

DO CASH TRANSFERS ALTER HOUSEHOLD COMPOSITION?
EVIDENCE FROM SUB-SAHARAN AFRICA

By

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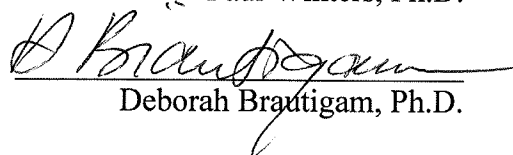
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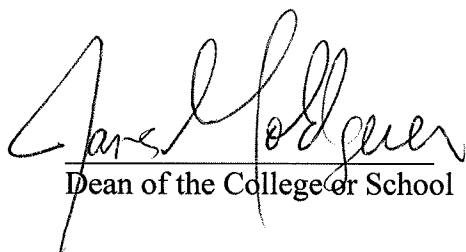
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ABSTRACT

Cash transfer programs have emerged as a core poverty reduction strategy and have been recently adopted by a few Sub-Saharan Africa countries, but there is a possibility that these programs have perverse effects on household behavior. This research uses experimental data from two cash transfer programs in Malawi and Kenya to evaluate the effects of cash transfer on household composition by focusing on the behavior of household members with respect to inwards and outwards migration. Analysis based on the data collected before and after the programs' implementation provide overall supportive evidence that cash transfers do alter household structure by affecting migration flows. The results show that in Kenya households that received transfers were more likely to send off young adult members, suggesting that the program provided resources to overcome short-term economic constraints. In contrast, in Malawi the provision of cash transfers increased the number of young adults in treatment households, although it is not clear if this is driven by new members joining the household or because members are less likely to leave. The discrepancy of findings between Malawi and Kenya suggests that programs with similar designs can have opposite effect when implemented in different context.

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INTRODUCTION

High levels of poverty have long been a major concern in Sub-Saharan Africa (SSA). During the 1990s, the number of poor people rose substantially in the region as a result of the rapid population growth (Kakwani, Veras & Son, 2005). For SSA, achieving the Millennium Development Goal of halving poverty between 1990 and 2015 is considered ambitious as many countries in the continent are not growing fast enough or because the growth they experience is not being translated into poverty reduction at a rapid rate (Ibid).

Cash transfers to the poor have emerged as a core poverty reduction strategy to fight the increasing levels of poverty in the region and have been implemented by many countries. Cash transfer Programs were first adopted in Latin America following the model of the Mexican *Progresa* program and later the concept spread across the world, including SSA. *Progresa*, launched in 1997, was pioneer in its approach as it dispensed money directly to beneficiary households, which represented a change from the traditional programs that provided subsidized necessities (Levy, 2006). In addition, the program was conditional on specific behaviors related to nutrition, health and education (Ibid).

SSA countries have adopted this model in recent years, implementing programs that provide immediate relief of poverty through direct cash transfers to poor household at the same time that it incentivizes human capital development. There are, however, two main differences between Latin America and African programs. First, African programs do not target all poor households, but focus on the extremely poor and labour-constrained

that cannot access labour-based interventions (Schubert & Slater, 2006). Second, most schemes in Africa do not include health and education conditionalities, although many of them have the goal of improving human capital (Ibid). There are also differences among the different programs that have been implemented within the region, as they may differ in their design and targeted population.

Like any public policy, Cash Transfer programs may have perverse effects on household behavior. A vast amount of research¹ suggests that the link between public policies and demographic behavior is complex. Public policies define opportunities and constraints to families through the levels of benefits it provides and the conditions of eligibility (Gauthier, 2001). The impact of the policies is additionally influenced by the income and opportunity sets of individuals, as well as the norms, stigma, and sanctions associated with the receipt of benefits and with non-traditional forms of behavior (Ibid). According to this rationale, cash transfers, as a public program, can influence demographic and economic behaviors of beneficiary households. This thesis confines the discussion on the impact of cash transfers on household structure change primarily through migration.

The objective of this research is to determine whether providing cash to poor Sub-Saharan households alters their composition by focusing on the behavior of household members with respect to inwards and outwards migration. More specifically, this thesis explores the manner in which households respond to changing economic incentives by

1. Chesnais Jean-Claude. (1996) "Fertility, Family, and Social Policy" *Population and Development Review*. 22 (4)

Gauthier, A.H. (1996). "The measured and unmeasured effects of welfare benefits on families: Consequences for Europe's demographic trends" *Europe's Population in the 1990s*. D. Coleman. Oxford: Oxford University Press

analyzing if existing household members stay in the household or leave or if new members join the household as a result of the cash transfer program. Therefore, the focus is on inwards and outwards migration as a driver of household adjustment. This study provides an insight on the socio-economic determinants of emigration in SSA and how public transfers that alter household resources can influence the decision to emigrate. It thus offers a unique opportunity to analyze how changes in household income can determine emigration. In addition, this research explores the main factors that determine the decision of individuals to remain or join a household and how this decision can be affected by short-term changes in economic incentives.

Previous empirical evidence found that indeed cash transfer programs alter household composition. Winters et al. (2009) analyzed the Nicaraguan Conditional Cash Transfer Program and find that households in control communities grew more compared to treatment households during an economic crisis. The authors explain that treatment households continued to send off young adult members while control households experience agglomeration. Similarly, Rubalcava and Teruel (2006) compare changes in household composition as a result of the Mexican PROGRESA. They found that households in the treatment group were more prone to sheltering new members of the extended family and at the same time more likely to send off young adults to start their own family.

With respect to emigration, studies on publicly provided transfers have presented contradictory evidence. Stecklov et al (2005) found that *Progresa*, Mexico's Conditional Cash Transfer program, reduced migration among beneficiary households to the United States although it had no impact on domestic migration. They attributed the results to the

conditionalities imposed by *Progresa* on adults from beneficiary households, who must have regular health check-ups otherwise the family loses the benefit. Posel, Fairbun and Lund (2005) focus their studies on pension transfers in South Africa and found the opposite, that the transfer increases emigration. According to their study, the pension transfer appears to facilitate emigration of household members, especially women, by relaxing financial constraints associated with migration start-up costs.

This study contributes to the existing literature by enhancing the understanding of how public programs that change household resources can influence emigration decisions. It also aims to unveil some of the causality links behind the decision to migrate. In addition, it adds to the literature on household composition by exploring the effects of changing household economic incentives.

The analysis presented is based on data from two experimental design programs from Kenya and Malawi. In Malawi, the Mchinji Social Cash Transfer Scheme provides cash transfers to ultra poor and labor constrained households to alleviate poverty, reduce malnutrition and improve school enrollment (Miller, 2009). Household panel data was collected in both treatment and control groups before the implementation of the program in March 2007 and again in April 2008 after the program was implemented. In Kenya, the Cash Transfers for Orphans and Vulnerable Children (CT- OVCs) Program transfers cash to households living with OVCs to encourage fostering and retention of OVCs within their families and to promote their human capital development (Ward et al. 2010). As in Malawi, household panel data was collected in both treatment and control groups before the program began, in 2007, and again two years later, 2009. As both programs

were randomly assigned among eligible beneficiaries, it is possible to identify the impact they had on household structure through decisions to stay, join or leave the household.

This thesis is organized as follows. The first chapter summarizes the theoretical literature on models of migration, intra-household allocation and household composition, considering gender aspects. The second chapter presents a brief description of both programs under study and analyzes family structures, social norms, migration patterns and gender roles in Malawi and Kenya. The third chapter describes the data and the empirical approach. The fourth chapter presents and discusses the results. The final section concludes and draws policy recommendation.

CHAPTER 1

CONCEPTUAL FRAMEWORK

To understand the pathways through which household structural changes happen this chapter reviews different theoretical models. First, migration and intra-household allocation theories, which have the potential to explain household fission through the decision of a household member to emigrate, are reviewed. Emigration is a topic of importance considering the growing intra-rural and rural-urban migration in SSA. Migration in the region has historically been strongly associated with a number of complex factors, such as rapid population and labour force growth, unstable politics, escalating ethnic conflict, poverty, HIV/AIDS pandemic and environmental deterioration (Adepoju, 2007). More recently, low incomes in rural areas and landlessness resulting from desertification and diminishing arable lands are driving out-migration, as individuals aim to supplement their income with earnings from non-farming activities (Ibid). The problem becomes more acute considering the fast urbanization rates in the region and the inability of the cities to absorb the large number of new workers.

Three different models of migration are considered in this chapter to help understand the determinants of emigration in SSA: the neoclassical model, the new economics of migration, and the network theory. The main assumptions as well as the limitations of each model as a theoretical tool are identified to help understand and generate hypothesis on the impact of cash transfers on emigration. Although judging or validating the models does not fall into the scope of this research, their limitations as explanatory tools are acknowledged. The unitary and the collective model of intra-household allocation are also reviewed to overcome the limitations identified on the

migration theories. In addition, because neither the migration nor intra-household allocation models can explain why existing household members decide to stay in the household or why a new member decide to join it, the household composition model is presented. Finally, gender aspects of household composition and migration are explored.

In sum, within this theoretical framework I consider how cash transfers provided to poor SSA households may affect household composition through member's decision to emigrate, to remain in the household, or to accept a new member. Migration and intra-household allocation models are used to predict the program's impact on emigration and the household composition model to predict the effect on the decision of existing household members to remain in the household or a new member to join in.

Models of Migration

Neoclassical Model

The first model of migration emanates from neoclassical economics and is based on tenets such as rational choice, utility maximization, expected net returns, factor mobility and wage (Arango, 2000). According to the neoclassical model of migration, individuals' decision to migrate is based on a "cost-benefit calculation where a potential migrant compares the expected income at the point of destination to the expected income in the point of origin" (Winters, De Janvry & Sadoulet, 1). An individual decides to migrate if he expects higher utility from discounted net income at a possible migration destination than at the point of origin (Ibid). To calculate the discounted net return, one multiplies the observed earnings at a destination point by the probability of obtaining a job there. These expected earnings are then subtracted from the expected earnings at the

point of origin and the difference is discounted by a factor that reflects the greater utility of money earned in the present (Massey et al., 1993). Individual characteristics, such as education, training, age, etc, may enhance the probability of employment and may lower migration costs and increase expected net returns (Ibid).

The neoclassical model assumes that migration stems from wage and employment rate differentials and predicts labor move from low-wage to high-wage areas. Labor migration should continue until equilibrium between different labor markets is achieved and should not stop until the gap in expected wages has been closed (Massey et al., 1994). It thus combines a micro perspective of individual decision-making and a macro-counterpart of structural determinants (Arango, 2000). Although this model has been widely accepted by scholars and policy makers, Massey et al. (1994) point out that it has not been put to rigorous test as generally studies focus on wage differentials and not on expected wages, a critical element of the theory.

Considering the theoretical framework proposed by the neoclassical model, receiving a cash transfers program should not change the cost-benefit calculation by the individual unless it establishes that only the named beneficiary can collect the transfer at a fixed payment site. In this case, the cost of migration would increase, as the individual would have to often go back to collect the payment or opt out of the program thus losing the benefit. If the program also imposes conditionalities on adults, such as health check ups and awareness sessions attendance, it may also alter the calculation by imposing an additional cost to migration. The cost refers to losing the household benefit in the case that the conditionalities are not fulfilled. Stecklov et al. (2005) found that *Progres*a, Mexico's Conditional Cash Transfer program, reduced migration among beneficiary

households to the United States although it had no impact on domestic migration. They attribute the stronger results for U.S. migration to the yearly health check-up condition placed by the program, as in the case of domestic migration this conditionality is relatively easy to meet.

One limitation of the neoclassical model identified by Stecklov et al (2005) is that it does not assume start-up costs to migration. If there is a monetary cost to migration and migrants are financially constrained, “the propensity to migrate as a function of income may follow an inverse –U pattern” (Stecklov et al., 772). As the authors explain, “at low levels of income, additional income may relax the financial constraint, leading to greater migration; at higher levels income, where financial constraints are less binding, additional income may reduce migration” (Stecklov et al., 772). Cash transfers to poor SSA regions may have the potential to relax these financial constraints and thus induce migration if there are substantial costs associated to it. Posel, Fairbun and Lund (2006) find an increase in migration associated with pension transfers in South Africa and explain that an increase in household income through the pension can enable the financial constraint to migration to be relaxed. In a similar way, Stecklov et al (2005) affirm that the Mexican program *Progresa* targets poor households that are likely to face substantial constraint and thus may increase migration if there are costs associated to it. The neoclassical model is also criticized for downplaying cultural determinants, for treating all societies as if they were homogeneous and for disregarding all migration that is not labor migration (Arango, 2000).

New economics of migration

A set of critics to the neoclassical model, which assumes that decisions to migrate are made by isolated individual actors, emerged during the eighties. This set of critics, referred to as new economics of migration, challenges the main assumption of the neoclassical model by stating that the decision to migration is made by units of related people – typically families or households (Massey et al., 1993). Migration decisions are made jointly by the migrant and some group of non-migrants, who share the costs and returns of migration (Stark & Bloom, 1985). Stark and Bloom (1985), by looking at patterns of remittance, explain that the migration decision can be better understood as a result of an implicit contract between the migrant and the family than by considerations of the individual migrant.

Under this model, the collective decision to send a migrant aims not only to maximize income but also to diversify income and minimize risk. Massey et al (1993) explain that in developing countries, unlike in developed countries where risks are minimized through private insurance markets or government programs, institutional mechanisms for managing risk are imperfect or absent. Thus, poor families have an incentive to diversify risk through migration by sending a family member to a different labor market, where earnings at destination are negatively or weakly correlated with the earnings at the point of origin (Massey et al., 1993). The household has the power to control risk through allocation of household resources, such as labor (Ibid).

One important concept to understand the decision to migrate under this line of thinking is that of relative deprivation. Households aim to maximize income not in absolute terms, but in relation to other households in the reference group (Arango, 2000).

In a community where income is unequally distributed, households that feel relatively deprived will have more incentives to migrate.

Some authors use the new economics of migration model to explain migration decisions at the household level. For instance, Winters, De Janvry and Sadoulet (2000) examine the decision to migrate out of Mexico to the United States from a household perspective. According to them, in rural Mexico credit insurance markets do not function properly and the only option for the household is to allocate labor to agriculture or to international migration. Thus their decision is based on the tradeoffs between returns to agriculture and returns to migration.

Following the logic of the model, Massey et al., (1993) indicate that government policies can influence migration by shaping insurance and capital markets and/or by changing income distribution of some households. For example, government insurances, such as unemployment insurance, have the potential to reduce migration. Policies that distribute income can operate both ways: it can increase migration if relatively poor households do not share in the income gain or it can reduce the incentive to migrate if relatively rich households do not share in the income gain (Massey et al., 1993). As a government program, well-targeted cash transfers have the potential to reach the poorest segments of the population, reducing their relative deprivation. By offering a steady income, these programs can also reduce the risk at origin and thus the need to diversify it through migration.

One limitation of this model refers to the fact that it assumes household has a single decision maker and pools its resources. Thus, it does not recognize that household members have different preference and does not consider how resources are allocated

within the household. To overcome this limitation I look at intra-household allocation models in the next section.

Network Theory

While the neoclassical model and the new economics of migration focus on the decision to migrate, the network theory explains how migration movements perpetuate. Networks constitute a form of social capital that connects migrants, former migrants and non-migrants in origin and destination areas (Massey et al., 1993). The logic behind it is that it can be costly for the first migrant who leaves for a certain destination, but after the first migrants have left, the costs of migration are substantially lowered for friends and relatives left behind (Ibid). Members of a network can provide assistance to new migrants in form of housing, food, job-search assistance and temporary lodging, thus reducing the cost of migration (Winters, De Janvry and Sadoulet, 2000; William, Detragiache, Vishwanath, 1996). The network can also lower the costs of adapting to a new environment, language, culture, etc. (William, Detragiache, Vishwanath (1996). By providing such services, members of a network can positively influence the expected return to migration and reduce the variability of returns (Winters, De Janvry and Sadoulet, 2000).

Once migration starts, network connections tend to diffuse in a sending region to a point that all people who wish to migrate can do so without difficulty (Massey et al., 1993). Migration then becomes institutionalized and independent of the causes that originated it (Ibid). As opposed to the predictions of the neoclassical model, migration flows are not correlated to wage differentials and employment rates. Although these

variables can promote or inhibit migration, they are overshadowed by the falling costs and risks stemming from an established network (Ibid).

Empirical studies show that networks are positively correlated with migration. Winters, De Janvry and Sadoulet (2000) show the importance of family and community migrant networks in both the decision to migrate and the level of migration between Mexico and United States. Deléchat (2003) also found that previous migration experience and migration-related variables are the strongest predictors of current migration decisions of Mexicans migrating to the USA. One limitation of theory, however, is that it explains the direction as opposed to the volume of migration and it does not explain how networks induce people to stay, move and return (Jong 2000)

The effect of cash transfers on migration may depend on the presence of previously established networks. As Stecklov et al. (2005) indicate in the case of *Progresa*, cash transfers may relax financial constraints and allow individuals to migrate where strong migrant networks are established. In this case, individuals can take advantage of the information provided by the network. If, however, migrant networks are poorly established, cash transfers will have a smaller impact because the added resources may do little to overcome the lack of information and existing risks.

Household Composition Model

Migration models predict contradictory outcomes regarding possible impacts of cash transfers on migration. The neoclassical model predicts cash transfers can reduce migration by changing the cost-benefit calculation and increasing the costs to migrate. Alternatively, it can increase migration if start-up costs of migration are considered, as

cash transfers can relax financial constraints. The rationale behind the new economics of migration suggest that cash transfers have the potential to decrease migration by providing a steady income and thus reducing the need to diversify risk through migration. The network theory predict that the impact of cash transfers on migration may depend on the presence of previously established networks: cash transfers may relax financial constraints and allow individuals to migrate where strong migrant networks are established, but will have smaller impact where migrant networks are poorly established

The migration models are important tools to understand the decision of household members to emigrate. However, they miss some internal household dynamics and aspects. To understand how cash transfer programs impact individuals' decision to remain or join a specific household I explore the household composition literature, which focuses on the factors that determine household fission or fusion. It does so by looking at the role of three main aspects within the household: scales of economy in production, consumption of public and private goods and market imperfections and risks. It is important to note that the household composition literature incorporates the main assumption proposed by the collective model of intra-household allocation, according to which household members have different preferences and resources are efficiently allocated according to a pre-fined sharing rule.

The household composition model predicts that gains from joint residence arise from the consumption of public goods and the savings associated with it. However, these gains depend on the total amount of public good that is being consumed and the share right of each member (Foster & Rosenzweig, 2002). Thus, intra-household allocation rules will influence an individual's share and consequently the decision to co-reside.

Household members also experience gains when large bulks of private goods are purchased at lower unit prices (Winters et al., 2009). Gains from public goods, however, depend on the existence of economies of scale within the household and can be offset when diseconomies to joint production arise (Foster & Rosenzweig, 2002). Economies of scale occur when assets used jointly bring greater income and growth than if used separately (Winters et al., 2009). Co-residence also affects how households ensure against risks. In the presence of market imperfections such as limited insurance and credit markets, “larger households may be better equipped to diversify economic activities and overcome liquidity constraints” (Winters et al 210). For instance, large households with different types of workers can diversify sources of income through labor allocation (Edmonds et al., 2005).

From the model it is possible to infer that a growth in income will result in an increase in consumption of public goods and in the amount that can be saved through joint consumption compared with separated consumption (Foster & Rosenzweig, 2002). An increase in income is thus expected to discourage household division. Following this logic and considering that both Kenya and Malawi programs provide a short-term growth in income through publicly provided cash transfers, one may expect existing household members to remain in the household as a result of the programs. In addition, the extra income may enable migrants previously separated from the household to return and young adults to afford to take their parents into the house (Edmonds et al., 2005). In fact, Winters et al. (2001) have recognized that elderly members incorporated to the household can provide childcare and free up young members for work. Incorporation of elderly may free up younger adults to migrate, as children are being taken care of by the elderly and

they have the necessary resources derived from the cash transfer program. Thus the household composition model also predicts mixed outcomes. On one side it provides an incentive for household members to stay as it encourages savings through the joint consumption of public goods. Alternatively, it may free up young adults to migrate through the incorporation of elderly.

Intra-household Allocation Models

The models of migration and household composition are important tools to understand outward and inward flows that might arise as a result of the implementation of cash transfers. However, understanding the dynamics within the household is also key to understand how decisions of staying or leaving are reached. The unitary model and the collective model of intra-household allocation are reviewed in this section. The unitary model is considered powerful in explaining the intra-household phenomena, but it is also associated with some theoretical difficulties that were in part overcome by the collective model. Although the collective model can probably offer more insight into the way decisions are made within the household, the unitary model is also reviewed as the basis from which the collective model arises.

Unitary Model

According to the unitary model of intra-household allocation, households are groups of individuals who fully pool their resources and agree on how best to combine time and purchase goods to maximize household welfare (Quisumbing & Maluccio 2003). The model assumes that preferences among all members over all goods are

homogeneous or that a self-interested or altruistic dictator makes all the decisions (Strauss & Beegle 1996). However, it does not explain the process of aggregating preferences: it is not clear if preferences are identical or if there is a “dictator”. Perhaps put in quotation marks? The model also assumes that individuals pool their resources and only total household income is relevant for demand, and not the specific male and female contribution (Quisumbing & Maluccio, 2003). Strauss and Beegle (1996) note that the “decision-making in the household is treated as a black box under unitary model” (Strauss & Beegle, 5).

The adherence to the unitary model by policy makers can influence policy outcomes as the intervention may reinforce power relationships within the household (Quisumbing & McClafferty, 2006). Following the logic of the unitary model, the impact of cash transfer programs on migration will be unaffected by the identity of the recipient of the transfer. However, that is usually not the case. Studies have found that cash transfers to mothers can increase women’s role and autonomy in household decision (Ibid). As a result of this and other drawbacks, the unitary model has been rejected empirically as a model that describes household behavior (Quisumbing & Maluccio, 2003).

Collective Model

As an alternative to the unitary model, Pareto-efficient collective models allow for different preferences for household members and assume decisions are made in a way that the outcomes are Pareto-optimal (Quisumbing & Maluccio, 2003). Resources are allocated according to a sharing rule, determined by each individual’s relative bargaining

power within the household. The bargaining power of each member, in turn, depends on his/her access to independent income. After resources are allocated, “each member of the household maximizes his/her own (sub-) utility subject to the income received” (Strauss & Beegle 14). According to this rationale, a more powerful individual would command a greater share of household’s resources (Ibid). One drawback of this model relates to the fact that they subsume a sub-set of non-cooperative cooperative bargaining models, and does not consider that household members may bargain over resource allocations given some threat point or fall-back position (Strauss & Beegle, 1996). For example, individuals can threaten divorce over short-term decision (Ibid).

Some empirical issues arise from the general model. For example, there is substantial literature on development that argues that men and women have different preferences and mothers, relative to fathers, care more about the health, education and well-being of their children (Strauss & Beegle, 21). If this is the case, then women may allocate more resources towards children welfare (Ibid). In fact, there is a growing literature suggesting that resources in the hands of different individuals in the household will have different impact on the welfare of the members (Ibid).

Most of the existing cash transfers programs around the world target women as the main recipients of the grant, implicitly rejecting the unitary model in favor of the collective model. As a result of the program women may have their bargaining power increased in the decisions concerning resource allocation. Thus, cash transfers targeted to women can change the decision-making patterns within the household (Quisumbing & McClafferty, 2006). In fact, a qualitative evaluation of *Progresa* found that as a result of the monetary transfers women do not need to ask their husbands for money and they have

more confidence in their ability to determine whether there is enough money to buy things they need and can make more decisions regarding the money spend on food, which is usually the women's domain (Ibid).

Evidence from previous studies show that transfers received by women tend to result in greater improvements to the wellbeing of children relative to resources receive by men. Evaluations of *Progresa* found that cash transfers to mothers improved human capital outcomes of children and had a positive impact on school attendance, health and nutritional status (Quisumbing & McClafferty, 2006). Based on the assumption that women are concerned with children's health and education, cash transfers may be an incentive for women to remain in the household and invest the money on the children's well being. Alternately, cash transfers may work to relax financial constrains and women may use the grant and their enhanced decision making power to migrate with the goal to increase investments in children welfare through remittances. There is previous evidence suggesting remittances may promote children's welfare. For example, Acosta (2006) analyzes the impact remittances have on children's human capital in El Savador and he found that girls and young boys under 15 years old from recipient households are more likely to be enrolled in school than those from non-recipient households. There is, however, a lack of data on the difference between male and female remittance behaviors. Engle (2004) acknowledges this problem but draws some conclusions from recorded trends. She states that men remit more than women because they earn more, but women tend to remit a larger portion of their earnings. In addition, migrant women tend to remit a large portion of their salaries for everyday needs, in support of household maintenance,

while men may tend to remit more for investment, such as buying land, a farm, housing, farm machinery or cattle (Engle, 2004).

The collective model suggests that the decision-making within the household is decentralized and thus the impact of cash transfer programs depend on which individual receive the grant. Receiving the transfer may change decision-making patterns within the household by increasing the bargaining power of the household member named to receive it, thus also influencing migration decisions. However, the direction of this change will depend on who is the main recipient of the transfer and on his/her preferences. For instance, if a woman is the main recipient, she may choose to stay in the household to provide better care for their children or may choose to migrate to increase children's wellbeing through remittances.

Gender Aspects of Intra-household

Allocation and Migration

Female's decision to stay or to leave a household is normatively prescribed by social norms, gender roles and the hierarchy of power and decision making structure within the household (Pedraza, 1991). For instance, gender divisions of labor within the household tend to release certain members while retaining others. As explained by the household composition literature, households have different types of workers that are allocated to different tasks in order to diversify activities and sources of income. Within this allocation process, women are usually responsible for the activities perceived as non-economic, such as care and maintenance of family resources, and even when they work, this labor division is rarely negotiable (Pant, 2000). Thus the labor division that is already

institutionalized imposes a barrier for females to leave the household. Davis and Winters (2001), illustrate how gender roles influence household decision making and present the example of a patriarchal family system, which “accepts and foments male migration, but hinders female migration” (Davis & Winters, 6).

Cultural and economic expectations of each gender are also reproduced within the household and influence women’s decision to stay or leave the household (Curran & Saguy, 2001). Thus not only gender, but also the position within the household – daughter, wife, mother, or head of the household -, has an impact on the decision to stay or leave (Curran & Saguy, 2001). As Curran and Saguy (2001) explain, “there are complex negotiations (either implicit or explicit) between family members where the outcomes are dependent upon both cultural expectations of each gender as well as the relative resource power available to each family member” (Curran & Saguy, 57). The allocation of power and control within the household is itself influenced by social norms and values, which produce unequal gender relations where men command authority and resources (Pant, 2000). If gender relations within the household are unequal, than the assumption that derives from the household composition model that an increase in income will increase consumption of public goods for all the members in the household can be questioned. Individuals in the household with greater authority may consume more of a public good in detriment of others, most likely women.

Specifically regarding emigration, gender roles may also differentiate male and female emigration decisions. As gender roles and social norms are recognized as important concepts in explaining the decision to emigrate, empirical and theoretical research have the challenge to link the micro and macro levels of analysis in a way to

“capture both individuals as agents, and the social structure delimiting and enabling them” (Pedraza, 1991). As Pedraza explains, “We need to consider the plight of individuals, their propensity to move, and the nature of the decisions they make. We also need to consider the larger social structures within which that individual plight exists and those decisions are made” (Pedraza 308).

There has been substantial amount of empirical case studies on gender and emigration, but migration models have not incorporated gender as a theoretical concern. Female migration, while governed by the same models of migration presented in this study, differs from male migration in terms of the different explanatory variables that influence the decision to migrate (Davis & Winters, 2001). Davis and Winters (2001) present a list, backed by theoretical and empirical support, of variables that are peculiar for women migration and that I summarize here. According to the authors, females are more risk averse, or households are risk averse on their behalf, and are thus less likely to migrate when there is high uncertainty. This assumption, however, is challenged by Conroy (2009), who found that the relationship between risk aversion and migration is actually a positive one. Conroy’s reasoning is that highly risk averted women are actually more likely to migrate away from places of high variability. Following this logic, cash transfers can reduce variability by ensuring a steady income and may potentially reduce migration.

Davis and Winters (2001) also note that female migrants may have different characteristics than male migrants, since different characteristics may be more beneficial to male or female. For example, an employer at a point of destination may be looking for different characteristics, such as age and education, depending on the occupational niche

of males and females. In addition, the authors point out that women are more constrained at doing certain types of work and have limited employment options as a result of gender segregated labor markets available to them. Finally, they state that women may be more dependent on gender-specific networks and may have to rely more on it for information and assistance.

Migration, Intra-household Allocation, Household Composition,

Gender and Cash Transfers: an inter-relationship

The different models described in this section contribute to a better understating of how cash transfer can influence decisions to migrate, including both inwards and outwards migration. The migration models reviewed predict ambiguous outcomes regarding possible impacts of cash transfers on migration. The neoclassical model predict cash transfers can reduce migration by changing the cost-benefit calculation as it increases the costs to migrate through conditionalities and fixed payment sights. However, if start-up costs to migration are taking into consideration, the program may relax existing financial constraints and facilitate migration by covering initial costs. Following the logic of the new economics of migration model, cash transfers have the potential to decrease migration by providing a steady income and thus reducing the need to diversify risk through migration. Finally, the network theory predicts that the impact of cash transfers on migration may depend on the presence of previously established networks: cash transfers may relax financial constrains and allow individuals to migrate where strong migrant networks are established, but will have smaller impact where migrant networks are poorly established.

To better understand why household members may decide to remain in the household or to incorporate new members, the household composition literature was explored. The predictions from this model are mixed. As cash transfers allow for an increase in income, they may provide an incentive for household members to remain in the household by encouraging savings through the joint consumption of public goods. However, this income growth may also allow young adults to bring new members, freeing adults to emigrate.

The intra-household allocations models, and especially the collective model, offered an insight in terms of internal household decision-making patterns and dynamics. Cash transfers have the potential to increase the bargaining power of the main beneficiary in the decisions concerning resource allocation and thus change the decision-making patterns within the household. As most cash transfer programs target women as the main beneficiary, these interventions have the potential to increase women's bargaining power and maybe even increase emigration if women choose to use the grant to migrate. However, ultimately the impact will depend on who in the household receives the transfer and on his/her preferences.

Finally, as none of the models reviewed incorporate a gender component, the gender literature was explored to offer an insight on how different variables explain male versus female decisions to stay or leave the household. According to the literature, female decision to remain or not in the household is determined by intra-household resource allocation, decision-making structures and by social norms and socially determined gender roles. Considering the recognized importance of larger social structures within

which decisions take place, I analyze the specificities of both programs under study as well as the social context in which they operate in the subsequent chapter.

From the theoretical models reviewed the effect of providing additional income on household composition will depend on the existence of previous financial constraints, presence of migration networks, the identity and gender of the main recipient, gender norms, intra-household allocation and decision-making patterns and household member's preferences. The question this research asks is this: Do cash transfers alter household composition? To this end, this study tests empirically what is the impact of providing cash to poor Sub-Saharan households on inwards and outwards migration flows. Ultimately, the idea is to assess if household composition changed as a result of the Kenyan and Malawian programs.

CHAPTER 2

CASH TRANSFERS AND THE LOCAL CONTEXT

In this chapter the main characteristics of both Cash Transfer programs that are being studied, the Malawian Mchinji Social Cash Transfer Scheme and the Kenyan Cash Transfers for Orphans and Vulnerable Children, are briefly reviewed. To gain a better understanding of the context in which these programs operate, the main characteristics of households, gender roles and migration patterns within both Malawi and Kenya are analyzed.

Malawi

The Mchinji Social Cash Transfer Scheme (SCT)

Poverty in Malawi has remained stagnant over the past ten years and 52% of the population lives under one dollar per day according to the 2004 Integrated Household Survey (HIS) (Schubert and Huijbreg 2006). The HIS reported that out of this 52%, 22% live under severe conditions of poverty with less than USD 0.20 per day (Ibid). Inequality is also high: the percentage share of household income in the poorest 10% of households is 3% compared to 32% in the wealthiest 10% (Miller, 2009). The social indicators are worrisome. According to the 2010 Human Development Index, infant mortality rates are as high as 1 death per 10 births, life expectancy is only 54 years, 29% of the population is undernourished and school life expectancy is 9 years. HIV/AIDS is also a major challenge to the country, as prevalence rate was 11.9% in 2007 (Miller, 2009). Circa 80% of the population in Malawi lives in rural areas, where vulnerability is increasing (Miller 2009; Schubert & Huijbreg 2006). According to Schubert and Huijbreg (2006),

Malawians are more vulnerable today “as repeated shocks mean that people’s assets have declined, savings have been eroded, and informal networks are less willing or able to provide assistance”.

Social protection in Malawi is gaining momentum as the government is increasing efforts directed to improve the national social protection system. Social protection is a key element in the country’s strategy to fight poverty. The government integrated a Social Support Policy (SSP) theme under the Malawi Growth and Development Strategy, which is a national strategy for both economic growth and social development. The SSP calls for programs and policies that confront poverty and vulnerability and strengthen human capital to break the cycle of poverty (Miller 2009). As the Malawian government defines, “Social Protection constitutes policies and practices that protect and promote the livelihoods and welfare of people suffering from unacceptable levels of poverty and/or are vulnerable to risks” (Schubert & Huijbreg 4). To coordinate social protection interventions, the government established the Social Protection Steering and Technical Committee, responsible for guiding and overseeing the design, implementation and monitoring of a National Social Protection Framework and Policy (Schubert and Huijbreg, 2006). However, as Schubert and Huijbreg (2006) acknowledge, there is, “little experience and no guidelines for such Government-led institutionalized Social Cash Transfer Program in Malawi”.

Partly due to this lack of experience, the government of Malawi, with UNICEF support, decided to launch, in 2006, a pilot scheme to test the feasibility and impact of social cash transfers. The new program, the Malawi Social Cash Transfer Scheme (SCT), was implemented at the Mchinji District, chosen for the pilot due to its strong District

Team, average poverty (it ranked 14th out of 28 districts in terms of poverty levels) and proximity to the capital Lilongwe (Schubert and Huijbreg, 2006). Within the district, four control and four treatment eligible village groups were selected to be part of the evaluation. The program has continued to expand since it was launched and by 2009, 7 out of the country's 28 districts were receiving the intervention (Miller, 2009). The government plans to scale up the program to national scope by 2012.

Under the SCT program, cash is transferred to ultra poor households and a bonus is given to households with school age children to encourage school enrollment and attendance (Barrientos, Holmes & Scott, 2008). The goal of the program is to alleviate poverty, reduce malnutrition, and improve school enrollment and attendance among the poorest households in Malawi (Miller 2009). The program targets the 10% ultra poor households that are also labor constrained, which usually are households headed by elderly, female or children with chronically ill, disabled or HIV infected members². Ultra poor households are the ones in the lowest expenditure quintile and live below the national ultra poverty line, meaning that they receive only one meal per day, are unable to purchase essential non-food items and have no valuable asset (Schubert and Huijbreg, 2006). Households are also labor constrained when there is no able member aged 19 to 64 or have a dependency ratio worse than three (one able household member has to care for more than three dependents) (Ibid).

The targeting criteria allows the State to focus and reach extremely vulnerable households that are not able to access or benefit from labor based interventions (Ibid). These households are victims of structural poverty, meaning that poverty is related to the

2. Unicef (2007) Malawi Project Profile.

structure of the household, which have a few or no able-bodied adult member to perform productive work (Ibid). AIDS affect many of these households and have been responsible for the death of parents, leaving grandparents, who are too old to work, and orphans, who are too young. The SCT has the potential lift these households out of poverty by enabling them to provide the basic needs to all household members. In fact, by adding a bonus to households with school age children, the program not only focuses on vulnerable households but also on vulnerable children, acting at the same time as Child Welfare Scheme (Ibid).

Miller (2009) describes the targeting method used by the SCT, which involves a multi-stage participatory process. First, at the community level, the Community Social Protection Committees (CSPC) visit and interview households at Village Group and rank all labor-constrained households according to neediness. The 10 percent most needy households are selected and the list is discussed at a community meeting to achieve a consensus. The final results are verified and approved by the Social Protection Sub-Committee, established by the District Assembly. Once beneficiaries have been selected, District Assembly staff pays a monthly disbursement of cash. The monthly transfer depends on the household size and if the household has children enrolled in primary and/or secondary school. A bonus of MK 200 (US\$1.3) is added for children in primary school and MK 400 (US\$2.6) for children in secondary school. The average transfer amount is MK1,700 per household per month.

Households, gender roles and migration in Malawi

In Malawi, households are characterized by a complex array of kinship relationships. Households contain members that do not belong to a single nuclear family, encompassing kin from several generations and individuals that are not blood related (Ansell & Van Blerk, 2004). Young adults play an important role in providing for the household in Malawi, with the young children and the elderly being excluded from the economic activities and assuming a dependent role (Mtika, 2003). Within Malawian households, there is a gendered division of labor where

“men are primarily responsible for providing income for items considered to be basic necessities, but which the household does not produce, such as salt, soap, and clothing; and women are primarily responsible for childcare and domestic chores, including collecting wood for fuel, fetching water, accessing local services” (Bignami-Van Assche et al., 675).

Both men and women are engaged in agricultural production, but men are more frequently hired for casual seasonal agricultural labor (*ganyu*). Because women work both on agriculture and on house chores, they usually work more hours (Bignami-Van Assche et al., 2011).

Large households and kin systems constitute an important strategy for household's survival in Malawi. Kin networks have been used in the country as a coping strategy that operates through kin support systems and reciprocal and redistributive transfers (Weinreb 2002). Household also use labor diversification and substitution to compensate for production losses (Bignami-Van Assche et al., 2011). Bignami-Van Assche et al (2011) found that AIDS-related mortality and morbidity are associated with a diversification of income sources, with women reallocating their time from work-intensive activities, such as farming, to cash-generating tasks, usually casual labor.

Because no effect was found on men's labor, the authors raise the possibility that new household members will substitute women's labor. They also found that new members are likely to join the household and share the work burden when another member dies. This study presents clear evidence that Malawian households change their composition and re-adapt labor allocation as a survival strategy. The Malawian Social Cash Transfer, by providing a steady income, may decrease the need for recipient households to diversify risk through labor allocation. It may also be an incentive for household members to remain in the household and enjoy joint consumption of public goods, as predicted by the household composition literature. In addition, well established gender divisions of labor may impose a barrier for women to leave the household.

Migration is another strategy used by income constrained households. Since the colonial area, circular movements have characterized migration in Malawi: individuals move to commercial farms or urban areas (within and outside Malawi) to work and after a few years they return to reconnect to their families for a short period of time and leave to work again (Mtika, 2007). Under the colonial state, the development of a few sectors such as mining, agriculture, and industrial activities stimulated wage-based labor migration to areas of concentrated activity, both within Malawi and in neighboring countries (Ibid). After independence in 1964, Hastings Banda, the new president, heavily emphasized state farming and recruited labor for the farms all over Malawi, giving continuity to the circular migration movements established during the colonial times (Ibid). Under Muluzi regime, which started in 1993, circular migration was also encouraged, but by commerce and trade. Individuals started buying goods in urban areas

to reselling in rural markets (Ibid). For the first time migration was driven not only by men, but also by women.

Currently, the main factors that lead rural Malawians to migrate are to work, to find new land for farming, to get married with individuals who live outside their village, or after marital dissolution (Anglewiicz 2007). Anglewiicz (2007) notes that HIV can also cause migration. He argues that marital instability is more frequently among HIV positive individuals, and individuals are more likely to migrate after marital dissolution. In fact, on his research he found that in Malawi HIV positive individuals are more likely to migrate than HIV negative individuals. Overall, emigration in Malawi has been used as a coping strategy by income stressed households. In the country there is a strong tradition of labor migration characterized by rural-to-rural, rural-to-urban and Malawi to South Africa migration flows, where men are the first to leave in search for work (Davison, 1993).

In this context, cash transfers may decrease emigration by providing a steady income and reducing the need to diversify risk through emigration, as predicted by the new economics of migration model. However, recipient households in Malawi may not have enough room for maneuver to diversify risk through migration. Considering that the Malawian Social Cash Transfer target labor constrained households, - those that have no able member aged 19 to 64 or have a dependency ratio worse than three-, able members may be constrained to migrate considering that they have to support and provide care for other disabled members in the household. In addition, disabled members are less likely to migrate for work. Thus, diversifying risk through migration may not be a feasible strategy to recipient household in first place. Alternatively to the new economics of

migration prediction, grants provided by the government may increase emigration by covering start-up costs. This could be especially valid in a context characterized by a strong migration tradition, such as in Malawi. The program does not impose any conditionality on recipients, and so it does not alter the individual cost-benefit calculation by imposing the cost of losing the benefit after emigration, as predicted by the neoclassical model. However, as stressed before, emigration may be inhibited by the need to provide care by other members in the household, which may also represent a significant cost on an individual's cost-benefit calculation. In sum, it is not possible to predict the impact of the program on individual's decision to remain, leave or join a household. The household composition and the migration models predict ambiguous outcomes even when considering the local context and the peculiarities of the program.

Kenya

Cash Transfers for Orphans and Vulnerable Children

Kenya is a country of around 38 million habitants with high levels of poverty and inequality. According to the 2010 Human Development Index, nearly 20% of the population lives below \$1.25 PPP per day. Inequality is also high: in 2006, the consumption decile ratios of the top 10 percent to the bottom 10 percent stood at 20: 1 in urban areas and 12: 1 in rural areas (World Bank, 2009). 72.8% of the population in Kenya live in rural areas (Nguvulu, 2010). As for the social indicators, infant mortality is 128 per 1,000 births, life expectancy is 55.6 years, mean years of schooling is 7 years and undernourishment rate of 30% of the population. Currently, more than 1.4 million

Kenyans are living with HIV/AIDS, with an estimated prevalence rate of 7.8 percent (Ibid).

The generalized HIV/AIDS pandemic has worsened poverty in Kenya and “increased the number of orphans in the country and also the vulnerability of affected households, both through the loss of productive adults and through the impact of chronic illness” (Ward et al. ii). Around 1.8 million Kenyan children under 18 years are orphans, meaning they lost one or both parents as a result of death (World Bank, 2009). Out of this, two thirds have lost their parents due to HIV/AIDS (Ibid). HIV/AIDS has also affected other children, that are not orphans, but have parents who are sick from HIV and are unable to work and support the household. It is estimated that there are about 600,000 vulnerable children in Kenya (Ibid). According to the Ministry of Gender, Children and Social Development³, a “vulnerable child is one whose safety; well-being and development is threatened” and includes “children who are emotionally deprived or traumatized”. In general, most families missing one or both parents or families with HIV/AIDS infected members are poorer than the general population. As the World Bank (2009) estimates, nearly one quarter of orphans and vulnerable children (OVCs) OVCs, amounting to 600,000 of them, live in extreme poverty, representing 30% of all children living in extreme poverty.

In response to growing poverty of OVCs, the Kenyan government, with support from UNICEF and DFID, launched the Cash Transfers for Orphans and Vulnerable

3. Ministry of Gender, Children and Social Development Website. Internet: <http://www.gender.go.ke/index.php/Divisions/cash-transfer-program-for-orphans-and-vulnerable-children.html>. Accessed in: June 9th.

Children, a program that falls under the scope of the National Policy and National Plan for Action for OVCs. The overall objective of the program is to

“Provide a social protection system through regular and predictable cash transfers to families living with OVCs [orphans or vulnerable children] in order to encourage fostering and retention of OVCs within their families and communities, and to promote their human capital development” (Ward et al. 1)

Ward et al. (2009) explain that the program was implemented in three different phases. A small pre-pilot phase was executed between 2004 and 2007 in three districts. A second larger pilot phase was initiated in four new districts in 2007. At the same time, the Government of Kenya expanded the Program reaching a total of 30 districts. The Program expanded further in 2008/09, covering a total of 30,315 households. In a third phase the program will expand to cover 100,000 households by 2012.

The program targets households that are (i) poor; (ii) contains at least one OVC; and (iii) do not receive benefits from other cash transfer programs. For the purpose of the program, OVC is defined as children who are orphans from one or both parents; or chronically ill; or looked after by a carer who is chronically ill. Poor households are the ones that exhibit at least eight out of seventeen characteristics established according to the program’s criteria. The targeting process involves several stages. The Location OVC Committee (LOC) visits and interviews households in two rounds to determine their eligibility based in a proxy means test. Following, the list of eligible households is sent to the District OVC Sub-committee to be validated by the LOC and the community in a community gathering (Ward et al., 2009).

Once the list of beneficiaries is approved, enrolled households receive Ksh 1,500 (approx. US\$ 18) every two months, irrespective of the number of OVCs. The payments

are made through post offices. During the second phase of program implementation, transfers were conditioned upon education and health requirements in three out of the seven districts. Households that did not comply with the conditions had Ksh 500 per infringement reduced from their payment (Ward et al. 2009). However, as Ward et al. (2009) point out, this was not fully implemented.

Households, Gender Roles and Migration in Kenya

As in Malawi, households in Kenya are characterized by a complex array of kinship relations that also serve as a support network in times of stress. These networks play an especially important role in the HIV/AIDS epidemic in Kenya, in which extended families incorporate and foster the orphans.

There is a clear gendered division of labour within Kenyan households, according to which women are responsible for the heavy duties, such as “raising the children, providing food from the garden, doing most of the farm work, getting water and firewood, thatching and plastering huts, and carrying loads to market” (Mburugu & Adams 15). Thus, women focus on unpaid subsistence production on the farm or in the household and men, in the other hand, are associated with the marketplace as they usually engage in labor market activities and earn an income (Agesa & Kim, 2001).

This division of labour made possible the establishment of a pattern of migration characterized by heavy male labour migration and female staying at the household for farm management (Nelson, 1992). Migration in Kenya is circulatory: many men migrate to urban cities for work and leave their wives and families in rural areas, coming back home after sometime (Ibid). Thus, migration dynamics in Kenya are mainly dominated

by circular rural-urban flows (Nguvulu, 2010). High youth unemployment and social and economic inequalities in rural areas are considered the main causes of emigration (Ibid).

Migration research attributes a few factors to the dominance of male over female migration in Kenya. First, high fertility rates among Kenyan women (above Africa average), reduces the likelihood of migration (Agesa & Agesa, 1999). Second, in Kenya rural males are more educated than rural females and are more likely to migrate as they have higher chances of finding a job (Ibid). Third, Agesa & Agesa (1999) found that the urban-to-rural wage gap is larger for males than for females, which would provide a stronger incentive for male migration based on the assumptions of the neoclassical model.

A slow movement of female migration began post-independence, but has not been deeply explored by researchers. Nelson (1992), when writing about female migration, argue that the motivations of female and male migration are different. Men's migration is a temporary endeavour as their goal is to return to rural areas. Women, on the other hand, decide to migrate to escape from unbearable social conditions, characterized by an unhappy family situation or a life of hard work. Consequently, as Nelson (1992) points out, when women migrate they totally separate themselves from the means of production in the rural area. This is the opposite of what happen in male migration, as men usually retain control of production due to the circular movements.

Because in Kenya the recipients of the transfers are usually women's head of the household (Ward et al. 2009), these grants have the potential to increase their bargaining power and influence their role in the household decision making process. Thus, it may give them more power and may make possible previous desires to migrate. Ward et al.

(2009), however, state that female caregivers do not report changes in their empowerment in relation to other household members. In fact, the authors report that most of the decisions are made in consultation with other adults in the household. Considering the assumptions of the new economics of migration model, by providing a steady income through cash transfers to households, they may jointly decide that there is no need to diversify risk through migration and thus emigration may decrease.

Alternatively to the predictions derived from the new economics of migration model and considering the tradition of rural-urban circular movements in the country, one could expect an increase in migration as a result of the program if transfers work to relax financial constraints and cover start up costs. In addition, pre-existing rural-urban networks can play an important role in facilitating migration. In fact, some authors⁴ have recognized the importance and impact that these networks can have in determining migration decisions in Kenya. However, the lack of data on migration networks for the districts that receive the program, make it impossible to analyze if and how networks influences migration decisions among program recipients.

In the treatment districts where conditionalities are imposed, the costs of migration may increase as the individual may lose the benefit by not complying with the conditionality, thus altering the cost-benefit calculation. Required awareness sessions on health and other issues once per year might increase the cost of adult migration but to a lesser extent, as it may be possible for migrant adults to return once a year to the point of origin. In addition, education requirements increase the value of staying at the point of

4. Ross, M. and Thomas S. Weisner (1977) *The Rural-Urban Migrant Network in Kenya: Some General Implications*. American Ethnologist, Vol. 4, No. 2.

Arne Bigsten (1996) *The Circular Migration of Smallholders in Kenya*. Journal of African Economy, Vol.4

origin for school-aged children, thus reducing migration among them. However, Ward et al. (2009) point out to the fact that in Kenya conditionalities are not rigorously implemented and monitored in the selected district. Thus, the cost-benefit calculation may not change as predicted.

It is unclear what are the outcomes in terms of individual's decision to remain, leave, or join a household in Kenya as a result of the program. Different predictions arise from different models and they may vary according to the presence or not of conditionalities. Overall, looking at the Kenyan context does not change the outcomes predicted by the different theories analyzed in the previous chapter and it is still not possible to predict the impact of the program on individual's decision to remain, leave or join a household.

CHAPTER 3

DATA AND METHODS

Sample Selection and Data

The impact evaluations of both the Kenyan and Malawian programs were experimentally designed. In both cases a target population was randomly assigned into treatment and control groups and cash transfers were given to eligible households in the intervention group. According to Baker (2000), experimental designs are known as the most robust of the evaluation methodologies. The power of this methodology relies on its ability to create a perfect counterfactual through the randomization process provided that the sample size is large enough. Because the programs are randomly assigned among eligible beneficiaries, the assignment process itself creates comparable treatment and control groups that are statistically equivalent to one another, given appropriate sample sizes” (Baker 10). This means that the control group generated through randomization should serve as a perfect counterfactual, able to capture what would have happened without the program. In both cases household and individual level data were collected in the treatment and control groups both before and after the interventions were implemented. Consequently, the programs include a baseline information survey and annual panel(s) on beneficiaries to measure outcomes and progress.

Although randomized trials are considered the gold standard in terms of impact evaluation, there are also drawbacks often associated to it that should be noted. Ravallion (2007) describes ethical issues that can arise from the randomization process. According to him, there may be a perception that social experiments treat people like “guinea pigs”,

as they deny the program to those who need it but are allocated to the control group. As Baker (2000) points out, it can also be politically difficult to provide the intervention to one group and not to another. Ravallion (2007) also identifies two threats for the internal validity of experimentally designed programs. The first relates to selective compliance: as free agents, people do not have to comply with the evaluation' assignment, generating concerns in terms of internal validity. The second refers to spillover effects, meaning that individuals in the control group could get some of the treatment. Blundell and Dias (2002) pinpoint another problem: observed behavior of the individuals may change as a consequence of the experiment, what is referred to as the hawthorne effect.

The evaluation surveys in both Kenya and Malawi did not address in depth demographic and migration outcomes that may result from program implementation. For this reason, I conduct one analysis using household level data and another one using individual level data. At household level the focuses of the analysis is on the number of household members by age and gender. This focus on household compositional provides an alternative approach to assess any impact on household structure. At individual level entry and exit information from household roster is used.

In Kenya, four locations in each of seven selected districts were randomly assigned to receive the program – two acting as control groups and two as treatment groups. Within the selected locations, samples were drawn from four different groups:

- **Group A** *Households with OVCs in the Program areas selected for inclusion in the Program – divided into two groups; areas with conditions with penalties, and those without;*
- **Group B** *Households with OVCs in control areas that were expected to have the met Program criteria and would therefore (in theory) have been selected by the Program if the Program had operated there;*

- **Group C** Households with OVCs in Program areas that were not selected for inclusion in the Program; and
- **Group D** Households with OVCs in control areas that were expected not to have met Program criteria and would not (in theory) have been selected had the Program operated there. (Ward et al. 9)

In this study, the comparison of trends between groups A (treatment) and B (control) over time provides the basis for the analysis of program impact. 2,759 households were interviewed prior to the intervention in 2007. A follow-up surveyed was conducted again in 2009 and 2,225 of the baseline households were interviewed at follow-up (82 percent of those interviewed at baseline). The final sample yielded 1328 treatment and 579 control households that were interviewed at both rounds and include recipient households that met the eligibility criteria and also households that received the program but did not meet the criteria. In this study I only focus on the eligible, excluding from the analysis households in the treatment and control groups that did not meet the eligibility criteria established by the program. According to the eligibility criteria, a household is eligible to receive the program if it is: (i) poor; (ii) contains at least one OVC; and (iii) do not receive benefit from other cash transfer programs.

The loss of households between baseline and follow-up in the Kenya Cash Transfer survey was partly attributed to post election violence that erupted in the country in 2008. The attrition rate, however, is not significantly different across treatment and control groups and thus does not threaten the validity of the results presented in this study.

In Malawi, eight eligible Village Development Groups (VDCs) in the Mchinji district were randomly assigned into intervention and comparison groups. Each VDC contains approximately 1,000 households. Out of these, the poorest 10% per VDC - that are also labor constrained - are eligible to receive the program. This yields a sample of

800 households to be included in the evaluation – 400 hundred in intervention and 400 in comparison VDCs. The initial targeted sample of approved households included 408 households in the treatment group and 411 households in the control group (Miller, Tsoka & Reichert 2008). Data was collected on every individual within each selected household prior to treatment in March 2007 and again in September 2007 and in April 2008, creating a panel. The three rounds of data yielded 374 treatment and 392 control households with complete questionnaires over the three rounds (Miller, Tsoka & Reichert 2008).

The random program allocation in Malawi, however, presented one main problem. The targeting process adopted by the program and its strong emphasis in community participation complicated the randomization (Stecklov & Winters, 2011). According to the process established, the CSPCs were responsible for ranking and selecting poor labor-constrained households according to neediness. However, CSPCs often used different criteria for choosing beneficiaries in different VDCs, leading to variations in recipients' selection. (Miller, Tsoka & Reichert 2010). Stecklov and Winters (2011) point out that this issue is magnified by the fact that the sample size is small, as in the case of Malawi it includes eight village groups. The authors explain that if the sample size was large and included many village groups, the community targeting mechanism would not be an issue as similar sets of priorities might emerge across communities. Thus, the ability of the randomization process in Malawi to create a perfect counterfactual can be questioned by the lack of data to compare VDCs and the variations in community in targeting.

Table 1. Malawi - Baseline Summary Statistics of Exogenous Variables for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Consumed one or fewer meals per day	0.405	0.507	0.548	0.270
Begged for food or money	0.280	0.329	0.4383	0.002**
Extremely poor	0.990	0.989	0.991	0.760
Monthly per capita expenditures	192.08	192.71	191.41	0.955
Household owns 0-1 asset	0.251	0.5233	0.482	0.260
Dependency Ratio	1.371	1.131	1.625	0.000***
Number of orphans	1.492	1.209	1.792	0.000***
Age of household head	61.55	63.05	59.96	0.015*
Household head female	0.653	0.668	0.630	0.272
Single headed household	0.723	0.732	0.717	0.646
Education of household head	1.587	1.204	1.991	0.000***
Not catholic	0.521	0.475	0.570	0.009
Log of household size	1.205	1.072	1.356	0.000***
Number of observations	751	386	365	

Note: Test for continuous variables are t tests and for dummy variables proportional tests.

* p<0.05; ** p<0.01; *** p<0.001

Table 2: Malawi - Baseline Summary Statistics of Household Composition for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Number of children 12-17	0.988	0.766	1.221	0.000***
Number of adults 18-34	0.446	.383	0.512	0.013*
Number of adults 35-54	0.320	0.267	0.378	0.006**
Number of adults 55 or older	0.893	0.940	0.843	0.044**
Number of girls 12-17	0.503	0.391	0.621	0.000***
Number of females 18-34	0.190	0.161	0.222	0.042**
Number of females 35-54	0.241	0.207	0.276	0.028**
Number of females 55 or older	0.619	0.665	0.569	0.009**
Boys 12-17	0.485	0.375	0.6	0.000***
Number of males 18-34	0.256	0.223	0.290	0.080
Number of males 35-54	0.080	0.060	0.102	0.035*
Number of males 55 or older	0.2743	0.274	0.2739	0.985
Number of observations	751	386	365	

* p<0.05; ** p<0.01; *** p<0.001

Descriptive statistics of both data sets are presented in Tables 1 and 2. The means are presented for households in the treatment and in the control groups, and the number of cases is noted in the bottom. The fifth column presents the p value for a test of difference in means between treatment and control groups. In this table and through out the paper, treatment group refers to those households that the program intended to treat, meaning that these households had the option to participate in the program. Stecklov and Winters (2011) explain that in Malawi “take-up rate was near universal and the intent-to-treat is equivalent to actual treatment” (Stecklov & Winters 11). In the case of Kenya there are differences in the take up rate and intent-to treat, but as Stecklov and Winters (2011), I also focus on intent-to treat to make the two analyses comparable and to avoid self-selection bias.

Summary statistics presented on Table 1 and 2 suggest that the randomization did not create a perfect counterfactual in Malawi, since there are some variables with significant differences at the baseline survey. Treatment households differ in their composition and size: they are larger by more than one person and they have more children, including more orphans, more adult females (age 18-54), more males age 35-54, but less elderly females (55 or older). Furthermore, household heads in the treatment group are three years younger and slightly more educated. Due to these significant differences, one can question the ability of the randomization process in Malawi to construct a perfect counterfactual.

In Kenya there are also differences in the measured household size and composition variables. According to the summary statistics presented in Tables 3 and 4,

treatment households are slightly smaller. Treatment households have more elderly individuals compared to control. Furthermore, treatment household heads are about eight years older, are slightly less educated and are more frequently headed by a female.

Table 3: Kenya - Baseline Summary Statistics of Exogenous Variables for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Monthly per capita expenditure	1197.91	1170.46	1209.602	0.287
Urban	0.130	0.099	0.144	0.013*
Number of OVCs	2.75	2.77	2.73	0.638
Household size	5.53	5.68	5.46	0.118
Number of orphans	2.81	2.79	2.82	0.716
Age of household head	55.53	48.98	58.32	0.0000***
Education of household head	1.01	1.39	0.85	0.0000***
Household head female	0.659	0.636	0.668	0.212
Number of observations	1658	1163	495	

Note: Test for continuous variables are t tests and for dummy variables proportional tests.

* p<0.05; ** p<0.01; *** p<0.001

Table 4: Kenya - Baseline Summary Statistics of Outcome Indicators for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Number of children 12-17	1.393	1.388	1.396	0.895
Number of adults 18-34	0.903	0.996	0.863	0.035*
Number of adults 35-54	0.467	0.549	0.433	0.000***
Number of adults 55 plus	0.776	0.584	0.857	0.000***
Number of girls 12-17	0.460	0.490	0.447	0.213
Number of females 18-34	0.288	0.352	0.261	0.002**
Number of females 35-54	0.315	0.368	0.292	0.003**
Number of females 55 or older	0.490	0.345	0.552	0.000***
Boys 12-17	0.700	0.679	0.709	0.483
Number of males 18-34	0.356	0.406	0.335	0.047
Number of males 35-54	0.108	0.129	0.099	0.071
Number of males 55 or older	0.204	0.147	0.229	0.000***
Number of observations	1658	495	1163	

* p<0.05; ** p<0.01; *** p<0.001

In terms of household composition, treatment households have less adult females (age 18-54) but more elderly males and females in comparison to treatment. Thus, there is also evidence that the randomization process in Kenya did not create a perfect counterfactual.

Even where control and treatment groups are not statistically equivalent to one another it is still possible to conduct an evaluation and measure impact as the difference-in-difference method can control for initial differences. According to this method, perfect equality between the two groups is not a necessary condition for the evaluation. However, if a first difference method is applied, the results could potentially be biased. The next section will explain in greater detail the different methodologies.

Empirical Approach

To estimate the impact of both programs, I use a difference-in-difference estimator if the outcome variable is included in both baseline and follow-up data. If, however, the outcome variable is not included in baseline data, I compare treatment to control in follow-up data. In this section I review three different methodologies that can be applied to randomized programs – reflexive comparison, first difference and difference-in-difference - in order to justify the methodological choice of this study.

The reflexive comparison estimates the difference over time for the treatment group ($I_1 - I_0$). A baseline survey of participants is conducted before the intervention, and a follow-up survey after. The baseline provides the counterfactual, and impact is measured by the change in outcome indicators before and after the intervention. It is considered to be a biased estimator as it includes all changes that have happened over time, regardless

of what have caused them. Therefore, it is not possible to determine if those changes were caused by the project or by some other unobservable factors. The estimating equation is illustrated below:

$$Y_{it} = \beta_0 + \beta_1 T + \mu$$

where

Y_{it} = variable of interest individual i at time t

β_0 = constant

$T = (1)$ if post treatment (year 2002); (0) if baseline (year 2000)

β_1 = captures the impact of the program plus general trends

μ = error

The first-difference (FD) method compares the difference between treatment and control after the program ($I_1 - C_1$). The counterfactual is provided by the comparison group. It therefore assumes that randomization worked perfectly and that control and treatment were equal before the intervention. If, however, the experiment does not work, then the impact coefficient (β_1) will capture the impact plus differences between treatment and control groups. The FD estimating equation is shown below:

$$Y_{it} = \beta_0 + \beta_1 P_i + \mu$$

where

Y_{it} = variable of interest individual i at time t

β_0 = constant

$P = (1)$ if individual i participated in the program; (0) if individual i did not participated in the program

β_1 = captures program impact

μ = error

The double difference (DD) compares the difference between control and treatment both before and after the intervention, which is $(I_1 - C_1) - (I_0 - C_0)$. Therefore, the counterfactual is represented by the changes over time for the non- participants. The DD estimating equation is shown below:

$$Y_{it} = \beta_0 + \beta_1 T + \beta_2 P_i + \beta_3 P_i T + \mu$$

where

Y_{it} = variable of interest individual i at time t

β_0 = constant

$T = (1)$ if post treatment; (0) if baseline

$P = (1)$ if individual i participated in the program (0) if individual i did not participated in the program

β_1 = captures general trends over time

β_2 = captures pre-existing differences between treatment and control groups

β_3 = captures program impact by estimating the change over time among treatment households compared to control households

μ = error

According to this specification, the coefficient β_1 on the time variable captures changes that occur over time among control households. The coefficient β_2 on the treatment variable captures time-invariant, unobservable initial differences between the treatment and control households. Finally, the coefficient β_3 on the interaction of time and treatment captures the impact of the program and provides an estimate of the change over time among treatment households compared to control households. It thus measures changes in household structure between control and treatment groups.

Table 5 below summarizes all these three methodologies. The columns represent

the groups that participated (treatment) and the ones that did not participate on the program (control). The rows represent the time period before (subscript 0) and after (subscript 1) the program.

Table 5: Methodologies to calculate program effect

	Treatment Group	Control Group	Difference across groups
Post Intervention	I_1	C_1	$I_1 - C_1$
Baseline	I_0	C_0	$I_0 - C_0$
Difference across time	$I_1 - I_0$	$C_1 - C_0$	$(I_1 - C_1) - (I_0 - C_0)$

This study adopts the DD methodology where possible as it accounts for any preexisting time-invariant unobservable differences between treatment and control in the event that randomization is not perfect. It calculates the treatment effect by first considering the total change over time in the treatment group, and then subtracting from this the total change over time in the control group. However, as this study focuses on individuals who left or joined the household over the course of the program, some outcome variables are only present in follow-up data. In this case, a FD strategy is applied. The downside of FD estimates is that it may ignore changes over time on control group and consequently overstate or understate the program effect. Because in both Kenya and Malawi programs randomization seems not to have worked perfectly, the DD method is applied where possible. Control variables are also included in the DD estimation to eliminate additional observable factors and ensure that estimated impacts are truly attributed to treatment (Stecklov & Winters 2011).

Further, because there is strong evidence for an imperfect counterfactual in both Malawi and Kenya, a propensity score matching (PSM) approach combined with a DD method will be used to ensure robustness of the results at household level. The idea is to

adjust the baseline in a manner that makes the treatment and control groups more comparable. PSM approach usually consists in finding “in a large group of non-participants those individuals who are similar to the participants in all relevant pre-treatment characteristics X ” (Caliendo 1). It does so through the propensity score, which is a predicted probability of participation given observed characteristics X . Thus, it constructs a control group based on a set of observable characteristics X . Within the control group there are households with the same probability of participation as other households within the treatment group. It is important to emphasize that the X variables must be independent of treatment, that is, not affected by participation. To fulfill this requirement, X variables should either be fixed over time or measured before participation (Ibid).

In Malawi data, differences between treatment and control groups in baseline can partially be attributed to the targeting process, which strongly emphasizes community participation and thus lead to variations on how the targeting was finalized. Some communities tended to target poor families with children while others the elderly and disabled (Stecklov & Winters 2011). For Malawi, twenty conditioning covariates were selected, including eligibility criteria variables and social, economic and demographic characteristics. As there were also differences between treatment and control groups in baseline in Kenya, 12 covariates were selected, which also include social, economic and demographic characteristics.

Once these covariates are selected, it is possible to predict the propensity scores for beneficiary and non-beneficiary households and to create a graph with the density distribution of the propensity score in both groups. The propensity scores are predicted

via a probit regression and the results are reported in Appendix 2, which includes all the detailed tables used in this analysis. A number of the variables included in the model are significant, and include household size and composition and head characteristics, such as education. The graph with the density distribution of the propensity scores allows a visual analysis of implementation of the common support condition, which ensures that any combination of characteristics observed in the treatment group can also be observed among the control group (Caliendo 2005). The graph is reported in Appendix 1.

It is also important to assess the matching quality. It has to be checked if the matching procedure is able to balance the distribution of the conditioning variables in both the treatment and control group, as the matching do not condition on all covariates but on the propensity score (Caliendo 2005). The idea is to compare the situation before and after matching and check if there remain any differences after conditioning on the propensity score (Ibid). This evaluation uses the stratification test approach to check the balancing property: observations are divided into blocks based on the estimated propensity score and t-tests are run within each block to test if the distribution of covariates is the same between both groups.

Once the matching quality is assessed, two different methods are used in the matching process for the outcome variables of interest: nearest five neighbors and kernel matching. The nearest five neighbors method uses information from five individuals in the control group to construct the counterfactual for each participant. It therefore increases bias that results from poorer matches, where participants are matched with nonparticipants who have quite different observable characteristics. (Caliendo 2005). As the matching is done without replacement, a caliper is set to impose a tolerance level on

the maximum propensity score distance and thus avoid poor matches. Applying a caliper means that individuals from the comparison group that are chosen as a matching partner for a treated individual will lie within the caliper ('propensity range') and is closest in terms of propensity score. According to this approach the nearest five neighbors are selected within a caliper of width 0.01. This evaluation ensured that the ordering was randomly done as estimates depend on the order in which observations get matched.

The nearest five neighbors method use only a few observations from the control group to construct a counterfactual for an individual in the treatment group. The kernel method, on the other hand, uses weighted averages of all individuals in the control group to construct the counterfactual. Weights depend on the distance between each individual in the control group and the treated individual for which the counterfactual is estimated (Caliendo 2005). A disadvantage of this method is that it may use observations that are a bad match. For both the nearest five neighbors and the kernel matching approaches I use a bootstrap method to estimate standard errors for the matching estimators.

In this study I combine the nearest five neighbors and the kernel method with a difference-in-difference approach to control for any remaining differences between treatment and control in the baseline. The PSM method can help ensure that the comparison group is similar to the treatment group before doing the difference-in-difference (Ravallion 2001).

The Kenya and Malawi data are analyzed first at household level. An analysis at individual level is further conduct for Kenya to confirm the results found. The PMS and DD strategies are mainly used to analyze the household level data. In Kenya, controls are included for urban residence and for basic characteristics of the household heads

including highest level of education completed, age and age-squared, and whether the head is female. In Malawi, all households in the sample are rural so control for urban is not included. As in Kenya, controls for basic characteristics of the household heads are incorporated, which includes age and age-squared, whether the head is female and highest level of education completed. In Malawi, however, education levels in the sample are low so fewer categories are used for education when compared to Kenya.

The FD strategy is used to analyze the Kenya data set at individual level. According to this specification, the coefficient β_1 on the treatment variable captures the impact of the program and provides an estimate of the difference between the treatment and control group after the program. Controls are included for age and age-squared, education, marriage status, household size and urban residency.

There are, however, pitfalls associated with these methods. First, the results from a FD or DD estimation pertain to the population studied, and cannot necessarily be extrapolated to other populations. This is called the external validity problem. Both in Malawi and Kenya it is not possible to claim that the areas chosen for the programs – VDCs or Districts - are representative of other areas in the countries. Thus the results found in these areas may or may not be valid for other parts of the country. Second, DD and FD cannot capture anticipation of effects (when households from the control group change their behavior as a result of their expectation to be part of the program in the future), or substitution bias (when households in the control group receive similar treatment but from different sources). Although I acknowledge the intrinsic problems associated with the randomization process and with FD and DD estimates, I still

considered the best approach to evaluate both Kenya and Malawi programs impact on household composition considering the randomized and panel nature of the data sets.

The main focus of this research is to analyze changes over time in household composition and to what extent these changes are a consequence of cash transfers received by the household. For this purpose, at household level two empirical models are used in this analysis. The first model examines count outcome, such as the number of family members in a given age category leaving in the household. The idea is to analyze if the number individuals within a given age category decreased as a consequence of the program. For this analysis I use poisson regression or negative binomial regression, depending on the dispersion of the data. A poisson regression is appropriate when the mean of the distribution is equal to its variance. If, however, the variance is greater than the mean, there is an over dispersion and in this case the appropriate model is a negative binomial distribution. The second model focuses on changes in the probability of finding males and females in a given age category within households before and after the intervention. Given the dichotomous nature of the indicator of whether or not an individual of a given age and gender is reported by the household at a given time, these models are estimated using probit regressions. In both models, standard errors are adjusted for clustering at the locality level.

To further explore the results found at household level for the Keya data analysis, a model at individual level is used to analyze changes in the probability of males and females in a given age category leaving or joining the household. Because each of the outcomes analyzed are binary variables- left or not a household, joined or not a household-, a probit regression is used. The models used in this study may offer insight

into whether the cash transfers alter household composition over the course of the program. I acknowledge, however, that one limitation of the models refers to the fact that it is not possible to identify the causes behind the changes in the living arrangements. For instance, it is not possible to affirm with certainty that individuals who left the household left for migration purposes.

CHAPTER IV

RESULTS

Household level analysis

To analyze the impact of cash transfers in Malawi and Kenya in household composition I first look at changes over time in the overall structure followed by a more specific analysis where age groups are defined more narrowly and gender is considered. Tables 6 and 7 compile the main results from a DD and a DD-PSM analysis. Negative binomial regressions are used to analyze count variables and capture changes in the number of individuals within an age category living in the household over time. To analyze the impact on the probability of individuals of a certain age category being reported by the household a probit regression is used. For both Kenya and Malawi programs, the main program coefficients from the double difference approach are reported: the coefficient on time variable, the coefficient on treatment, and the coefficient on the interaction of treatment and time. Along with DD results, the impact estimates using the PSM combined with DD approach are also reported. Appendix 2 includes detailed tables reporting program coefficients as well as coefficients on control variables.

The first part of Table 6 focuses on the Malawian cash transfer program impact on overall change in the number of adults by age groups living in the household over the course of the program. A negative binomial regression is used to estimate changes in the number of children age 12-17 over time. For all the other age groups (age 18-34, age 35-54, age 55 and over) the dispersion parameter $\ln(\alpha)$ is not significant, indicating that a poisson regression would be more appropriate considering the data distribution.

Table 6: Malawi - Difference-in-Difference and Propensity Score Matching Estimates of Impact of Malawi Social Cash Transfers on Reported Individuals in Household by Age Group and Gender

	<u>Difference-in-Difference</u>			<u>PSM-DD</u>	<u>PSM-DD</u>
	Treatment	Post	Treat. x Post	5 Neighbors	Kernel
<u>Count Variables</u>					
<u>HH Composition</u>					
*Age 12–17	0.396** (0.000)	0.164** (0.000)	-0.157** (0.002)	-0.064 (0.346)	-0.129^ (0.053)
Age 18-34	0.163 (0.137)	0.082 (0.143)	0.158* (0.044)	0.094* (0.031)	0.088* (0.039)
Age 35-54	0.129 (0.138)	0.097^ (0.067)	-0.069 (0.327)	0.031 (0.412)	0.013 (0.644)
Age 55 plus	-0.030 (0.343)	-0.024 (0.152)	0.052* (0.038)	0.018 (0.476)	0.003 (0.905)
<u>Dummy Variables</u>					
<u>HH Composition</u>					
Age 12–17	0.149** (0.000)	0.076** (0.000)	-0.053^ (0.093)	-0.028 (0.331)	0.036 (0.169)
Age 18-34	0.034 (0.355)	0.017 (0.419)	0.069* (0.028)	0.075* (0.032)	0.071* (0.018)
Age 35-54	0.043 (0.156)	0.024 (0.208)	-0.022 (0.359)	0.035 (0.291)	.013 (0.630)
Age 55 plus	-0.000 (0.902)	-0.000 (0.635)	0.000 (0.627)	-0.010 (0.611)	-0.021 (0.216)
<u>By Gender</u>					
Girls Age 12-17	0.117** (0.001)	0.067** (0.001)	-0.071** (0.009)	0.027 (0.416)	0.029 (0.362)
Female Age 18-34	0.025 (0.367)	0.003 (0.890)	0.027 (0.318)	0.027 (0.416)	0.029 (0.362)
Female Age 35-54	0.025 (0.354)	0.035* (0.041)	-0.025 (0.245)	-0.020 (0.431)	-0.011 (0.672)
Female Age 55 plus	-0.047 (0.291)	-0.024 (0.445)	0.045 (0.235)	0.020 (0.367)	0.007 (0.700)
Boys Age 12-17	0.084* (0.021)	0.036* (0.036)	0.012 (0.659)	0.022 (0.476)	0.015 (0.614)
Male Age 18-34	0.024 (0.443)	0.019 (0.222)	0.033 (0.159)	0.039 (0.119)	0.038 (0.114)
Male Age 35-54	0.014 (0.190)	-0.004 (0.346)	0.006 (0.366)	0.055* (0.029)	0.027 (0.108)
Male Age 55 plus	-0.006 (0.823)	-0.014 (0.383)	0.016 (0.469)	-0.010 (0.449)	-.0012 (0.310)
Observations	1502	1502	1502	1502	1502

Note: Difference-in-Difference model estimated using negative binomial regression for *, poisson regression for all other discrete variables. Probit regression used for dummy variables with coefficients presented in terms of marginal change in the probability of the outcome.. Regressions control for household head years of education, age and gender. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

The second part of Table 1 describes probit results for the change in probability of reporting individuals within an age group and gender living in the household over the course of the program.

The DD coefficient *treatment x time* of the negative binomial regression estimates show that the program is associated with a decline in the number of children age 12-17 ($p = 0.002$) living within the household over the program period. The *treatment* coefficient confirms that there is a significantly larger number of children age 12-17 ($p = 0.000$) living in treatment group households before the intervention. The *post* coefficient indicates a small significant increase in the number of children age 12-17 ($p = 0.000$) in control group households over time. Thus, the general increase over time in the number of children age 12-17 appears to be balanced by a relative decline in treatment households, as indicated by the interaction parameter. This result is consistent with kernel estimates and with five nearest neighbors approach, but significant only for the later ($p = 0.053$). The probit estimates on the probability of finding children age 12-17 over the course of the program confirm the results of the negative binomial regression specification ($p = 0.093$). The probit results, however, dissipate when using PSM. Girls are the primary driver of the decline in the number of children in this age category among treatment households. The interaction parameter of the probit regression indicates a significant decline in the probability of reporting girls age 12-17 in treatment households over time ($p = 0.009$). However, when looking at the PSM estimates, this result disappears. Overall, as the results on children age 12-17 are not significant across estimations, one can question the decline of children found using the DD estimation.

Table 7: Kenya - Difference-in-Difference and Propensity Score Matching Estimates of Impact of Kenya Social Cash Transfers on Reported Individuals in Household by Age Group and Gender

	<u>Difference-in-Difference</u>			<u>PSM-DD</u>	<u>PSM-DD</u>
	Treatment	Post	Treat. x Post	5 Neighbors	Kernel
<u>Discrete Variables</u>					
<u>HH Composition</u>					
*Age 12-17	-0.006 (0.920)	0.055 (0.239)	0.010 (0.843)	0.015 (0.848)	0.019 (0.787)
Age 18-34	-0.059 (0.532)	0.207** (0.000)	-0.091 (0.111)	-0.217** (0.000)	-0.180** (0.003)
Age 35-54	-0.072 (0.353)	0.091** (0.008)	-0.082 (0.200)	-0.068* (0.045)	-0.063* (0.023)
Age 55 plus	0.031 (0.650)	-0.293** (0.000)	0.200** (0.008)	0.086* (0.032)	0.078* (0.045)
<u>Dummy Variables</u>					
<u>HH Composition</u>					
Age 12-17	-0.029 (0.295)	0.006 (0.693)	0.018 (0.409)	-0.010 (0.701)	0.004 (0.857)
Age 18-34	-0.042 (0.251)	0.137** (0.000)	-0.047 (0.200)	-0.083** (0.008)	-0.062* (0.031)
Age 35-54	-0.027 (0.527)	0.060** (0.005)	-0.064* (0.042)	-0.052^ (0.090)	-0.053* (0.031)
Age 55 plus	-0.019 (0.545)	-0.164** (0.000)	0.096** (0.001)	0.71** (0.006)	0.062** (0.006)
<u>By Gender</u>					
Girls Age 12-17	-0.046^ (0.064)	0.078** (0.000)	0.025 (0.269)	-0.018 (0.586)	0.005 (0.843)
Female Age 18-34	-0.012 (0.755)	0.144** (0.000)	-0.008 (0.779)	-0.024 (0.382)	-0.020 (0.449)
Female Age 35-54	-0.048 (0.223)	0.061** (0.002)	-0.044 (0.116)	-0.036 (0.189)	-0.043^ (0.068)
Female Age 55 plus	0.010 (0.847)	-0.142** (0.000)	0.128** (0.008)	0.015 (0.548)	0.023 (0.303)
Boys Age 12-17	-0.022 (0.421)	0.049** (0.005)	0.026 (0.228)	0.020 (0.727)	0.008 (0.736)
Male Age 18-34	-0.023 (0.474)	0.160** (0.000)	-0.029 (0.104)	-0.076** (0.007)	-0.062* (0.016)
Male Age 35-54	0.007 (0.444)	0.018** (0.004)	-0.008 (0.327)	-0.025^ (0.083)	-0.019 (0.149)
Male Age 55 plus	0.041* (0.024)	-0.011 (0.309)	0.025^ (0.072)	0.023^ (0.076)	0.023* (0.043)
Observations	3316	3316	3316	3316	3316

Note: Difference-in-Difference model estimated using negative binomial regression for discrete variables. Probit regression used for dummy variables with coefficients presented in terms of marginal change in the probability of the outcome. Regressions control for household head years of education, age and gender. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

The results reported in Table 7 also indicate an increase in the number of adults age 18-34 living in the household and in the probability of households reporting individuals within this age category over the course of the program. The interaction parameter for both the poisson and the probit regressions are positive and significant ($p = 0.044$; $p = 0.093$). In addition, these results are consistent with the PSM specifications, which are significant and indicate the same direction of change. An estimation of the probit model but separated by gender show no significant impact on the probability of households reporting males or females age 18-34. The lack of results when the model is divided by gender is likely due to the decrease in the sample size. For the Malawi data, no differences between treatment and control groups were found for other age groups (35 - 54 years old or over 55).

Table 7 reports the main results from the Kenya data analysis at the household level. The first part of Table 7 presents the results from a poisson regression model that analyzes the cash transfer program impact on overall change in the number of adults by age groups living in the household over the course of the program. The second part of Table 7 describes probit results for the change in probability of reporting individuals in the household over the course of the program. PSM results are reported for all the outcome variables.

The DD coefficient *treatment x time* of the poisson estimates show a decrease in the number of working age household members (18-34). This result is on the border of significance at conventional levels ($p = 0.011$) but it disappears with probit estimates ($p = 0.200$). The *post* coefficient for both the poisson and the probit estimates show a highly significant increase in the number or probability of individuals within this age category (p

= 0.000; $p = 0.000$) living in control group households over time. Thus, the general decrease over time in the number of working age adults is balanced by an increase in treatment households, as indicated by the interaction parameter. Although the decrease in the number of adults age 18-34 in treatment households is only significant for the poisson estimate, this result is confirmed by both the nearest five neighbors and the kernel match approaches, which indicate a highly significant decrease in the number of working age adults over time ($p = 0.000$; $p = 0.003$). The PSM approach is also negative and significant for the probability of households reporting working age adults over the course of the program ($p = 0.008$; and $p = 0.031$). Examining changes by gender revealed that these results are mainly driven by males living the household. The probit interaction parameter is marginally significant ($p = 0.104$) and indicates a decrease in the probability of households reporting working age males. These results persist when looking at PSM coefficients, which are also negative and significant ($p = 0.007$; and $p = 0.016$).

The DD interaction parameters for individuals age 35-54 are negative for both the poisson and probit regressions, but significant only for the probit specification. Because most of the households in the treatment and control groups in Kenya have none or only one individual within this age category⁵ the poisson regression may not capture changes in the overall number of individuals over time. The *post* coefficient shows a significant increase in the probability of reporting individuals within this age category in the control group over time. This result is balanced by the DD coefficient *treatment x time* of the probit estimate, which suggests that the program is associated with a decline in the

⁵ In 94.57% of the households there was none or only one adult age 34-55 living in the household at the baseline.

probability of reporting individuals age 34-55 living in the household over time. This result is consistent with the PSM estimates, which also indicate a significant decline in the number of adults ($p = 0.045$; $p = 0.023$) and in the probability of households reporting adults within this age category ($p = 0.090$; $p = 0.031$). The results from the analysis, separated by gender are somewhat ambiguous. The decline in the probability of reporting females in this age category is marginally significant for the DD interaction parameter coefficient ($p = 0.116$) and significant for the kernel approach ($p = 0.068$), but not for the five nearest neighbors ($p = 0.189$). The DD coefficient *treatment* $\times$ *time* of the probit estimate is not significant for the decline in males age 35-54, nor is the coefficient for the kernel approach. However, the five nearest neighbors indicate a significant decline in the number of males ($p = 0.083$). Because the results for male are not significant across specifications it seems that the decline has been driven primary by females age 35-54 living the household. Overall, the decline in adults age 35-54 living the household is similar to the one found for working age adults (18-34). However, the magnitude of the DD interaction parameter coefficients and the PSM coefficients is smaller for adults age 35-54.

The DD interaction parameter for the poisson regression suggests that treatment significantly increase the number of individuals age 55 or older living in the household over the course of the program ($p = 0.009$). The *post* coefficient indicates a highly significant decrease in the number of individuals within this age group ($p = 0.000$) in control group households over time. Thus, the general decrease over time in the number of individuals age 55 or older is balanced by an increase in treatment households. The probit estimates are consistent with the poisson regressions results: it shows a significant

increase in the probability of treated households to report individuals age 55 or older living in the household over time. The DD estimations are also consistent with the PSM results, which also suggest a significant increase in the number and in the probability of elderly individuals living in treatment households. Analyzing the probit model separated by gender reveals that the DD interaction parameter was positive and significant for the probability in reporting both males and females age 55 or older ($p = 0.548$; $p = 0.008$). Although the nearest five neighbors and kernel matching coefficients point to the same direction of change, they are only significant for elderly males. Thus, the increase in the number of individuals age 55 or older living in households over the program period is significant across all estimations and is driven primarily by an increase in the number of men in this age group.

Individual level analysis

To test and explore in greater depth the changes in household structures found in the household level analysis for Kenya, I conduct an analysis at the individual level focusing mainly on adults, as the results for children age 12-17 indicated no changes for these population. I analyze inwards and outwards movements of individuals older than 18 years old and to test how they differ for treatment and control households. Table 8 compiles the main results from a FD specification and reports the main coefficient on program impact. Probit regressions are used to analyze the impact on the probability of individuals within a certain age category leaving or joining the household over time. The first column of Table 8 reports treatment coefficients for the probability of individuals of a given age category and gender leaving the household over time. The second column

reports treatment coefficients for the probability of individuals of a given age category and gender joining the household over time. Appendix 2 includes detailed tables with number of observations, program coefficient and coefficients on control variables.

Table 8: Kenya – First-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on the Probability of Individuals Leaving or Joining the Household by Age Group and Gender

	<u>Left the HH</u> Treatment	<u>Joined the HH</u> Treatment
<u>By Age</u>		
Age 18-34	0.083** (0.000)	0.013 (0.512)
Age 35-54	0.005 (0.761)	0.012 (0.467)
Age 55 plus	-0.057* (0.015)	-0.021 (0.138)
<u>By Age and Gender</u>		
Female Age 18-34	0.078* (0.024)	0.092** (0.004)
Female Age 35-54	-0.001 (0.973)	0.012 (0.467)
Female Age 55 plus	-0.054* (0.036)	-0.021 (0.123)
Male Age 18-34	0.071* (0.020)	-0.052* (0.047)
Male Age 35-54	-0.009 (0.863)	0.024 (0.579)
Male Age 55 plus	-0.074 (0.135)	-0.024 (0.384)

Note: Marginal effects are reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

The FD coefficient *treatment* of the probit regression estimate indicates a highly significant increase in the probability of adults age18-34 leaving the household over the course of the program ($p = 0.000$). This result seems to be equally driven by both female and males leaving the household ($p = 0.024$; $p = 0.020$) over time, as females in treatment households are 7.8 percent more likely to leave the household and males 7.1 percent. The FD *treatment* coefficient is not significant for the probability of adults age18-34 joining

the household over time ($p = 0.512$). However, analyzing the model separated by gender reveals that the treatment parameter was positive and significant for the probability in of females age 18-34 joining the household ($p = 0.092$) and negative and significant for the probability in of males age 18-34 joining the household ($p = 0.041$). Thus, the outflow of young females is balanced by a trend in inflows. Males, on the other hand, are not only more likely to leave but also less likely to join a treatment household. These results are consistent with the findings at the household level analysis which showed an overall decline in the number of individuals age 18-34 living in the household, which was driven primarily by the decrease in probability of households reporting male adults within this age category.

The probit results also show that the elderly in treatment households are less likely to leave ($p = 0.015$), but not more likely to join a household over the course of the program ($p = 0.138$). An analysis divided by gender show that this result is primarily driven by females ($p = 0.036$) but is also negative for male, although not significant. Therefore, the increase in the number of elderly individuals in treatment households found in the household level analysis is not driven by adults 55 plus joining the household but by the fact that they are 5.7 percent less likely to leave compared to elderly individuals in control households.

Finally, no differences between treatment and control groups were found on the probability of individuals age 35-54 leaving or joining a household over the course of the program. The sparse indications of adults age 34-55 leaving the household found in the household level analysis do not hold at the individual level.

Discussion

The Malawi data analysis showed an increase in the number of young adults (age 18-34) living in treatment households compared to control households. In contrast, the Kenya analysis indicated a decrease in the number of young adults. The Kenya results clearly show that young males and females (age 18-34) in treatment households were leaving more compared to control households and that elderly females were less likely to leave treatment households. Ambiguously, the results indicated that young females are also more likely to join treatment households, showing that young females were both more likely to leave and to join a treatment household compared to control. Possibly because female flows are in both directions, inwards and outwards, the household level analysis did not show any significant change in the probability of reporting females in this age category.

Table 9 below presents summary statistics for control and treatment groups in Kenya on the individuals who left the household by age category and relationship to the head of the household. The vast majority of young adults leaving the households are sons or daughters of the household head, counting for over half of the young who leave both treatment and control households. Following this group sons-in-law and daughters-in-law and grandchildren are more likely to leave. The fact that sons-in-law, daughters-in-law and grandchildren are also migrating, although in a smaller number, could mean that some of the young members who leave the household take their spouse or partner and their children.

Table 9: Kenya- Number of Individuals Who Left by Age Category and Relationship to the Head of the Household in Treatment and Control Groups

	Treatment Group						Control Group					
	Age 18-34	%	Age 35-54	%	Age 55+	%	Age 18-34	%	Age 35-54	%	Age 55 +	%
Head	2	0.66	12	32.43	45	77.59	4	3.88	14	73.68	20	76.92
Wife / Husband / Partner	8	2.66	8	21.62	8	13.79	4	3.88	4	21.05	3	11.54
Son / Daughter	165	54.82	12	32.43	2	3.45	55	53.40	1	5.26	2	7.69
Son-in-law/ Daughter-in-law	43	14.29	1	2.70	0	0.00	15	14.56	0	0.00	0	0.00
Grandchild	54	17.94	0	0.00	0	0.00	11	10.68	0	0.00	0	0.00
Father / Mother	0	0.00	1	2.70	2	3.45	0	0.00	0	0.00	0	0.00
Father-in-law/ Mother-in-law	0	0.00	0	0.00	0	0.00	-	-	-	-	-	-
Brother / Sister	6	1.99	1	2.70	1	1.72	1	0.97	0	0.00	0	0.00
Brother-in-law/Sister-in-law	2	0.66	0	0.00	0	0.00	1	0.97	0	0.00	0	0.00
Stepchild	6	1.99	0	0.00	0	0.00	6	5.83	0	0.00	1	0.00
Nephew / niece	8	2.66	0	0.00	0	0.00	5	4.85	0	0.00	0	0.00
Adopted – related to the head	2	0.66	1	2.70	0	0.00	-	-	-	-	-	-
Fostered - related to the head	-	-	-	-	-	-	1	0.97	0	0.00	0	0.00
Other relative	2	0.66	1	2.70	0	0.00	-	-	-	-	-	-
Not related – servant	1	0.33	0	0.00	0	0.00	-	-	-	-	-	-
Not related – other	2	0.66	0	0.00	0	0.00	-	-	-	-	-	-
Total	301	100	37	100	58	100	103	100	19	100	26	100

The results could also mean that treatment households are sending off young members to start their own families and/or to migrate outside the community for other purposes, such as work. Possibly, the government grant worked to relax financial constraints and cover start-up costs to migration. This result is consistent with those of Rubalcava and Teruel (2006), who reported that the Mexican *Progres*a Program contributed to young household members departure by providing resources.

The results for Kenya also showed that the elderly female were less likely to leave compared to control households. Considering the benefits associated with the joint consumption of public and private goods, the growth in income experienced by treatment households possibly provided an incentive for the elderly to save by remaining in the households.

The results for Malawi indicated that the provision of cash transfers increase the number of young adults in treatment household, which is the exact opposite effect found in Kenya. Because there was not enough variation in the data at individual level for Malawi, this result could not be tested at individual level. Consequently, it is not possible to know if this increase is due to individuals joining the treatment households or if individuals in control households were more likely to leave. However, considering the financial constraints faced by young adults in control households, most likely this result can be attributed to individuals joining the household to benefit from the subsidy. The discrepancy of findings between Malawi and Kenya suggests that programs with similar designs can have opposite effect when implemented in different context.

CONCLUSION

In recent years, Sub-Saharan African countries have implemented cash transfer programs that aim to provide immediate relief to poverty at the same time that it incentivizes human capital development. Like any public policy, however, there is a possibility that these programs may have perverse effects on household behavior. This research used experimental data from two cash transfer programs in Malawi and Kenya to analyze the extent to which household structures change through inward and outward movements as a result of a short-term economic incentive.

The results provide overall supportive evidence that cash transfers do alter household structure by affecting migration flows. The data analysis show that in Kenya households that received transfers were more likely to send off young adult members, suggesting that the program provided resources to overcome short-term economic constraints. Possibly, young couples with their children detached from their original household to migrate or live in their own house. The results could also mean that treatment households are sending off young members to start their own families or to migrate outside the community for other purposes, such as work. Either way, most likely the program operated to relax financial constraints and cover start-up costs to migration. Although the initial costs of migration are not addressed in the cost-benefit analysis proposed by the neo-classical model, this research shows they are an important factor to understand migration decisions. These results found for Kenya are consistent with those of Posel, Fairbun and Lund (2006) and Rubalcava and Teruel (2006). Posel, Fairbun and Lund (2006) found that pension transfers in Sub-Saharan Africa relaxed financial

constrains and enabled migration. Rubalcava and Teruel (2006) found that recipients of Mexican *Progresa* cash transfer programs were more likely to send off young adults by providing resources.

The results in Kenya also showed that elderly females in the treatment group were more likely to remain in the household compared to those in the control group, indicating a reluctance to leave a household that receives the grant. The household composition literature, which assumes that gains from joint residence arise from the consumption of public goods and the savings associated to it, can shed light into these results. Possibly a raise in economic resources provided by the public transfer encouraged the elderly females to remain in the household and enjoy an increased consumption of public goods.

Malawi results contrast with those of Kenya in that the provision of cash transfers increased the number of young adults in treatment households, although it is not clear if new members joining the household drive this or because members are less likely to leave. Considering the Malawi program targets the ultra-poor households, possibly this result can be attributed to individuals joining the household to benefit from the increased consumption of public goods, as predicted by the household composition literature.

Overall, the discrepancy of findings between Malawi and Kenya suggests that programs with similar designs can have opposite effect when implemented in different context. The results from this research illuminate a few points and contribute to the international development and social policy themes analyzed in the annexes 1 and 2. First, this research adds to the body of literature on cash transfer programs, a topic of growing importance under social policy themes. Sub-Saharan African countries began implementing cash transfer programs following the success and positive evaluations of

Conditional Cash Transfers (CCTs) in Latin America (Schubert & Slater 2006). There are, however, two main differences between Latin America and African programs. First, African programs do not target all poor households, but focus on the extremely poor and labour-constrained that cannot access labour-based interventions (Ibid). Second, most schemes in Africa do not include health and education conditionalities, although many of them have the goal of improving human capital (Ibid). As a consequence of these differences in program design and also in implementation contexts, the findings from Latin American evaluations cannot be automatically exported to Africa. This research contributes to cash transfer programs literature by analyzing African programs' specificities and by evaluating some of its possible impact.

The contradictory findings for Kenya and Malawi highlight the importance of understanding the dynamics at the micro level, as emphasized by the micropolitics literature, in order to avoid perverse effects. Cash transfers are programs often established at the macro-level with little influence from perceptions and realities on the ground. Using the concepts of uppers and lowers, Chambers (1997) illustrates how power politics are determinant of social change at the local level. Chambers classifies uppers as those who are powerful and the others who relate to them are lowers. Uppers tend to impose their realities and deny those of others. Both Malawian and Kenyan cash transfer initiatives originated as a result of what uppers - national governments and international institutions-, perceived as a lowers' reality and needs. For Chambers (1997), poor people's reality is local, complex, diverse, dynamic and unpredictable. As social relations and livelihoods on the ground are complex, cash transfers can have an impact at the local level in a way unforeseen by policy designers, who do not fully understand this reality.

The discrepancy of findings between Malawi and Kenya point out to the need to think how the specificities of the local reality and lowers perception of their own needs can be incorporated into the program design, as there is no “one size fits all” solution.

This research also provides important input for establishing targeting criteria of cash transfer programs, a topic highly discussed under social policy literature themes. Many institutions and governments defend targeting policies based on the argument that given limited budgets for social programs targeting can maximize coverage of the poor and vulnerable and minimize leakage to the non-poor (World Bank, 2007). A well-targeted program avoids errors of inclusion – admit non-poor into the program leading to leakages and consequently excessive coverage – and errors of omission – identify poor people as non-poor and deny them access to the program (Cornwall & Nyamu-Musembi, 2004). However, targeting can be done through a wide range of mechanisms, some of which may not promote the desired outcome. For instance, this study described the challenges faced by community targeting in Malawi. Although the community targeting mechanism has the advantage of including the local population in the targeting process, the selection of beneficiaries may not reflect the criteria that were first established in the program design. In Malawi, according to the process established, the CSPCs were responsible for ranking and selecting poor labor-constrained households according to neediness. However, CSPCs often used different criteria than the one that was determined, and as a consequence some selected beneficiaries did not meet the criteria established by the program. The inability of some targeting mechanisms to minimize leakage, as argued by Cornwall & Nyamu-Musembi (2004), give prominence to the

argument that universal programs are likely to be more effective at identifying and reaching the population in need (Barnett et al. 2004)

Both Kenya and Malawi program were experimentally design. According to the program evaluation literature, experimental designs are know as the most robust of the evaluation methodologies (Baker, 2000). According to Baker (2000), the power of this methodology relies on its ability to create a perfect counterfactual through the randomization process. However, this research pointed out to the fact that the randomization process in both countries did not create a perfect counterfactual. This pitfall reflects a set of critics identified by Ravallion (2007) that challenge the assumption according to which experimental designs are considered the gold standard in terms of evaluation. These types of evaluation design face not only conceptual problems that threat the internal validity of the evaluation but also face practical problems in its implementation. The Malawian case is a good example, where an attempt to promote community participation in the targeting process ended up complicating the randomization and consequently did no create a perfect counterfactual.

Both cash transfer programs analyzed in this study received funds from major international donors/lenders – such as World Bank, UNICEF, DFID, and SIDA -, and thus have to be understood in the context of aid politics, a highly debated topic in the foreign aid literature, included in the international development themes. Cash transfer programs that aim to reduce poverty and invest in education and health fit well into donors’ recently emerged goal of poverty reduction and on the “Big Plans” centered on broad goals related to the end of world poverty that were put in place by the West (Easterly 2006). However, this approach focusing on the decrease of absolute levels of

poverty deviates attention from the existing inequality gap between countries in the international system and within countries (Wade, 2003). By giving money to poor households cash transfers alleviate current poverty and fall into donor's mainstream approach, but the issue of reducing inequality within countries is not explicitly addressed.

Following the foreign aid politics and the current donors' emphasis on poverty reduction policies, cash transfer have been evaluated based on their impact on poverty and human capital. Hardly ever perverse effects of cash transfers, such as possible impacts on migration, are studied. This research innovates by focusing on possible effects of cash transfers on household structure through migration. There is still, however, a need for evaluations that capture possible perverse effects of cash transfer programs and that aim to understand its broader impact, such as its effect on social relations within and between households.

ANNEX I. International Development Themes

Foreign aid (International Development)

Both Cash Transfer Programs analyzed in this study received funds from major international donors/lenders – such as World Bank, UNICEF, DFID, and SIDA -, and thus have to be understood in the context of aid politics. This section reviews the shift in donor's focus from structural adjustment to poverty reduction policies.

Before poverty reduction strategies were in place, the West and the main international organizations advocated for structure adjustment policies. These policies were in vogue especially during the 1980's and led, among other things, to trade liberalization, fiscal austerity and privatization in the developing countries. According to Stiglitz (2003), because these processes occurred before safety nets were put in place, they resulted in an increase in poverty and unemployment in many developing countries (Stiglitz 2003). There is, however, a debate over whether the adjustment policies caused these effects, or whether the economic and debt crisis caused them. The growing disapproval from the society both in the West and on the developing world regarding the structural adjustment policies can be seen as one of the causes that led to a shift toward strategies focusing on poverty reduction. Instead of policies focusing on macroeconomics, “Big Plans” centered on broad goals related to the end of world poverty were put in place by the West and attracted attention from politicians, celebrities and activists (Easterly 2006). In the context of the failure of structural adjustment policies and a consequent increase in poverty, the new approach centered on poverty reduction looked very appealing and morally right to Western taxpayers.

Cash Transfer Programs that aim to reduce poverty and invest in education and health fit well into donors' new goal of poverty reduction. However, this approach focusing on the decrease of absolute levels of poverty deviates attention from the existing inequality gap between countries in the international system and within countries. The idea that there should be an egalitarian structure in place is not taken into account by the main international institutions, responsible for formulating poverty reduction policies.

Wade (2003) states that it is important to look at the trend on increase or decrease of the inequality gap. Besides from justice and fairness issues, the gap should be addressed by international public policy because it can lead to political instabilities and flows of immigrants (Wade 38). The issue gets worrisome when looking at indicators: seven out of eight measures of inequality indicate that the gap has been increasing over the past 20 years (Wade 2003). The current silence world wide regarding the inequality gap can be explained as it serves mutual interests of the elites in both north and south (Saith 2006). Because there are so many powerful interests behind the current focus on poverty reduction and the perpetuation of the inequality gap, the main global initiatives fail in addressing any type of policy centered on redistribution of income/land within the countries or in reducing international economic inequality (Saith 2006). By giving money to poor households cash transfers alleviate current poverty and fall into donor's mainstream approach, but the issue of reducing inequality within countries is not explicitly addressed.

I.2. Linking the Global/Macro and the Local/Micro levels (Micropolitics of Development)

Development initiatives can lead to a complex set of impacts at the local level. Macro-level policies at the international or national level and development projects/programs can affect the dynamic at the micro level that come into play from cultural norms and social categories, such as ethnicity, class and gender. As cash transfers are programs often established at the macro-level with little influence from perceptions and realities on the ground, it becomes important to acknowledge and to assess their impact on the local level.

Using the concepts of uppers and lowers, Chambers (1997) illustrates how power politics are determinant of social change at the local level. Chambers classifies uppers as those who are powerful and the others who relate to them are lowers. Uppers tend to impose their realities and deny those of others. Cash Transfer initiatives many times originate as a result of what uppers - national governments or international institutions-, perceive as a lowers' need.

For Chambers (1997), poor people's reality is local, complex, diverse, dynamic and unpredictable. He explains that poor people engage in a diversity of livelihood strategies and that they are also themselves diverse, with contrasts in preferences that change according to age, gender, social and ethnic groups. As social relations and livelihoods on the ground are complex, cash transfers can have an impact at the local level in a way unforeseen by policy designers.

Joseph Stiglitz (2003), when talking about the effects of globalization policies in people lives, illustrates how macro-level policies did not bring the expected benefits at

the micro-level. According to the author, structural adjustment⁶ policies established by the Washington Consensus and imposed by the International Monetary Fund (IMF) forced developing countries to open themselves up to imported products that would compete with the products produced by the national industries that were vulnerable to competition. Because in many countries this trade liberalization process occurred before safety nets were in place, there were severe social and economic consequences. Poor farmers in developing countries were not able to compete with highly subsidized goods from the developed world, resulting in an increase in poverty and unemployment. As Stiglitz states it: *“The unemployed are people with families, whose lives are affected – sometimes devastated – by economic policies that outsiders recommend”* (Stiglitz, 24).

Understanding how macro-level policies impact the local dynamics also changes how evaluations are conducted. Cash transfers are usually evaluated based on their impact on poverty and human capital. Hardly ever cash transfers are evaluated based on their impact on social relations within and between households. In addition, perverse effects of cash transfers, such as possible impact on migration, are rarely studied.

In addition, taking into account how the poor perceive their reality also change how evaluations are conducted and how you interpret their results. Naila Kabeer (2001) illustrates the importance of understanding the poor's' reality in evaluating the success of a development program/project. She explains how loans to poor women in Bangladesh could be considered a successful empowerment strategy in terms of the local context even though women did not have access to local markets due to purdah norms. When the

⁶ Conditions imposed by the structural adjustment included: austerity (by cutting social expenditures); trade liberalization; privatization; removal of price controls and state subsidies, etc.

decision of not going to the local markets was understood in terms of the local values, it became clear that empowerment, as an expansion in the range of choices, actually had happen.

In sum, the literature provides evidence on the importance of understanding how Cash Transfer Programs impact the social relation and the livelihoods of people at the local level.

Rights-based Approach to Development (Social Policy)

As cash transfers become a wide spread approach to fighting poverty, the idea of establishing a social protection floor is being debated by different States. Although social protections are guarantee by the Universal Declaration of Human Rights (Articles 22 and 25), many States around the world have not yet incorporated the right to social security - or the instrument to make it enforceable, the social minimum-, within their legal framework. The current debate on the need to incorporate social security guarantees is part of a broader discussion related to the rights-based approach to development, which is reviewed in this section.

Although it has been widely accepted by governments that civil and political rights should be codify in domestic law, there are still doubts on how to incorporate socio-economic rights, such as the right to social security. Human rights have been part of governments' agenda for some time, but the focused has relied heavily on civil and political rights. However, as Piron and O'Neil (2005) point out, there is current shift, and human rights are now being mainstreamed in other policy areas, such as health, education, gender equality, minorities, etc. This represents a more strategic use of human

rights, influencing how situations are analyzed and how objectives are set (Piron & O'Neil 2005).

As positive rights, socio-economic rights entail responsibilities by the State to act in behalf of the individuals. Negative rights, on the other hand, place limits on state authority and protect individuals from the power of the state. Because of these differences, some argue that, contrary to negative rights, there are fiscal limits to the realization of positive rights, which require high financial investments. In fact, one of the main criticisms to cash transfers refers to the economic burden they can impose on low-income countries. If social security were to be established as a constitutional right, it would represent an obligation for the State to act and provide the necessary services, such as cash transfers, regardless of the amount of resources available. Although this is usually seen as a barrier, Cadwell (1986) presents evidence from Costa Rica, Sri Lanka, China and the Indian State of Kerala that the problem of resource constrain faced by developing countries can actually be overcome by a combination of political and social will.

One possible solution to the resource constrain dilemma is to establish the right to social security, as to other socio-economic rights, as high priority goal that guide state policy. In this sense, they can represent aspirational principles the State should apply when making laws. Gauri (2003) points out that the role played by socio-economic rights established as principles is often overlooked. As he observes, because socio-economic rights have become critical elements of the modern society, a failure by a government to pursue it can raise serious concerns about its legitimacy and long-term stability. According to this view, social security, as an aspirational principle, would serve to guide State action in terms of social assistance, which includes provision of cash transfers.

ANNEX II. Social Policy Themes

Cash Transfers (Child and Family Policy)

After the Cash Transfer Program *Progresa* was first launched in Mexico in 1997, the concept spread across Latin America and later to the World. As Levy (2006) explains, *Progresa* was pioneer in its approach: it dispensed money directly to beneficiary households, which represented a change from the traditional programs that provided subsidized necessities. In addition, the program was conditional on specific behaviors related to nutrition, health and education (Levy 2006). So the program provided immediate relief of poverty through direct cash transfers to poor household at the same time that it incentivized human capital development. *Progresa* was designed to have a measurable impact on selected indicators, and its evaluations have been very positive (Ibid).

Following the success and positive evaluations of Conditional Cash Transfers (CCTs) in Latin America, a few sub-Saharan African countries, including Malawi and Kenya, began implementing cash transfer schemes (Schubert & Slater 2006). There are, however, two main differences between Latin America and African programs. First, African programs do not target all poor households, but focus on the extremely poor and labour-constrained that cannot access labour-based interventions (Ibid). Second, most schemes in Africa do not include health and education conditionalities, although many of them have the goal of improving human capital (Ibid).

The decision to implement conditionalities is still a debated one. Das and colleagues (2005) argue that households who benefit from CCT programs would behave differently if given cash with no conditionalities imposed. According to them, in this

situation “households would consume less of the conditioned-on good and more of other commodities” (Das et al. 58). Thus, conditionalities would serve as an incentive to alter individuals’ behavior when they do not match societal preferences (Das et al. 2005).

As illustrated by Schubert and Slater (2006) and Das and colleagues (2005), there is still controversy on some aspects of cash transfers, such as the conditionality component and the targeted population. Although these programmes have been very successful in some countries in Latin America, this does not mean they can automatically be exported to sub-Saharan African countries. Thus, studies that aim to understand the peculiarities of the African context and how CCTs can or not be adapted to it are of extreme importance.

Targeting (Social Policy / Program Evaluation)

Most Cash Transfer Programs adopt some type of targeting mechanism to ensure the poorest segment of the population is reached. Although targeting is widely incorporated in these types of program, it is still a highly debated approach. This section presents an overview of the forces behind targeting and the main arguments in favor and against it.

The adoption of targeting as opposed to universalism in Cash Transfer programs has to be understood in the context of neoliberal ideology dominance. As Mkandawire (2005) explains, while in the 1960s and 1970s universalistic policies would prevail, since the 1980s the dominant approach has shifted towards targeting. She points out that the choice for targeting is parallel to the emergence and spread of the neoliberal policy. According to her, “societies chose either targeting or universalism in conjunction with

other policies that are ideologically compatible with the choice, and that are deemed constitutive of the desired social and economic policy regime” (Mkandawire 22).

International institutions such as the World Bank⁷ defend targeting policies based on the argument that given limited budgets for social programs targeting can maximize coverage of the poor and vulnerable and minimize leakage to the non-poor. Barnett and colleagues (2004) disagree with this vision and argue that targeted programs are actually inherently unfair as among beneficiaries of similar circumstances some receive the program and others do not. In fact, in most cash transfers eligibility is based on an income threshold and those just above the eligibility cut off are not reached, although they may also need the benefits provided by the program. For Barnett and colleagues (2004) universal programs are likely to be more effective at identifying and reaching the population in need.

Mkandawire (2005) also calls attention to another pitfall of targeting: that it can have high administrative costs, especially to developing countries. As many people work in the informal sector, their visibility to the state is low, and thus the State capacity to identify them is hindered. He explains that due to poor implementation and weak governance, many Cash Transfer programs in Latin America have had poor targeting results. A well-targeted program avoids errors of inclusion – admit non-poor into the program leading to leakages and consequently excessive coverage – and errors of omission – identify poor people as non-poor and deny them access to the program⁸. In general, there is a trade off between both mistakes, as the pursuit of low errors of inclusion

⁷ World Bank (2007). Targeting Works!

⁸ Cornwall, Andrea and Celestine Nyamu-Musembi (2004) “Putting the Rights-based Approach to Development into Perspective” *Third World Quarterly* 25(8).

tends to raise errors of omission because some members of the target group tend to be eliminated from the scheme along with the non-target population⁹.

It is clear from the literature that establishing and implementing targeting mechanisms can be very challenging, especially in the context of weak institutional settings, as it is the case of most States implementing Cash Transfer schemes. Understanding these challenges and addressing them are critical factors for the success of these programs.

Experimental Designs (Program Evaluation)

The rapid widespread of Cash Transfer programs can be partially attributed to positive results found in rigorous impact evaluations of experimentally design programs. This section reviews strengths and drawback associated to randomization.

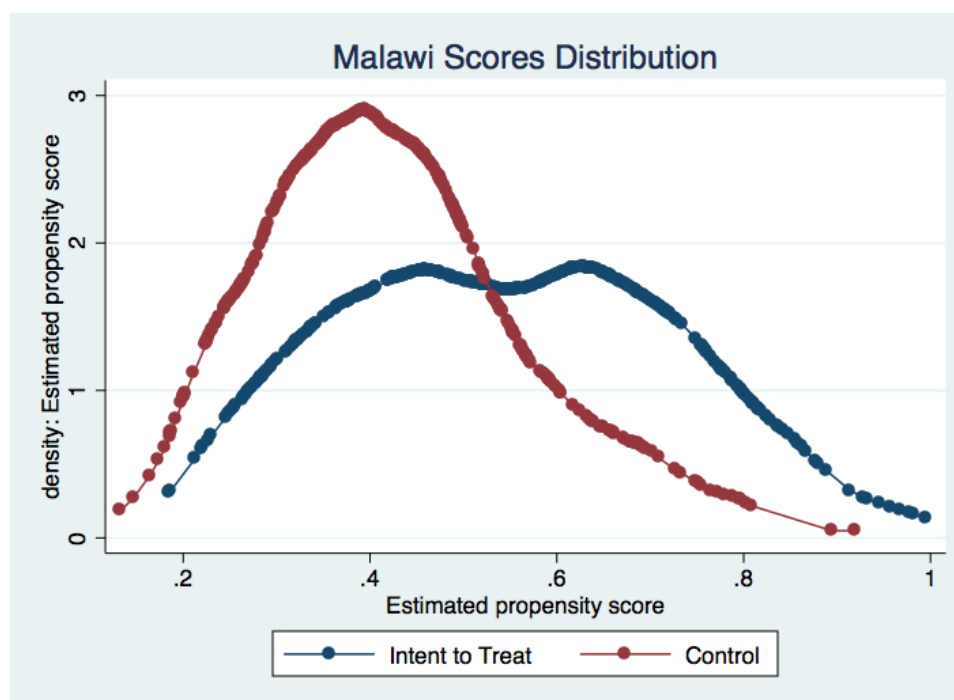
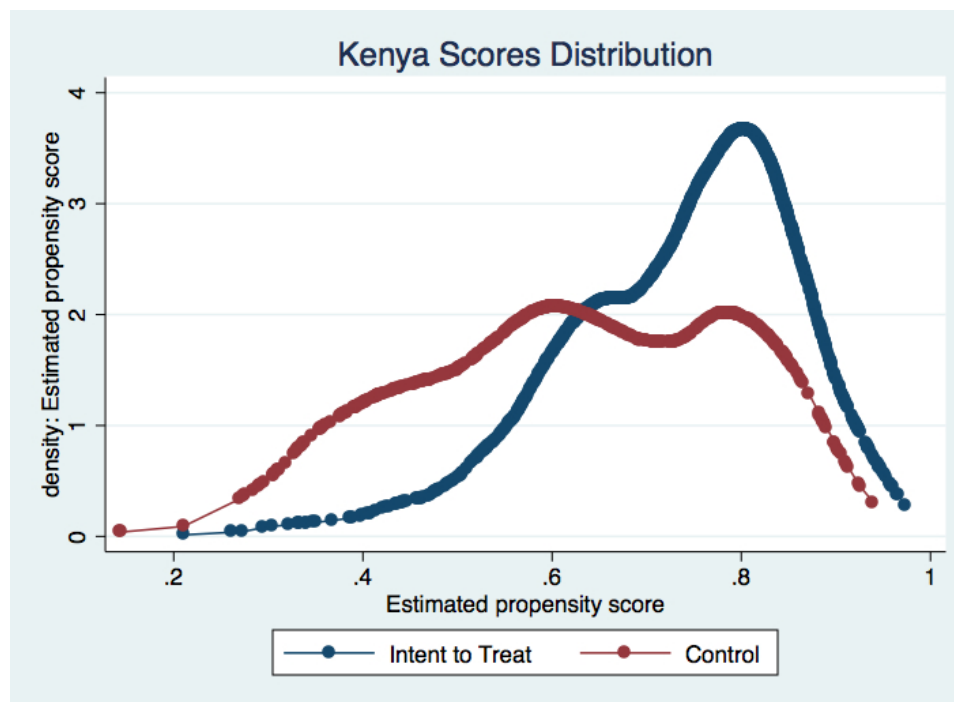
According to Baker (2000), experimental designs are know as the most robust of the evaluation methodologies. The power of this methodology relies on its ability to create a perfect counterfactual through the randomization process. As she explains, “by randomly allocating the intervention among eligible beneficiaries, the assignment process itself creates comparable treatment and control groups that are statistically equivalent to one another, given appropriate sample sizes” (Baker 10). In the case of cash transfers, the target population is randomly assigned into treatment and control groups and transfers are given to eligible households in the treatment group. The impact of the program is than measured as the difference in the selected outcome between treatment and control groups across time.

⁹ Ibid.

Although experimental designs are considered the gold standard in terms of evaluation, some authors have pointed out pitfalls associated to it. Ravallion (2007) describes ethical issues that can arise from the randomization process. According to him, there may be a perception that social experiments treat people like “guinea pigs”, as they deny the program to those who need it but are allocated to the control group. As Baker (2000) points out, it can also be politically difficult to provide the intervention to one group and not to another. Ravallion (2007) also identifies two threats for the internal validity of experimentally designed programs. The first relates to selective compliance: as free agents, people do not have to comply with the evaluation’ assignment, generating concerns in terms of internal validity. The second refers to spillover effects, meaning that individuals in the control group could get some of the treatment. Blundell and Dias (2002) pinpoint another problem: observed behavior of the individuals may change as a consequence of the experiment. In fact, Stecklove and colleagues (2006) found that a Cash Transfer program in Honduras increased fertility rates among the beneficiary population.

Some of the problems described are intrinsic to experimentally designed evaluations and would be hard to tackle them. Others, however, have been addressed in the evaluation design of cash transfers. For instance, to avoid the ethical objections, most programs extend the benefits to eligible individuals in the control group after the evaluation is conducted. However, most of the other challenges remain, as well as the decision to conduct a randomized trial.

APPENDIX 1: Graphs



APPENDIX 2: Additional Tables

Table 1: Malawi - Difference-in-Difference Probit Estimates of Impact of Malawi Social Cash Transfers on Reported Individuals in Household by Age Group

	Age 12–17	Age 18-34	Age 35-54	Age 55 plus
Age of Household Head	0.010 (0.102)	-0.012* (0.041)	0.032** (0.000)	-0.000 (0.453)
Age of Household Head Square	-0.000** (0.004)	0.000 (0.613)	-0.000** (0.000)	0.000 (0.458)
Head Educ Some Primary	0.112** (0.001)	0.059^ (0.076)	-0.007 (0.784)	0.000 (0.519)
Head Educ Some Secondary +	-0.206 (0.131)	0.136 (0.343)	-0.098 (0.114)	0.000 (0.509)
Household Head Female	0.051 (0.162)	-0.082* (0.020)	-0.073* (0.014)	0.000 (0.558)
Treatment	0.149** (0.000)	0.034 (0.355)	0.043 (0.156)	-0.000 (0.902)
Post	0.076** (0.000)	0.017 (0.419)	0.024 (0.208)	-0.000 (0.635)
Treatment x Post	-0.053^ (0.093)	0.069* (0.028)	-0.022 (0.359)	0.000 (0.627)
PSM-DD	-0.028 (0.331)	0.075* (0.032)	0.035 (0.291)	-0.010 (0.611)
Nearest 5 Neighbors	-0.036 (0.169)	0.071* (0.018)	.013 (0.630)	-0.021 (0.216)
Kernel				
Observations	1502	1502	1502	1502

Note: Marginal effects are reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 2: Kenya - Difference-in-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Reported Individuals in Household by Age Group

	Age 12–17	Age 18-34	Age 35-54	Age 55 plus
Urban	0.030* (0.022)	0.180** (0.000)	0.128** (0.002)	0.006 (0.787)
Age of Household Head	0.007** (0.001)	-0.009* (0.022)	0.047** (0.000)	-0.035** (0.000)
Age of Household Head Square	-0.000** (0.004)	0.000 (0.561)	-0.001** (0.000)	0.001** (0.000)
Head Education Some Primary	-0.003 (0.879)	0.004 (0.844)	-0.005 (0.878)	-0.053* (0.014)
Head Education Standard 7	-0.014 (0.643)	0.086* (0.015)	0.026 (0.592)	-0.022 (0.494)
Head Education Standard 8	-0.035 (0.303)	0.018 (0.713)	-0.165** (0.000)	0.026 (0.314)
Head Education Form 1-2-3	-0.035 (0.424)	0.064 (0.251)	0.129 (0.188)	-0.038 (0.371)
Head Education Form 4+	0.001 (0.975)	0.018 (0.802)	0.113 (0.164)	-0.028 (0.518)
Household Head Female	-0.018 (0.445)	-0.085** (0.000)	-0.198** (0.000)	0.029 (0.160)
Treatment	-0.029 (0.295)	-0.042 (0.251)	-0.027 (0.527)	-0.019 (0.545)
Post	0.006 (0.693)	0.137** (0.000)	0.060** (0.005)	-0.164** (0.000)
Treatment x Post	0.018 (0.409)	-0.047 (0.200)	-0.064* (0.042)	0.096** (0.001)
PSM-DD	-0.010	-0.083**	-0.052^	0.71**
Nearest 5 Neighbors	(0.701)	(0.008)	(0.090)	(0.006)
PSM-DD	0.004	-0.062*	-0.053*	0.062**
Kernel	(0.857)	(0.031)	(0.031)	(0.006)
Observations	3316	3316	3316	3316

Note: Marginal effects reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 3: Malawi - Difference-in-Difference Negative Binomial Regression and Poisson Regression to Estimate Estimates of Impact of Malawi Social Cash Transfers on Number of Person by Age Groups

	*Age 12–17	Age 18–34	Age 35–54	Age 55 plus
Age of Household Head	0.025* (0.025)	-0.008 (0.557)	0.288** (0.000)	0.220** (0.000)
Age of Household Head Square	-0.000** (0.001)	-0.000 (0.254)	-0.003** (0.000)	-0.001** (0.000)
Head Educ Some Primary	0.163** (0.010)	0.232* (0.017)	-0.086 (0.242)	0.033 (0.260)
Head Educ Some Secondary +	-0.217 (0.512)	0.424^ (0.052)	-0.419 (0.116)	0.153 (0.575)
Household Head Female	0.050 (0.491)	-0.285** (0.003)	-0.595** (0.000)	-0.382** (0.000)
Treatment	0.396** (0.000)	0.163 (0.137)	0.129 (0.138)	-0.030 (0.343)
Post	0.164** (0.000)	0.082 (0.143)	0.097^ (0.067)	-0.024 (0.152)
Treatment x Post	-0.157** (0.002)	0.158* (0.044)	-0.069 (0.327)	0.052* (0.038)
Constant	-0.554^ (0.070)	0.148 (0.660)	-6.116** (0.000)	-8.074** (0.000)
PSM-DD	-0.064 (0.346)	0.094** (0.031)	0.032 (0.412)	0.018 (0.476)
Nearest 5 Neighbors	-0.129 (0.053)^	0.088** (0.039)	0.013 (0.644)	0.003 (0.905)
Kernel				
Ln(Alpha)	-13.813**			
Observations	1502	1502	1502	1502

Note: Difference-in-Difference model estimated using negative binomial regression for * and poisson regression for all other discrete variables. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 4: Kenya - Difference-in-Difference Poisson Regression Estimates of Impact of Kenya Social Cash Transfers on Number of Person by Age Groups

	Age 12–17	Age 18-34	Age 35-54	Age 55 plus
Urban	0.055 (0.355)	0.480** (0.000)	0.237** (0.000)	-0.009 (0.863)
Age of Household Head	0.013* (0.034)	-0.004 (0.571)	0.227** (0.000)	0.124** (0.000)
Age of Household Head Square	-0.000* (0.039)	-0.000 (0.571)	-0.003** (0.000)	-0.001** (0.007)
Head Education Some Primary	0.007 (0.852)	-0.053 (0.423)	-0.003 (0.953)	-0.064* (0.019)
Head Education Standard 7	0.021 (0.620)	0.175 (0.136)	0.024 (0.748)	-0.235** (0.002)
Head Education Standard 8	-0.029 (0.677)	0.042 (0.669)	-0.358** (0.004)	0.028 (0.651)
Head Education Form 1-2-3	0.031 (0.663)	0.164 (0.114)	0.119 (0.344)	-0.226 (0.166)
Head Education Form 4+	0.139^ (0.080)	0.113 (0.398)	0.010 (0.925)	-0.229* (0.032)
Household Head Female	-0.101* (0.022)	-0.227** (0.000)	-0.608** (0.000)	-0.397** (0.000)
Treatment	-0.006 (0.920)	-0.059 (0.532)	-0.072 (0.353)	0.031 (0.650)
Post	0.055 (0.239)	0.207** (0.000)	0.091** (0.008)	-0.293** (0.000)
Treatment x Post	0.010 (0.843)	-0.091 (0.111)	-0.082 (0.200)	0.200** (0.008)
Constant	0.038 (0.851)	0.320 (0.159)	-4.835** (0.000)	-4.874** (0.000)
PSM-DD	0.015 (0.848)	-0.217** (0.000)	-0.068* (0.045)	0.086* (0.032)
Nearest 5 Neighbors	0.019 (0.787)	-0.180** (0.003)	-0.063* (0.023)	0.078* (0.045)
Kernel				
Observations	3316	3316	3316	3316

Note: p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 5: Malawi -Difference-in-Difference Probit Estimates of Impact of Malawi Social Cash Transfers on Reported Individuals by Gender and Age

	Girls Age12-17	Female Age 18-34	Female Age 35-54	Female Age 55 +	Boys Age12-17	Male Age 18-34	Male Age 35-54	Male Age 55 +
Age of Household Head	0.007 (0.210)	-0.012** (0.006)	0.031** (0.000)	0.046** (0.006)	0.011^ (0.050)	0.001 (0.868)	0.006** (0.000)	0.039** (0.000)
Age of Household Head Square	-0.000* (0.041)	0.000 (0.192)	-0.000** (0.000)	-0.000 (0.218)	-0.000** (0.002)	-0.000 (0.251)	-0.000** (0.000)	-0.000** (0.000)
Head Educ Some Primary	0.077* (0.022)	0.030 (0.210)	-0.016 (0.502)	0.061 (0.101)	0.061^ (0.066)	0.042 (0.160)	-0.008 (0.339)	0.027 (0.334)
Head Educ Some Secondary +	-0.120 (0.337)	-0.028 (0.768)	-0.135** (0.000)	0.275** (0.000)	-0.167 (0.113)	0.034 (0.782)	0.018 (0.627)	-0.074^ (0.056)
Household Head Female	0.073* (0.036)	-0.036 (0.176)	-0.020 (0.448)	0.515** (0.000)	-0.014 (0.686)	-0.086** (0.006)	-0.119** (0.000)	-0.740** (0.000)
Treatment	0.117** (0.001)	0.025 (0.367)	0.025 (0.354)	-0.047 (0.291)	0.084* (0.021)	0.024 (0.443)	0.014 (0.190)	-0.006 (0.823)
Post	0.067** (0.001)	0.003 (0.890)	0.035* (0.041)	-0.024 (0.445)	0.036* (0.036)	0.019 (0.222)	-0.004 (0.346)	-0.014 (0.383)
Treatment x Post	-0.071** (0.009)	0.027 (0.318)	-0.025 (0.245)	0.045 (0.235)	0.012 (0.659)	0.033 (0.159)	0.006 (0.366)	0.016 (0.469)
PSM-DD	0.004 (0.918)	0.027 (0.416)	-0.020 (0.431)	0.020 (0.367)	0.022 (0.476)	0.039 (0.119)	0.055* (0.029)	-0.010 (0.449)
Nearest 5 Neighbors	-0.027 (0.415)	0.029 (0.362)	-0.011 (0.672)	0.007 (0.700)	0.015 (0.614)	0.038 (0.114)	0.027 (0.108)	-0.012 (0.310)
Kernel								
Observations	1502	1502	1502	1502	1502	1502	1502	1502

Note: Marginal effects reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 6: Kenya - Difference-in-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Reported Individuals by Gender and Age

	Girls Age12-17	Female Age 18-34	Female Age 35-54	Female Age 55 +	Boys Age12-17	Male Age 18-34	Male Age 35-54	Male Age 55 +
Urban	0.068** (0.003)	0.209** (0.000)	0.088* (0.023)	0.036 (0.320)	0.005 (0.871)	0.113** (0.002)	0.041^ (0.069)	-0.026^ (0.067)
Age of Household Head	0.008** (0.002)	-0.015** (0.000)	0.047** (0.000)	0.025* (0.035)	0.004 (0.191)	0.004 (0.208)	0.007** (0.001)	0.006^ (0.069)
Age of Household Head Square	-0.000** (0.002)	0.000^ (0.070)	-0.001** (0.000)	0.000 (0.871)	-0.000 (0.152)	-0.000^ (0.067)	-0.000** (0.000)	-0.000 (0.672)
Head Education Some Primary	0.002 (0.946)	-0.031 (0.287)	0.035 (0.119)	-0.039 (0.256)	-0.007 (0.752)	0.008 (0.717)	-0.018* (0.026)	-0.016 (0.243)
Head Education Standard 7	0.071^ (0.084)	0.066^ (0.058)	0.045 (0.320)	-0.069 (0.205)	-0.073^ (0.084)	0.072 (0.192)	0.001 (0.910)	-0.040* (0.015)
Head Education Standard 8	0.008 (0.856)	0.031 (0.410)	-0.084* (0.046)	0.027 (0.576)	-0.066 (0.203)	-0.030 (0.529)	-0.037** (0.000)	-0.002 (0.935)
Head Education Form 1-2-3	0.066 (0.142)	0.053 (0.366)	0.139 (0.158)	-0.188** (0.009)	-0.045 (0.283)	0.048 (0.467)	-0.010 (0.535)	-0.034^ (0.092)
Head Education Form 4+	0.076 (0.156)	0.084 (0.271)	0.121 (0.143)	-0.242** (0.000)	-0.007 (0.903)	0.031 (0.598)	-0.028** (0.003)	0.001 (0.959)
Household Head Female	-0.009 (0.735)	-0.104** (0.000)	0.006 (0.847)	0.362** (0.000)	-0.053^ (0.055)	-0.046 (0.156)	-0.264** (0.000)	-0.568** (0.000)
Treatment	-0.046^ (0.064)	-0.012 (0.755)	-0.048 (0.223)	0.010 (0.847)	-0.022 (0.421)	-0.023 (0.474)	0.007 (0.444)	0.041* (0.024)
Post	0.078** (0.000)	0.144** (0.000)	0.061** (0.002)	-0.142** (0.000)	0.049** (0.005)	0.160** (0.000)	0.018** (0.004)	-0.011 (0.309)
Treatment x Post	0.025 (0.269)	-0.008 (0.779)	-0.044 (0.116)	0.128** (0.008)	0.026 (0.228)	-0.029 (0.104)	-0.008 (0.327)	0.025^ (0.072)
PSM-DD	-0.018 (0.586)	-0.024 (0.382)	-0.036 (0.189)	0.015 (0.548)	0.020 (0.727)	-0.076** (0.007)	-0.025^ (0.083)	0.023^ (0.076)
Nearest 5 Neighbors	0.005 (0.843)	-0.020 (0.449)	-0.043^ (0.068)	0.023 (0.303)	0.008 (0.736)	-0.062* (0.016)	-0.019 (0.149)	0.023* (0.043)
Kernel								
Observations	3316	3316	3316	3316	3316	3316	3316	3316

Note: Marginal effects reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 7: Malawi - Baseline Summary Statistics of Exogenous Variables for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Consumed one or fewer meals per day	0.405	0.507	0.548	0.270
Begged for food or money	0.280	0.329	0.4383	0.002**
Extremely poor	0.990	0.989	0.991	0.760
Monthly per capita expenditures	192.08	192.71	191.41	0.955
Household owns 0-1 asset	0.251	0.5233	0.482	0.260
Dependency Ratio	1.371	1.131	1.625	0.000***
Number of orphans	1.492	1.209	1.792	0.000***
Age of household head	61.55	63.05	59.96	0.015*
Household head female	0.653	0.668	0.630	0.272
Single headed household	0.723	0.732	0.717	0.646
Education of household head	1.587	1.204	1.991	0.000***
Not catholic	0.521	0.475	0.570	0.009**
Log of household size	1.205	1.072	1.356	0.000***
Number of observations	751	386	365	

Note: Test for continuous variables are t tests and for dummy variables proportional tests.

* p<0.05; ** p<0.01; *** p<0.001

Table 8: Malawi - Baseline Summary Statistics of Outcome Indicators for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	p Value
Number of children 12-17	0.988	0.766	1.221	0.000***
Number of adults 18-34	0.446	.383	0.512	0.013*
Number of adults 35-54	0.320	0.267	0.378	0.006**
Number of adults 55 or older	0.893	0.940	0.843	0.044**
Number of girls 12-17	0.503	0.391	0.621	0.000***
Number of females 18-34	0.190	0.161	0.222	0.042**
Number of females 35-54	0.241	0.207	0.276	0.028**
Number of females 55 or older	0.619	0.665	0.569	0.009**
Boys 12-17	0.485	0.375	0.6	0.000***
Number of males 18-34	0.256	0.223	0.290	0.080
Number of males 35-54	0.080	0.060	0.102	0.035*
Number of males 55 or older	0.2743	0.274	0.2739	0.985
Number of observations	751	386	365	

* p<0.05; ** p<0.01; *** p<0.001

Table 9: Kenya - Baseline Summary Statistics of Exogenous Variables for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	<i>p</i> Value
Monthly per capita expenditure	1197.91	1170.46	1209.602	0.287
Urban	0.130	0.099	0.144	0.013*
Number of OVCs	2.75	2.77	2.73	0.638
Household size	5.53	5.68	5.46	0.118
Number of orphans	2.81	2.79	2.82	0.716
Age of household head	55.53	48.98	58.32	0.0000***
Education of household head	1.01	1.39	0.85	0.0000***
Household head female	0.659	0.636	0.668	0.212
Number of observations	1658	1163	495	

Note: Test for continuous variables are t tests and for dummy variables proportional tests.

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 10: Kenya - Baseline Summary Statistics of Outcome Indicators for Whole Sample, Treatment, and Control With Tests of Difference

	Total	Control	Treatment	<i>p</i> Value
Number of children 12-17	1.393	1.388	1.396	0.895
Number of adults 18-34	0.903	0.996	0.863	0.035*
Number of adults 35-54	0.467	0.549	0.433	0.000***
Number of adults 55 plus	0.776	0.584	0.857	0.000***
Number of girls 12-17	0.460	0.490	0.447	0.213
Number of females 18-34	0.288	0.352	0.261	0.002**
Number of females 35-54	0.315	0.368	0.292	0.003**
Number of females 55 or older	0.490	0.345	0.552	0.000***
Boys 12-17	0.700	0.679	0.709	0.483
Number of males 18-34	0.356	0.406	0.335	0.047
Number of males 35-54	0.108	0.129	0.099	0.071
Number of males 55 or older	0.204	0.147	0.229	0.000***
Number of observations	1658	495	1163	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 11: Malawi Propensity score estimation

	Probit
Consumed one or fewer meals per day	0.123 (0.207)
Begged for food or money	0.336** (0.001)
<i>Extremely poor</i>	0.264 (0.690)
Monthly per capita expenditures	0.000 (0.315)
Household owns 0-1 asset	-0.020 (0.845)
<i>Dependency Ratio</i>	0.022 (0.574)
Number of orphans	-0.007 (0.858)
Age of household head	0.005 (0.286)
Household head female	-0.111 (0.614)
Single headed household	0.254 (0.204)
Education of household head	0.065** (0.004)
Not catholic	0.201* (0.039)
Log of household size	-0.528* (0.035)
Number of children 0-5	0.113 (0.252)
Number of children 6-11	0.351** (0.000)
Number of children 12-17	0.378** (0.000)
Number of males 18-54	0.290* (0.011)
Number of males 55 or older	0.243 (0.246)
Number of females 18-54	0.241^ (0.082)
Number of females 55 or older	0.129 (0.509)
Constant	-1.648* (0.032)
Number of observations	751

Note: Variables in italics reflect the eligibility criteria used by the program. *p* values in parentheses.

^ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$

Table 12: Kenya Propensity score estimation

	Probit
Monthly per capita expenditure	0.000 (0.427)
Urban	0.548** (0.000)
Number of OVCs	0.052 (0.126)
Log of household size	-0.155 (0.405)
Age of household head	0.017** (0.000)
Education of household head	-0.141** (0.000)
Household head female	0.011 (0.918)
Number of children age 0-17	-0.000 (0.996)
Number of males age 18-54	-0.009 (0.877)
Number of males age 55 or older	0.238* (0.042)
Number of females age 18-54	0.033 (0.622)
Number of females age 55 or older	0.168^ (0.063)
Constant	-0.395 (0.133)
Number of observations	1658

Note: *p* values in parentheses.

^ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$

Table 13: Kenya - First-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Individuals Joining the Household by Age Group

	Age 18-34	Age 35-54	Age 55 plus
Age	0.095** (0.006)	-0.037^ (0.094)	0.001 (0.809)
Age Square	-0.002** (0.008)	0.000 (0.136)	-0.000 (0.779)
Some Primary	0.050^ (0.072)	-0.002 (0.890)	-0.006 (0.542)
Some Secondary	0.044 (0.207)	0.023 (0.454)	0.003 (0.879)
Individual is married	0.066* (0.011)	0.036* (0.037)	0.003 (0.764)
Household Size	-0.002 (0.531)	-0.003 (0.279)	0.004* (0.022)
Urban	-0.013 (0.589)	0.017 (0.460)	0.015 (0.435)
Treatment	0.013 (0.512)	0.012 (0.467)	-0.021 (0.138)
Observations	1304	771	1181

Note: Marginal effects are reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 14: Kenya - First-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Individuals Leaving the Household by Age Group

	Age 18-34	Age 35-54	Age 55 plus
Age	0.092** (0.002)	0.029 (0.235)	-0.005 (0.509)
Age Square	-0.002** (0.001)	-0.000 (0.166)	0.000 (0.393)
Individual is working	0.024 (0.335)	-0.021 (0.431)	-0.117** (0.000)
Some Primary	0.030 (0.302)	-0.029 (0.102)	0.016 (0.370)
Some Secondary	-0.074* (0.021)	0.048 (0.164)	0.002 (0.962)
Individual is married	0.001 (0.972)	0.001 (0.931)	-0.001 (0.938)
Household Size	0.023** (0.000)	0.001 (0.799)	0.001 (0.848)
Urban	-0.108** (0.000)	-0.014 (0.457)	-0.027 (0.177)
Treatment	0.083** (0.000)	0.005 (0.761)	-0.057* (0.015)
Observations	1579	821	1128

Note: Marginal effects are reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 15: Kenya - First-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Individuals Leaving the Household by Age Category and Gender

	Female Age 18-34	Female Age 35-54	Female Age 55 +	Male Age 18-34	Male Age 35-54	Male Age 55 +
Age	0.116* (0.014)	0.026 (0.228)	0.002 (0.829)	0.081* (0.045)	0.051 (0.459)	-0.026 (0.103)
Age Square	-0.003** (0.004)	-0.000 (0.170)	-0.000 (0.943)	-0.001^ (0.086)	-0.001 (0.401)	0.000^ (0.096)
Individual is Working	0.044 (0.218)	0.008 (0.684)	-0.114** (0.003)	-0.008 (0.820)	-0.024 (0.704)	-0.135** (0.009)
Some Primary	0.057 (0.153)	-0.004 (0.766)	0.008 (0.693)	-0.020 (0.648)	-0.151** (0.006)	-0.000 (0.992)
Some Secondary	-0.039 (0.425)	-0.014 (0.468)	0.408 (0.281)	-0.142** (0.001)	0.041 (0.534)	-0.062^ (0.092)
Individual is married	-0.052 (0.138)	-0.007 (0.655)	-0.005 (0.765)	0.002 (0.957)	-0.105 (0.117)	-0.096 (0.121)
Household Size	0.029** (0.000)	-0.004 (0.242)	-0.002 (0.449)	0.016** (0.001)	0.008 (0.229)	0.004 (0.528)
Urban	-0.121** (0.000)	0.010 (0.654)	-0.027 (0.121)	-0.103** (0.003)	-0.055 (0.243)	-0.016 (0.776)
Treatment	0.078* (0.024)	-0.001 (0.973)	-0.054* (0.036)	0.071* (0.020)	-0.009 (0.863)	-0.074 (0.135)
Observations	706	610	768	873	211	360

Note: Marginal effects reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

Table 16: Kenya - First-Difference Probit Estimates of Impact of Kenya Social Cash Transfers on Individuals Joining the Household by Age Category

	Female Age 18-34	Female Age 35-54	Female Age 55 +	Male Age 18-34	Male Age 35-54	Male Age 55 +
Age	0.066 (0.245)	-0.037^ (0.075)	-0.004 (0.252)	0.109** (0.008)	-0.007 (0.904)	0.037* (0.045)
Age Square	-0.001 (0.210)	0.000^ (0.099)	0.000 (0.269)	-0.002* (0.017)	0.000 (0.947)	-0.000* (0.037)
Some Primary	0.098* (0.014)	0.009 (0.585)	-	-0.001 (0.990)	-0.059 (0.240)	-
Some Secondary	0.108^ (0.078)	-0.002 (0.957)	-	-0.003 (0.944)	-0.003 (0.957)	-
Schooling	-	-	-0.003 (0.658)	-	-	-0.025 (0.216)
Individual is married	0.058 (0.115)	0.017 (0.326)	-0.004 (0.577)	0.031 (0.379)	0.020 (0.668)	-0.053 (0.216)
Household Size	0.003 (0.605)	0.000 (0.902)	0.003* (0.015)	-0.009* (0.049)	-0.013 (0.105)	-0.000 (0.890)
Urban	-0.060^ (0.090)	0.042 (0.135)	0.023 (0.243)	0.003 (0.913)	-0.043 (0.341)	-0.017 (0.448)
Treatment	0.092** (0.004)	0.001 (0.925)	-0.021 (0.123)	-0.052* (0.047)	0.024 (0.579)	-0.024 (0.384)
Observations	585	771	823	719	203	358

Note: Marginal effects reported. p-values are in parenthesis.

^p<0.10, *p<0.05, **p<0.01

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