard deviation derived with clustering at the sub-location level. The mean difference captures the difference in means between households in control and treated sub-locations. A joint F-test of orthogonality of all control variables has a value of 1.07 with associated *p*-value of 0.411. A joint F-test of orthogonality of all baseline control variables excluding shocks has a value of 1.19 with associated *p*-value of 0.323. A joint F-test of orthogonality of all shock variables has a value of 0.05 with associated *p*-value of 0.985.

Finally, we also account for household constraints in the form of disability and chronical illness. Treated and control households do not differ in terms of the share of individuals with disability (6%). Similarly, across households, the share of chronically ill household members in the three months prior to the survey is 28%.

Since shocks have been identified as triggers for private transfers, we also include their prevalence as part of our control variables (Table 2, Panel B). Note that contrary to the socio-economic control variables, which we measure at baseline, we include contemporaneous shocks. This is in line with our theoretical considerations that have identified insurance motives as possible reasons for private transfers. Most importantly, even at a glance, it can be seen that at baseline, treatment and control households do not differ in their experience of shocks. Across treatment and control sub-locations 12% of the households reported the death or serious injury of a productive member as a major challenge. Moreover, 14% of households reported a reduction in income as an important shock to them. But the most experienced shock is an asset shock that accounts for the loss of assets or a reduction in the value of assets. This shock was reported by 52% of the households. Control households report the occurrence of this shock slightly more often but the difference is not statistically significant.

Last but not least, we also assess the impact of weather shocks since Northern Kenya experienced a major drought shock in the period. Our weather data,[7] covering the period January 1976 to December 2011 is obtained from the University of Delaware (Matxuura & Willmott, 2015). The data is gridded with a resolution of 0.5×0.5-degrees. We make use of monthly rainfall and temperature data in the construction of the Standardized Precipitation-Evapotranspiration Index (SPEI) as is common practice in the climatology literature (Ongudi & Thiam, 2020). To mimic local agricultural seasons, we apply six-month time frames. We merged the SPEI with the HSNP dataset using the names of the sub-locations. For sub-locations without data, we opted for the nearest available weather station data. Following Agnew's (2000) classification, about 53% of the households in treated sub-locations were exposed to drought at baseline compared to about 52% of households in control sub-locations.

Overall, baseline observable characteristics are well-balanced across treatment and control households. Only one control variable shows a statistically significant difference at baseline. Importantly, when we conduct a joint F-test of the similarity of the control variables at baseline, we fail to reject the null hypothesis of similarity in means (*p*-value = 0.41). Equally, when excluding the shocks from the orthogonality test and only considering the remaining household level control variables, we fail to reject the null hypothesis of similarity in means (*p*-value = 0.32). When only testing for orthogonality in the shocks we obtain a *p*-value of 0.99. Thus, at the level of the control variables as well as the outcome variables we have a balanced sample. Next, we turn to our empirical strategy.

5. Empirical strategy

Our empirical strategy proceeds in three steps (i) from the direct impact of HSNP on income and private transfers, to (ii) assessing the transfer derivative to (iii) the identification of discontinuities in the private transfer-income relationship and sub-sample analyses. First, we estimate the direct effect of HSNP participation on household pre-transfer income and private transfer akin to similar study set-ups in the context of cash grants to micro-entrepreneurs (McKenzie, 2017; De Mel et al., 2008). Since HSNP has been implemented as a randomized controlled trial, we apply an Analysis of Covariance (ANCOVA) model to assess the impact of the HSNP-induced shock on income and private transfers. We apply ANCOVA as we have a low level of serial correlation in the outcome variables and in such contexts, ANCOVA improves in power over the difference-in-difference estimator (McKenzie, 2012). The model is specified as follows:

$$I_{ic1} = \beta_0 + \beta_1 I_{ic0} + \beta_2 HSNP_{ic1} + \beta_3 X_{ict} + \vartheta_{c-pair} + \varepsilon_{ict}, \quad (1)$$

where I_{ic1} denotes the outcome (in this case the value of household pre-transfer income or of any type of private transfer) for household i in sub-location c and year 1, i.e., the first follow-up in 2011. We proxy the household's pre-HSNP situation in the outcome with the baseline value I_{ic0}. The term I_{ic0} represents the baseline level of income in 2010 when

[7] This weather data are available at: https://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html. [Last accessed: 20th September 2019].

depicting the income relationship and the baseline level of private transfers when assessing the latter. $HSNP_{ic1}$ corresponds to the receipt of HSNP by household i who lived in sub-location c in 2011. It is equal to 1 for treated households and zero otherwise. X_{ict} controls for baseline household level variables and contemporaneous shocks. The baseline control variables are household size, the dependency ratio, the age, gender and marital status of the household head, the value of household assets, total household livestock as captured by TLUs, household mobility, whether any household member is chronically ill, and whether the household has a disabled member. The contemporaneous shocks consist of the death or severe injury of a household member, a shock to household assets, and a self-declared negative income shock. In addition, we control for the experience of a drought shock. We include the drought shock based on externally provided SPEI data since it was a large shock in Norther Kenya and given the nature of our analysis that tries to identify, inter alia, whether insurance motives feed into private transfers. Since the randomization was implemented at the sub-location pair level we account for sub-location-pair specific effects ϑ_{c-pair}. We cluster standard errors (ε_{ict}) at the sub-location pair level. With this initial set-up, we study the direct effect of being an HSNP recipient on income and private transfers.

Yet, we know from the literature about capital grants to micro-entrepreneurs in developing countries that financial injections first and directly affect the capital stock of a firm and only in a second step possibly materialize in increased profits (McKenzie, 2017; De Mel et al., 2008). The same logic applies for income-constrained households. The receipt of the HSNP transfer directly affects income, which we consider a program output. In a next step, households make transfer decisions based on the new income situation and the such realized transfers are the outcome or second step. Therefore, as a second step we attempt to capture how a rise in household pre-transfer income (due to receipt of the HSNP transfer) impacts private transfers received by household i or given from household i to other households. We thus estimate the following equation:

$$T_{ic1} = \beta_0 + \beta_1 I_{ic1} + \beta_2 X_{ict} + \vartheta_{c-pair} + \varepsilon_{ict}, \tag{2}$$

where T_{ic1} denotes the private transfer received by household i or given to other households by household i in sub-location c in year 1 which corresponds to 2011. Our variable of interest is I_{ic1} and captures household i's income. All other variables are as explained in equation (1). We estimate equation (2) with Two-Stage Least Squares (2SLS) treating income as an endogenous variable and using equation (1) as the first stage. We can treat equation (1) for the income specification as first stage and HSNP receipt as instrument as the program was randomly introduced (Heckman, 1996). When discussing the results, we will present the relevant identification tests.

Our transfer outcomes of interest are the cash, non-cash, and total transfers received by household i and the same three categories given by household i to other households. Based on our theoretical considerations, we observe crowding-out (crowding-in) of private transfers if the coefficient on β_1 is negative (positive) and statistically significant.

Since in our HSNP dataset about 31% of the households did not participate in private transfers at baseline (see Table 1), OLS and 2SLS are not the ideal models as we need to account for a high concentration of the value of zero for private transfers received or given. This is akin to a left-censoring problem. To account for the censoring, we also estimate a Tobit model (Tobin, 1958). The model is specified as follows:

$$T^*_{ic1} = \pi_0 + \pi_1 T_{ic0} + \pi_2 X_{ict} + \vartheta_{c-pair} + \varepsilon_{ict}, \tag{3}$$

where T^*_{ic1} is a latent variable[8] in 2011 that allows defining the transfer as it absorbs both the process of participation and the outcome of interest. All other variables are as defined in Eq. (1) above. To account for the endogeneity of income (Joulfaian & Wilhelm, 1994; Juarez, 2009), we estimate an Instrumental Variable (IV) Tobit model using the maximum likelihood estimator (Tobin, 1958). The model is akin to the above postulated 2SLS model where income is considered endogenous and instrumented with HSNP receipt which is a valid instrument as the program was randomly introduced and thus independent of household characteristics, preferences or sharing motives.

Third, we turn to discontinuities in the private transfer-income relationship. In the theoretical framework, the association between a private transfer and household income is assumed to be linear. However, as Cox et al. (2004) showed, there is the possibility of non-linearities in the private transfer-income relationship, especially when donors switch from altruistic to exchange motives.

To capture non-linearities, we estimate a spline model (Cox, 1987; Cox & Jakubson, 1995). The model looks as follows:

$$T_{ic1} = \gamma_0 + \sum_k^4 \gamma_{1k} I_{ic1} + \gamma_2 X_{ict} + \vartheta_{c-pair} + \varepsilon_{ict} \tag{4a}$$

$$I_{ic1k} = \pi_0 + \pi_1 I_{ic0k} + \pi_2 HSNP_{ic1} + \pi_3 X_{ict} + \vartheta_{c-pair} + \varepsilon_{ict}, \tag{4b}$$

where k indicates household pre-transfer income quartiles; I_{ic1k} is the quarterly value of household i' pre-transfer income in spline k.[9] We instrument income in each spline with the spline income in the previous period I_{ic0k} and with the value of HSNP receipt. The remaining control variables are as introduced before. Similar to Grimm et al. (2021), we treat knots as known and estimate equations (4a) and (4b) with 2SLS and IV Tobit.[10]

6. Results

Our results are presented in Table 3. We start with the ANCOVA results for the impact of HSNP on household pre-transfer income (Table 3). We identify that benefitting from HSNP increases a household's pre-transfer income albeit the relationship only being significant at the 10% level. Yet, a receipt of HSNP increases household quarterly, pre-transfer income by KES 1998 (~USD 25.2). The most important determinant of household pre-transfer income in 2011 is baseline household income. The coefficient amounts to 0.23 and is statistically significant at the 1% level. Unsurprisingly, we obtain identical results when employing the Tobit model since our household income data are not censored. Importantly, statistical significance is improved with the Tobit model. Thus, the HSNP program has an economically non-negligible effect on income and we are able to detect the effect despite the fact that income (here: consumption; see section 4 for details) is intricate to capture in developing countries. In line with the project logic, one might expect that this rise in household pre-transfer income might help households acquire nutritious diets and, in this way, help reduce the high incidence of malnutrition in the districts under study.

Next, we turn to the direct effect of being an HSNP beneficiary on private transfers. We estimate the ANCOVA model akin to the one for income and condition on the respective pre-program private transfer values. As can be seen from Column (1), Panel A of Table 3, there is no direct effect of HSNP on private transfers received. While all coefficient estimates are negative, pointing towards crowding-out effects, they are imprecisely measured and statistically insignificant. Yet, we identify a

[8] $.T_{ict} = \begin{cases} 0 if T^*_{ict} \le 0 \\ T^*_{ict} if T^*_{ict} > 0 \end{cases}$

[9] The knots for creating linear splines are placed at four equal quartiles of household pre-transfer income. These knots are as follows in our context: $\frac{\delta T_{ic1}}{\delta I_{ic1}} = \begin{cases} \gamma_1, if I_{ic1} < 14,036.61 \\ \gamma_2, if 14,036.61 \le I_{ic1} < 20,860.80 \\ \gamma_3, if 20,860.80 \le I_{ic1} < 30,550.30 \\ \gamma_4, if I_{ic1} \ge 30,550.30 \end{cases}$

[10] We are grateful for the STATA codes shared by Grimm et al. (2021).

small positive effect on private cash transfers given. We show that receipt of HSNP increases the value of cash transfers given to other households by about KES 61 (~USD 0.77, Column 1, Panel B). Although this effect is statistically significant at conventional levels, it's small in practical terms. Roughly the same increase is documented in the total transfers given.

As motivated when introducing our empirical strategy, the OLS model is potentially biased as it does not account for the left-censoring of the transfer data. Therefore, we also implement the Tobit model to assess the direct HSNP transfer effects on private transfers (Table 3, Column 2). The findings stemming from the Tobit model mirror the OLS findings but coefficient estimates are larger in absolute terms. We do find some indication of a negative impact on the total receipt of private transfers. Turning to the overall effect on total transfers received, we show that being an HSNP beneficiary is associated with roughly a KES 387 (~USD 4.9) reduction in the total value of transfers received (Column 2, Panel A).

Furthermore, we obtain support for the previously identified positive effect on transfers given. Particularly, receipt of HSNP is associated with an increase of approximately KES 766 (~USD 9.7) in the value of cash given to other households. The effects identified with the Tobit model are considerably larger, for the case of cash given, they are as much as twelve times larger compared to the coefficient estimates obtained with the OLS model. Again, the effects mainly manifest themselves in the giving of *cash* transfers, non-cash giving is not affected. For the giving of transfers, it is even more obvious that the extra household cash was equally shared with other households in the form of cash (Merttens et al., 2013). In turn, other, non-cash transfers remain largely unaffected.

We derive three observations from the findings so far. First, the rise in pre-transfer income due to HSNP is most pronounced in practical terms and most precisely identified. Second, there is an indication of a negative (positive) relationship between being an HSNP beneficiary and the value of private cash transfers received by (given to) other households. Third, not controlling for the left censoring of the transfer data results in a small absolute magnitude of the coefficient estimates and might lead to wrong conclusions and policy implications. Similar results have been reported by Gibson et al. (2011) and Grimm et al. (2021). Both studies identified the bias inherent in using linear models when testing for crowding-out and crowding-in effects of private transfers.

Since we observe a positive and statistically significant impact of HSNP on household pre-transfer income, we proceed with instrumental variables models to assess whether the HSNP income shock is also visible in altered transfer patterns. Thus, we have already established the relevance of HSNP receipt as instrument as it is correlated with the endogenous variable. Furthermore, Heckman (1996) derived that the exclusion restriction holds when randomization of program receipt is used as instrumental variable as experiments make the treatment variable orthogonal to the error term and the other regressors. Results are presented in Table 3, Column (3) for the 2SLS model, and in Column (4) for the IV Tobit model.

Before turning to the second stage findings, note that at the bottom of Table 3, Columns (3) and (4) we report the coefficient estimates from the first stage of our 2SLS and IV Tobit models. We show that the coefficients associated with our instruments are positive and statistically significant at conventional levels as already established. We further provide identification tests showing that both IV models are properly identified. For the linear model we provide the Kleibergen-Paap *rk LM* statistic that is rejected at the 5% level suggesting that the instruments are not irrelevant. We further provide the Hansen *J* statistic that we fail to reject providing evidence in support of the null hypothesis that the overidentifying restrictions are valid. For the Tobit model we provide the Wald test of no endogeneity that we reject at the 0.01% level.

Table 3
Response in private transfers to the HSNP shock, direct and IV results.

	OLS	**TOBIT**	**2SLS**	**IV Tobit**
	(1)	(2)	(3)	(4)
Household pre-transfer income	1997.519* (1004.719)	1996.997** (997.985)		
Panel A: Transfer received				
Cash	−149.933 (104.791)	−196.153 (273.382)	−0.007 (0.012)	−0.085** (0.034)
Non-cash	−5.559 (34.336)	−100.000 (84.948)	−0.014** (0.007)	−0.070*** (0.021)
Total	−157.928 (116.555)	−386.733* (218.333)	−0.021° (0.014)	−0.115*** (0.035)
Panel B: Transfer given				
Cash	61.005** (26.961)	765.849*** (257.350)	0.019** (0.008)	0.187*** (0.055)
Non-cash	8.589 (6.644)	−24.092 (64.634)	0.003 (0.003)	0.017 (0.016)
Total	69.655** (26.383)	297.542** (134.638)	0.022** (0.009)	0.110*** (0.032)
First-stage statistics				
Receipt of HSNP transfer			0.233*** (0.029)	0.232*** (0.029)
Household income at baseline			1997.519** (1004.719)	2117.895** (855.608)
Baseline covariates	Yes	Yes	Yes	Yes
Contemporaneous shocks	Yes	Yes	Yes	Yes
Sub-location pair FE	Yes	Yes	Yes	Yes
Kleibergen-Paap *rk LM* statistic			7.34	
p-value			0.026	
Hansen *J* statistic			0.612	
p-value			0.434	
Wald test of no endogeneity				7.37
p-value				0.007
Observations	**2,847**	**2,847**	**2,847**	**2,847**

Note: The dependent variables are pre-transfer income, followed by cash, non-cash, and total private transfer received (Panel A) and given to other households (Panel B). Robust standard errors (in parentheses) are clustered at the sub-location pair level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, °<0.13; all estimations include sub-location pair dummies (with Kaitede and Kalem as baseline pair), the contemporaneous shock of death of a household member or major injury, the shock of a reduction in household income, and a negative shock to the assets. In addition, we control for the incidence of a drought since the region experienced a major drought in the period. All these shocks are indicated with a dummy variable. We also condition on baseline covariates: we control for the household size per adult equivalent, the dependency ratio, the age of the household head, whether the household head is male, whether the household head is divorced, the value of household assets, the TLUs, whether a household is fully or partly mobile (being fully settled serves as the excluded category), the incidence of disability, and the incidence of chronic illness. The models in Columns (1) and (2) further control for the lagged outcome variable. Furthermore, we control for receipt of HSNP in the first year. We only present the coefficient associated with this value in the above table, all other coefficient estimates are not represented for the sake of brevity. Results in Columns (3) and (4) derive from instrumental variables models. We use the receipt of HSNP and baseline household income as instruments. For the sake of brevity, we only display the coefficients associated with the receipt of the HSNP transfer and income. Detailed results are made available by the authors upon request.

Next, we turn to the second stage outcomes: Our 2SLS results show that the rise in household pre-transfer income due to HSNP receipt is roughly KES 2,000 and is accompanied by a decrease in the *total* value of private transfers received by about KES 42 (~USD 0.5) every quarter. Yet, the effect is only significant at the 13% level. We do not establish a significant effect on cash transfers received and a small effect of a reduction of KES 28 on non-cash transfers (p-value < 0.10). For transfers given, we show that a rise in pre-transfer income by 2,000 KES as triggered by HSNP is associated with an increase in the value of cash and total transfer given to other households by KES 38 and 44, respectively. These effects seem negligible but should not be ignored given that we are dealing with poor households for whom HSNP transfers cover about 12% of baseline consumption expenditures.

Moreover, in Column (4) of Table 3 we provide the results of our preferred IV Tobit model that accounts for the left censoring in the transfer variables. In contrast to 2SLS, it yields large, negative, and statistically significant income coefficients for the receipt of private transfers (Panel A). These results suggest an attenuation bias in the linear models. Our results show that a rise in household pre-transfer income due to HSNP receipt of about KES 2,000 is accompanied by a decrease of about KES 230 in the value of *total* private transfer received. These results are about 5.5 times higher than those reported under 2SLS. At the same time, we show that a rise in pre-transfer income by KES 2,000 due to HSNP receipt is associated with a decrease in the value of cash and non-cash transfer received by KES 170 and 140, respectively. The results buttress the notion that private transfers adjust to social policy and mitigate the effects of redistributive policies. Notably, our findings (on cash and total transfer received) mirror those from Juarez (2009) for the case of Mexico.

Interpreting the results presented in Columns (3) and (4) of Table 3 from the perspective of transfer derivatives, we observe that for the sample as a whole the transfer derivatives are negative pointing to the above discussed crowding-out effects, yet since the coefficient estimates are far below 1 in absolute magnitude, the results suggest that the redistributive dynamics of HSNP are limited when considering average effects. As we will discuss below, dynamics are different for poor households.

In Panel B (Table 3, Column 4), we present IV Tobit results for the giving of private transfers. We find a statistically significant effect of household pre-transfer income on the value of *cash* and *total* private transfer given to other households. Particularly, we show that a rise in household pre-transfer income by KES 2,000 due to HSNP receipt increases the value of cash and total transfers given to other households by KES 374 and 220, respectively. The effects are statistically significant at conventional levels and confirm crowding-in effects for giving in response to a rise in household income. In addition, we evidence, yet again, that the estimates of the IV Tobit model are larger in absolute terms compared to 2SLS. The coefficient estimates increase by a factor of five.

In general, we can conclude that the rise in household pre-transfer income due to HSNP receipt has a moderate crowding-out effect on private transfers received and a more pronounced crowding-in effect on private transfers given. Overall, this points at changing dependencies due to HSNP in particular and suggests that in general there are very likely, non-negligible external effects of cash transfer programs on existing transfer schemes in developing countries.

While we have identified changing transfer dynamics due to HSNP, we have not yet answered the question of the underlying transfer motives. This is what we try to address in the next section.

7. Heterogeneity and robustness checks

We proceed by assessing the heterogeneity of our results across the income distribution. We disaggregate household pre-transfer income into four continuous, linear quartile splines. The splines are ordered from the lowest (i.e., poorest households) to the highest (i.e., relatively better-off households). Results are presented in Table 4.

Even at a glance, we can observe a negative and statistically significant relationship between private transfers received and pre-transfer income that is most pronounced for the first and second quartile, dissipates but is still significant for the third quartile and largely disappears for the fourth quartile (Panel A). In particular, our results show that for the poorest households located in income quartile 1, a rise in pre-transfer income by KES 2,000 due to HSNP receipt is associated with a reduction in *total* private transfer received by KES 2,314 every three months. For these poor households in the first income quartile, this effect corresponds roughly to the amount of the HSNP transfer and suggests a complete crowding-out. Our findings are similar to those reported by Grimm et al. (2021) for Burkina Faso. For the households in the second quartile, a rise in income by KES 2,000 due to HSNP receipt is followed by a reduction of about KES 2,934 in the value of total transfers received. Here, our findings contradict those by Grimm et al. (2021) for Burkina Faso although overall we come to the same conclusion of most effects being realized for the low-income quartiles. Put differently, for the two poorest income quintiles we identify a negative transfer derivative for the received of total transfers. This derivative is above one in absolute magnitude (compare coefficient estimates in Table 4, Column 3). It suggests that those households that depend most on private transfers, i.e., the poorest, are also most affected by the crowding-out effect in response to HSNP. Notably, this effect has been disguised by the average estimates presented in Table 3.

For medium net-worth households (i.e., those in the third quartile), we find that an HSNP-induced rise in household pre-transfer income by KES 2,000 is followed by a reduction of approximately KES 1,072 in the value of cash transfer received (Column 3, Panel A). This effect is roughly half in size compared to those obtained for the first and the second quartile, implying that the effect of a rise in income follows a pyramid-shaped pattern. This entails that those at the lowest levels of the pyramid experience higher effects compared to those at the top.

For households in the fourth quartile, which are the relatively better-off households in our sample, we only observe a small negative effect associated with a rise in pre-transfer income on transfers received and this effect is statistically insignificant for cash transfers and total transfers. For these relatively better-off households, an HSNP-induced extra KES 2,000 is associated with a reduction by KES 118 in the value of non-cash transfers received. The effects on total transfers received and cash transfers are zero suggesting at most a minimal impact of HSNP on non-cash transfers received by better-off households. Overall, the results give an indication that a rise in income induced by an unconditional cash transfer affects the sharing of all types of households, especially when private transfers are non-cash in nature. It is interesting that the effect on non-cash receipts is most pronounced. This might imply that exchange related sharing as manifested in non-cash transfers respond elastically to the HSNP receipt, making donors less inclined to share food, gifts, and services with households benefitting from a cash transfer (Secondi, 1997; Bernheim et al., 1985; Cox, 1987).

Concomitantly, we note that the social program impacts poor households the most and makes them less dependent on the grace of other households. Yet, the net redistributive welfare effect seems minimal. This raises the question whether HSNP wants households to transition out of poverty or whether the program "just" aims to make poor households less dependent on private transfers. We deduce that the finding that transfer receipt is relatively more crowded-out by HSNP for poor households may suggest, inter alia, that in the absence of government provided support a strong transfer motive by rich households to the originally poor households was altruism and the need for altruistic giving disappears due to HSNP (Becker, 1993; Becker, 1974).

In panel B of Table 4, we zoom in on heterogeneous effects in transfers given along the income distribution. Undoubtedly, the results highlight that a rise in income induces households to provide private transfers to other households. These effects are considerably stronger amongst the low net-worth (or poor) households. For poor households, we show that a HSNP-induced rise in pre-transfer income by KES 2,000

Table 4
Transfer responses to changes in pre-transfer income using quartile income splines with IV Tobit.

	Cash	Non-cash	Total transfer
	(1)	(2)	(3)
Panel A: Private transfer received			
1st income spline	−1.057*** (0.348)	−0.416** (0.166)	−1.157*** (0.353)
2nd income spline	−1.589*** (0.535)	−0.384*** (0.133)	−1.467*** (0.439)
3rd income spline	−0.337 (0.266)	−0.308*** (0.109)	−0.536** (0.252)
4th income spline	0.012 (0.033)	−0.059*** (0.023)	−0.026 (0.034)
Panel B: Private transfer given			
1st income spline	2.517** (1.265)	0.116 (0.138)	1.293* (0.685)
2nd income spline	1.114*** (0.390)	0.071 (0.086)	0.598*** (0.196)
3rd income spline	0.898*** (0.314)	−0.049 (0.079)	0.410*** (0.149)
4th income spline	0.148*** (0.052)	0.022 (0.016)	0.094*** (0.036)
Panel C: First stage results			
1st income spline			
Receipt of HSNP transfer	184.852*** (62.225)		
Household income at baseline	0.043* (0.023)		
Wald test of no endogeneity	4.98		
p-value	0.026		
2nd income spline			
Receipt of HSNP transfer	380.711*** (138.345)		
Household income at baseline	0.136*** (0.020)		
Wald test of no endogeneity	8.12		
p-value	0.004		
3rd income spline			
Receipt of HSNP transfer	374.651** (191.425)		
Household income at baseline	0.156*** (0.025)		
Wald test of no endogeneity	4.7		
p-value	0.03		
4th income spline			
Receipt of HSNP transfer	1090.456* (618.604)		
Household income at baseline	0.356*** (0.077)		
Wald test of no endogeneity	3.98		
p-value	0.046		
Observations	**2,847**	**2,847**	**2,847**

Note: The dependent variables are cash, non-cash, and total private transfers received (Panel A) and given to other households (Panel B) sorted into four income splines. Robust standard errors (in parentheses) are clustered at the sub-location level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For details about the control variables consult the note to Table 3.

is associated with a rise in the value of *total* transfers given to other households by about KES 2,586. The high net-worth households tend to give fairly limited amounts of total transfers compared to those in the other income quartiles; their giving is mainly in the form of cash transfers. Since the lower income households are sharing the largest part of the transfer, we interpret it as an attempt of theirs to obtain insurance (Townsend, 1994). Now that they have cash available, they are in the position to insure themselves through sharing. We are thus not surprised that non-cash giving is not affected by HSNP receipt. Approaching these transfer dynamics from the perspective of transfer derivatives it implies again that the poorest are most affected by the redistributive pressure as the transfer derivative for cash and total giving are above one for the lowest income quintile.

The extra income provided by the HSNP cash transfer untightens the budget constraints of the poor to, for example, insure against future shocks by making pre-payments. It is important to note that such behavior is against the traditional norms that dictate that high-net-worth households give to poor households in the aftermath of a shock. It's further noteworthy to highlight that such giving is mainly in the form of non-cash items and might reflect a direct passage of HSNP support from poor recipients to other households.

Finally, in Panel C of Table 4, we present the first stage results for the spline regressions. Our instruments are positive (as expected) and statistically significant at conventional levels. Moreover, the Wald test with the null hypothesis of no endogeneity is consistently rejected further supporting the implemented IV strategy.

Next, we turn to sub-sample analyses to further shed light on the question of transfer motives. We first look at the sub-sample of households that have experienced an asset shock and second at the sub-sample of households that have a dependency ratio above 66% implying that one working-age adult has to come up for at least two dependent household members. We opt for these two sub-sample analyses as the resulting sub-samples are still large enough to produce credible results. The findings are presented in Table 5. We start with assessing the receipt of private transfers for households that have experienced an asset shock. Compared to the crowding-out effects we identified for the overall sample (Table 3), the crowding-out effect of those affected by an asset shock is even larger in absolute terms (Table 5, Panel A, Columns 1 to 3). The HSNP-induced rise in pre-transfer income of KES 2,000 is associated with a decline in the value of *total* transfers received of KES 452. In comparison, for the overall sample the decline corresponds to only KES 230. Importantly, this difference is statistically significant at the 1% level, suggesting that those experiencing a shock are no longer equally insured by the community when being HSNP recipients (Sturpat & Klohn, 2018). This sub-sample finding points to insurance mechanisms being at play when poor households receive transfers (Townsend, 1994).

This notion is further reinforced when turning to the private transfers giving by households experiencing an asset shock. Akin to the previous findings, we do not find an increased giving of non-cash transfers, indicating that they are not as much affected by the government cash transfer (Table 5, Panel B, Columns 1 to 3). In turn, private cash and total transfers given are again considerably higher compared to the overall sample despite the fact that the households experienced an asset shock. The *p*-value of the difference in coefficient estimates for cash and total transfers given between the full and the sub-sample is below 0.000 for both cases. This indicates that despite experiencing an asset shock,

Table 5
Sub-sample analyses for households experiencing an asset shock and households with a dependency ration above 66%.

	Asset shock			Dependency ratio above 66%		
	Cash	**Non-cash**	**Total transfer**	**Cash**	**Non-cash**	**Total transfer**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A: Private transfer received						
	−0.172	−0.072**	−0.226*	−0.067	−0.061***	−0.098**
	(0.131)	(0.036)	(0.129)	(0.049)	(0.023)	(0.048)
Panel B: Private transfer given						
	0.402***	−0.007	0.225**	0.201***	0.020	0.116***
	(0.153)	(0.029)	(0.093)	(0.078)	(0.015)	(0.045)
Panel C: First-stage statistics						
Receipt of HSNP transfer	1556.011***			1985.738**		
	(638.713)			(882.571)		
Household income at baseline	0.136***			0.211***		
	(0.030)			(0.031)		
Baseline covariates	Yes	Yes	Yes	Yes	Yes	Yes
Contemporaneous shocks	No	No	No	Yes	Yes	Yes
Sub-location pair FE	Yes	Yes	Yes	Yes	Yes	Yes
Wald test of no endogeneity	4.27			4.11		
p-value	0.039			0.043		
Observations	1,486	1,486	1,486	1,829	1,829	1,829

Note: Sub-sample analyses for households experiencing an asset shock and households with a dependency ratio above 66%. Robust standard errors (in parentheses) are clustered at the sub-location pair level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For details about the control variables consult the note to Table 3.

households receiving HSNP support are socially obliged to share more compared to the full sample of households. Given that these sub-sampled households are at the same time those who experienced an asset shock, we argue that the extra income provided by HSNP translates into increased risk premia.

Next, we turn to households that are under a different constraint, namely those having a high dependency ratio. We opted for the 66% cut-off as this contains all households with a dependency ratio that is roughly above the baseline mean (Table 2). While these households also experience a decline in private transfers received in response to being an HSNP recipient, the effect is less pronounced as compared to the overall sample (Table 5, Panel A, Columns 4 to 6). We reject the null hypothesis of no difference in coefficient estimates between the full and the sub-sample for all types of transfers received, suggesting that their situation might be more related to altruistic and exchange-motivated sharing and that the community does not punish them equally as the average household for the social support they receive. But even these households tend to *give* more than the average household due to the HSNP-induced increase in their pre-transfer income, hinting at the strong community sharing norms (Table 5, Panel B, Columns 4 to 6) (Grimm, Hartwig, Reitmann, & Bocoum, 2021; Hammond, 1996; Kazianga, 2006; Nordman, 2016).

Taken together these results suggest that it is not obvious to distinguish between the three sharing motives that were theoretically motivated and that we likely observe a mix of these motives at play in real world interactions. Undoubtedly, households adjust their sharing and reweigh their underlying motives in response to the observed reality of the other households around them.

Having identified the above-discussed heterogeneous effects, we now turn to some robustness analyses to further scrutinize our results. In Table 6, we present estimates akin to those presented in Columns (3) and (4) of Table 3 but for the combined net private transfers. Thus, we identify the effect of an HSNP-induced shock on household pre-transfer income and its second-stage effects on net transfers. We calculate net transfers as the difference between private transfers received by and given to other households. We conduct this analysis because previous studies have shown that a rise in household income is negatively associated with net transfers (Grimm et al., 2021).

In Column 1 of Table 6, we present the 2SLS results indicating an overall negative impact of an increase in pre-transfer household income on net transfers. While effects are statistically significant at conventional levels, the coefficient estimates are relatively small in absolute terms.

Table 6
Impact of a shock to household income on net transfers.

Variables	**2SLS**	**IV TOBIT**
	(1)	**(2)**
Panel A: Net transfers		
Net cash	−0.026** (0.013)	−0.101*** (0.036)
Net non-cash	−0.017** (0.008)	−0.076*** (0.022)
Net total transfer	−0.043** (0.017)	−0.135*** (0.039)
Panel B: First stage		
Receipt of HSNP transfer	1997.519** (1004.719)	2081.420** (955.348)
Household income at baseline	0.233*** (0.029)	0.232*** (0.029)
Baseline covariates	Yes	Yes
Contemporaneous shocks	Yes	Yes
Sub-location pair FE	Yes	Yes
Kleibergen-Paap *rk LM* statistic	7.34	
p-value	0.026	
Hansen *J* statistic	0.826	
p-value	0.365	
Wald test of no endogeneity		3.92
p-value		0.048
Observations	**2,847**	**2,847**

Note: The dependent variables are net cash, net non-cash, and net total private transfers. Robust standard errors (in parentheses) are clustered at the sub-location level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For details about the control variables consult the note to Table 3.

Particularly, we find that a rise in household pre-transfer income by KES 2,000 due to HSNP receipt reduces the net value of cash transfers received by KES 52 (Table 6, Column 1). As extensively argued, our preferred estimates are those obtained with the IV Tobit model because of the left-censoring of our data (Table 6, Column 2). We demonstrate that the negative effect stemming from an HSNP-induced increase of KES 2,000 in pre-transfer income is considerably more pronounced: it amounts to a reduction of KES 270 in *total* net transfers, a reduction of KES 202 in net cash transfers and a reduction of KES 152 in net non-cash transfers (Table 6, Column 2). Thus, the analysis of net transfers supports our overall analysis that has identified bigger reductions in transfers received compared to smaller increases in transfers given in response to the HSNP shock on pre-transfer income. Taken together, the results associated with net transfers support the notion that HSNP crowded-out private transfers.

8. Conclusion

In this paper, we contribute to a growing literature about crowding-in and -out effects in the presence of public social programs. We study the effect of an exogenous increase in household income occasioned by the receipt of HSNP transfer on the amount of private transfer received by or given to other households. The program we study provides a bi-monthly transfer of about USD 20 to poor families across four poverty-prone districts of Northern Kenya. With our data, we assess pastoralist communities that are known for their decade-old networks and sharing arrangements, making them a particularly interesting case study. We document two important findings that are consistent with previous studies. First, we show that the receipt of private transfer responds negatively to an exogenous shock in household pre-transfer income. This negative effect is strongest at the lower levels of the income distribution, i.e., among low-income households. This distributional pattern is consistent with the prediction of risk-sharing models. Second, we find evidence of a positive relationship between household income and the transfer given to other households. The effects are again largest among the lowest-income households possibly depicting the untightening of previously experienced income constraints. In addition, we show that households that experience an asset shock are even more affected by the HSNP induced decline in the receipt of private transfers, suggesting that the other households in the community consider them as state-insured and pointing to insurance as one possible motive for the observed sharing among pastoralist communities. Yet, insurance motives do not seem to be the only motives for sharing. Households with comparably larger dependency ratios tend to experience a smaller reduction in the receipt of private transfers when being concomitantly an HSNP recipient, indicating the presence of altruistic and/or exchange-related motives. Lastly, we do observe increases in transfers given across all scenarios that likely reflect a mix of insurance but also altruistic motives in the context of strong sharing norms. Overall, the findings do not allow us to rule out any of the three underlying sharing motives of altruism, insurance, and exchange but rather suggest that depending on the situation of the own household and the other households in the community the motives are jointly appealed to.

Moreover, assessing the robustness of our results using net cash and total transfers received, we obtain similar findings as Cox et al. (2004), Grimm et al. (2021), and Kazianga (2006). While the identified net effects might seem small in monetary terms, given the resource-poor setting under study, the identified extent of sharing is evidently non-negligible. Concerning our choice of empirical model, there are two important take-aways. First, OLS models tend to underestimate the effects because they do not account for the left-censoring of private transfers. Second, the HSNP transfer serves as an income shock, and only if we study transfer derivates by instrumenting income with the HSNP shock we seem to fully capture the crowding-in and -out effects.

What are the implications of our study? Since we do not only observe strong sharing norms among the pastoralists of Northern Kenya but across many African societies that are characterized by deeply-routed kinship relationships (Grimm, Hartwig, Reitmann, & Bocoum, 2021; Hammond, 1996; Kazianga, 2006; Nordman, 2016), we expect our results to be relevant beyond the actual study population. For example, also for Burkina, it has been documented that private transfers are common (Hammond, 1996; Kazianga, 2006). Especially in West Africa, family and kinship ties play important roles not only in consumption smoothing but also in the start of businesses (Nordman, 2016). Similarly, Asian countries are characterized by intergenerational support and the expectations for children to take care of their aging parents resulting equally in private transfers (Lin & Yi, 2013). Moreover, we identify a positive relationship between income and transfers given that is most pronounced at lower income quartiles suggesting insurance-related motives. We contribute to the economic debate, especially with the identification of effects related to the giving of private transfers as this effect has received considerably less attention compared to the receipt of private transfers and is worth further investigation. Overall, we conclude that understanding the interplay between public and private transfers is key to the design of effective social policies in resource-poor settings. Evidently, private transfer dynamics change in response to public programs resulting in the crowding-out of private transfers received by the beneficiaries of public support.

We do not want to conclude without acknowledging that we are not in a position to consider the donor side, i.e., the extent to which donors are relieved from the pressure to share due to social safety net programs. Accounting for these externalities has shown to unfold a whole set of benefits not only for the donors themselves but also for the overall society (Grimm et al., 2017). Moreover, an important extension of this study is the analysis of social programs that have been in place for several years to determine whether there are long-term effects of an exogenous rise in household income on private transfers to and from households. It seems further worthwhile to analyze whether the crowding-in and -out effects stemming from cash transfer programs are similar in other types of social protection programs such as public work programs that do not provide direct monetary support.

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CRediT authorship contribution statement

Silas Ongudi: Conceptualization, Data curation, Formal analysis, Writing – original draft, Visualization. **Djiby Thiam:** Conceptualization, Data curation, Supervision, Validation, Writing – review & editing. **Natascha Wagner:** Validation, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix 1:. List of all variables

- **Household size per adult equivalent -** We employ the modified scale by the Organization for Economic Co-operation and Development (OECD). This scale assigns a value of 1 to household heads, 0.5 to any other adult household member, and 0.3 to every child (Hagenaars et al., 1994).
- **Dependency ratio** – is the number of dependents in a household divided by a household size at baseline. The dependents here included children (those aged below 18 years, people aged 55 years and above, chronically ill or disabled) per household.
- **Age of the household head –** is the age of the household head measured in years.
- **Household head is male** – is a dummy variable that equals 1 if the household head is male and 0 otherwise.
- **Household head's marital status –** is a dummy variable that equals 1 if the household head is divorced and 0 otherwise.
- **Household assets –** is the value of household-owned mobile phone(s), radio, television, computer, paraffin lamp, jewelry/beads, satellite disk, gun, and a washing machine.

- **Tropical Livestock Unit (TLU)** – Asset-based poverty measure tied to the number of livestock (cattle, goat, sheep, donkey/ass/mule, camel) owned by a given household. We assign a value of one for every cattle owned: 0.1 for donkey/ass/mule, 0.1 for sheep or goat 0.01 for poultry, and 1.4 for a camel. We summed these values to create a composite index called the Tropical Livestock Unit (TLU) (Lybbert, Barrett, Desta, & Coppock, 2004).
- **Fully mobile –** is a dummy variable that equals 1 if a household reports being fully mobile at baseline and 0 otherwise. This variable captures the full nomadic livelihood of some pastoralists in the HSNP districts.
- **Partly mobile –** is a dummy variable that equals 1 if a household reports being partly mobile at baseline and 0 otherwise. This variable captures the semi-nomadic livelihood of some pastoralists in the HSNP districts.
- **Disability** – is a dummy variable that equals one if any household member suffers from any permanent disabilities at baseline
- **Chronically ill** – is a dummy variable that equals one if any household member has suffered from any chronic illness/injury in the last 3 months prior to the baseline survey.
- **Death of a productive household member**– is a dummy variable that equals one if a household member of productive age has died or was severely injured in the last 3 months prior to the survey.
- **Shock reducing income** – is a dummy variable that equals one if a household reported a negative income shock in the six months prior to the survey.
- **Shock reducing assets** – is a dummy variable that equals one if a household reported a negative asset shock in the six months prior to the survey.
- **Other shocks** – is a dummy variable that equals one if a household reported other income shocks such as debt repayment in the six months prior to the survey.
- **Drought shock** – is a dummy variable that equals one if a sub-location was classified as having been exposed to drought, i.e., having an SPEI $<$ -0.84 in the six months prior to baseline
- **Consumption expenditure** – It is the total monthly value of household consumption expenditure including rent (in nominal terms) and expressed in Kenya Shillings. We converted this into quarterly values by multiplying through by three.
- **Received any private transfer** – Dummy variable which equals 1 if the respondent household reported having received any transfer in the three months prior to the survey.
- **Value of transfer received** – Monetary value of private transfer received in cash or non-cash by a respondent's household during the three months prior to the survey.
- **Value of cash received** – Monetary value of cash transfer received by a respondent's household during the three months prior to the survey.
- **Value of non-cash received** – Monetary value of the non-cash transfer and in-kind donations received by a respondent's household during the three months prior to the survey.
- **Given any private transfer** – Dummy variable which equals 1 if a respondent's household reported having given any private transfer to another household during the three months prior to the survey.
- **Value of private transfer given** – Monetary value of private transfer given by a respondent to another household during the three months prior to the survey.
- **Value of cash transfer given** – Monetary value of cash transfer given to other households during the three months prior to the survey.
- **Value of non-cash given** – Monetary value of non-cash transfer given by a respondent's household to other households during the three months prior to the survey.

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