IMPACTS OF POVERTY REDUCTION PROGRAMS IN REMOTE RURAL LANDSCAPES: EVIDENCE FROM CASH TRANSFERS IN ZAMBIA

Kathleen Lawlor

A dissertation submitted to the faculty at the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Public Policy.

Chapel Hill
2015

Approved by:

Sudhanshu Handa

Erin Sills

Richard Andrews

Richard Bilsborrow

Benjamin Davis

ABSTRACT

Kathleen Lawlor: Impacts of Poverty Reduction Programs in Remote Rural Landscapes: Evidence from Cash Transfers in Zambia
(Under the direction of Sudhanshu Handa)

This dissertation, composed of three studies, examines the potential for unconditional cash transfers to reduce poverty in rural Africa and considers the serious challenges posed by weak market access, natural resource dependence, and climate shocks that threaten food supplies. To investigate these questions we harness the randomized roll-out of Zambia's Child Grant Program, which extends – unconditionally – payments of 60 kwacha (about $12) per month to households with a child under the age of five.

We find that these relatively small cash payments are transformative for rural Zambian households in numerous ways. First, cash transfers empower poor, rural households facing weather and other negative income shocks to employ coping strategies typically used by the non-poor, such as spending savings. The transfers also enable households to substantially increase their food consumption and overall food security over time, despite widespread drought and flooding. Second, cash transfers allow households to expand their farms. Third, the income effects of cash are powerful enough to shift livelihood strategies and convert subsistence farmers into small-scale farmers that sell some fraction of their crops in markets, purchase agricultural inputs, and own non-farm businesses.

However, there is significant impact heterogeneity moderated by households' market access. We find that while cash is more transformative than bicycle ownership (which can facilitate market access) in terms of converting subsistence farmers into small-scale sellers,

bicycles can empower households already engaged in agricultural markets to increase their crop sales over time – even in the context of declining crop revenues. We also find that cash has a greater impact on farm expansion for households living far from markets, while households living close to markets are more likely to use the transfer to start non-farm businesses and consume charcoal.

These three studies provide evidence that unconditional cash transfers facilitate rural households' autonomous adaptation and development decisions and these decisions are helping households escape poverty, despite challenges posed by climate change and remoteness. However, the productive impacts of cash transfers in rural areas could be enhanced by complementary initiatives that improve market access and promote sustainable use of natural resources.

ACKNOWLEDGEMENTS

Completion of this dissertation would not have been possible without the support of many individuals and organizations. Thanks must be extended to my committee members – Ashu Handa, Erin Sills, Pete Andrews, Dick Bilsborrow, and Ben Davis – for their advice and support. This dissertation has also benefitted from very helpful comments from David Seidenfeld and participants at the 2014 APPAM Fall Conference. I must extend special thanks to my advisor, Ashu Handa, for sharing his data and guidance and, most importantly, for being an excellent teacher of microeconomic theory and econometrics. I am also particularly grateful for Erin Sills' insightful advice on numerous projects over the years. I would also like to acknowledge the support I received from the UNC Doctoral Dissertation Completion Fellowship, UNC Public Policy Hammer Fund, UNC Transportation Grant, UNC Weiss Urban Livability Fellowship, and the EPA Science to Achieve Results (STAR) Fellowship during my doctoral studies. Finally, this dissertation analyzes data collected for the impact evaluation of the Zambian Child Grant Program, which is being implemented by the American Institutes for Research and the University of North Carolina at Chapel Hill under contract to UNICEF-Zambia. The evaluation is commissioned by the Government of Zambia's Ministry of Community Development, Mother and Child Health, with support from DFID, Irish Aid, and UNICEF-Zambia. Other organizations part of the evaluation team include FAO and Palm Associates. Thank you to everyone involved in this study for sharing your data with me.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1:
BACKGROUND AND OVERVIEW

1.1. Introduction

Over the past decade, numerous econometric studies have investigated the effectiveness of cash transfer programs in reducing poverty in developing countries. This large and growing body of evidence reveals that cash transfers are highly effective in reducing poverty in various countries across the world (Journal of Development Effectiveness, 2010). Cash transfer programs, which extend regular cash grants to poor households, are designed to relieve the immediate acute effects of extreme poverty and break the intergenerational transmission of poverty to children. Many of the most studied and well-known cash transfer programs, such as Mexico's *Progresa* (now known as *Oportunidades*) and Brazil's *Bolsa Familia*, make the extension of payments conditional on children's health clinic visits as well as school enrollment and attendance.

The main goal of cash transfer programs is social protection, with a specific focus on improving children's welfare and well-being. Blank et al. (2010) review several definitions of *social protection* and note that most definitions emphasize the reduction of households' vulnerability to economic shocks, which enables them to "protect" their consumption and achieve a minimum standard of living, above that of extreme poverty. The general theory of change motivating conditional cash transfer programs is that parents require a pecuniary incentive to vaccinate their children or enroll them in school and the payments provide households with cash they can use to buy more nutritious food for themselves and their children.

Taken together, the cash plus conditions should lead to an improvement in children's human capital and ability to escape poverty over the long-term.

Economic theory suggests that conditions attached to transfers change the relative prices of goods and thus introduce substitution effects that affect behavior. This behavior may be economically efficient, if cash encourages households to consume more of a good that is socially beneficial (i.e., has positive externalities), such as childhood vaccinations, than they would have in the absence of this incentive. However, economic theory also suggests that conditionalities may be inefficient for multiple reasons. Because compliance with conditions imposes transaction and opportunity costs on households, there is risk of adverse selection, where only those who would have taken the obliged actions anyways opt-in to the program (because their costs of compliance are minimal). Additionally, there are real programmatic costs associated with monitoring compliance with conditions and these program expenditures could instead be spent on increasing the size of the transfer or enrolling more beneficiaries. For these reasons and others, cash transfer programs in Africa tend to be unconditional, though the focus remains on social protection for children.[1]

Beyond protecting households' consumption and children's human capital, cash transfer programs also have significant potential to contribute to poverty reduction more broadly. For example, if households use the cash grants to increase agricultural production and sell their production and labor in markets, cash transfers could push households onto self-propelled growth trajectories that allow them to escape poverty. Particularly in Africa, where the depth of

[1]While some studies find that conditional programs produce better outcomes for children's health and schooling (e.g., Baird et al., 2011, Attanasio et al., 2015), others question the methodological rigor of these studies (e.g., Kidd and Calder, 2012) and many of the first generation evaluations of unconditional cash transfers in Africa are identifying positive impacts on children's health and schooling (UNICEF Office of Research-Innocenti, 2014) as well as reductions in risky sexual behavior amongst youth (Handa et al., 2014(a)).

poverty is especially severe[2] and there are few employment opportunities, these small infusions of cash have the potential to be transformative.

Historically, poverty reduction programs in low-income countries have focused on targeted sector interventions, including in-kind transfers of livestock, agricultural inputs, improved cookstoves, or other assets; training in agricultural techniques, health practices, or small-business development; supply-side interventions to increase the quantity and quality of educational and health care facilities; and the extension of microcredit. However, as Blattman and Niehaus (2014) observe, evidence is accumulating that many of these targeted sector interventions have seriously underperformed.[3] When put in this larger historical context, cash transfers – conditional or not – clearly represent a revolutionary approach to fighting poverty.

All of these approaches are based on certain assumptions – explicitly or implicitly – about what works to reduce poverty. Implicitly, traditional development interventions that give in-kind transfers rather than cash are suggesting that donors/governments/NGOs know what the poor need to get out of poverty – and they know better than the poor themselves. Supply-side interventions assume there is existing demand for education and health services that is not being met due to lack of infrastructure, whereas educational training programs assume demand is lacking and technological adoption and agricultural output low due to a lack of information. And while the explicit assumption guiding microcredit approaches is obviously that the poor are credit-constrained, the implicit assumption – given the way microcredit lending operates – is that

[2]Nearly half of Sub-Saharan Africa's population lives in extreme poverty (measured as living on less than $1.25/day) (World Bank (2013(a)). Rural poverty remains particularly severe on the continent; in some African countries 90% of those living below the poverty line reside in rural areas (Chen and Ravallion, 2007).

[3]For example, recent evidence from six randomized evaluations of microcredit programs implemented across the developing world reveals that microcredit does not increase household consumption or income (see Banerjee et al., 2015).

poverty is perpetuated by a lack of credit for profit-making endeavors, rather than a lack of credit and finance for basic needs.

In contrast, an unconditional cash transfer approach might assume that the poor themselves are best placed to decide how small amounts of development finance should be spent in order to improve their lives; that demand for health care, education, and improved technologies is low due to income constraints; and that an inability to satisfy basic needs – rather than start a small business – is the major force perpetuating poverty, with food consumption and agricultural production constrained by a lack of income, credit, and savings.

Cash transfers could potentially be more effective in reducing poverty than targeted sector interventions for several reasons. First, it may be that the primary constraint on household agricultural production, market engagement, and savings is income, rather than information. Second, because cash transfers enable the poor themselves to decide what changes to make to their livelihood strategies, this could allow those who are more entrepreneurial to diversify their livelihoods beyond farming, while also allowing those more skilled at agriculture to expand their farms. From an economic standpoint, such self-selection could lead to efficiency gains as well as avoid saturation of agricultural markets by enabling diversification of livelihoods at the local level. Finally, because cash transfers respect individual's autonomy and agency and empower the poor to make their own decisions, transfers could be more effective than traditional sector approaches at tackling multiple dimensions of poverty, including capability deprivation and lack of voice, choice, and action (per Sen, 1999).

However, questions remain about the effectiveness of cash transfers in achieving development impacts beyond protection of children's human capital. Unconditional cash transfers, in particular, face skepticism; some worry that the poor won't use the money to protect children's human capital or that the transfers won't be put towards productive uses and will instead foster dependency and idleness (Blattman and Niehaus, 2014). Additionally, cash transfer programs' emphasis on the demand side might cause these programs to overlook important supply-side constraints that hinder households' ability to convert cash transfers into health visits, education, or purchases. Supply-side constraints could also cause cash transfers to induce localized inflation if, for example, a rising demand for food cannot be met by increased agricultural production. In rural Africa, supply-side constraints may be particularly problematic.

Experience with cash transfers in remote rural areas of Africa is still being tested (Davis et al., 2012). As the "last frontier" of global poverty eradication (World Bank, 2013(a)), these settings face unique challenges given weak market access (Barrett et al., 2001) and the complex poverty-environment relationships that characterize agricultural communities living on less-favored lands (Barbier, 2010). Moreover, these challenges facing rural Africa will only be compounded in coming years by the erratic weather patterns induced by climate change, which are predicted to take devastating tolls on rain-fed agriculture and food security in Africa (IPCC, 2014).

All of these characteristics of rural Africa suggest strong potential for poverty traps – the self-reinforcing conditions that cause poverty to persist (Dasgupta, 1997). For example, subsistence farmers coping with drought and a failed harvest may have no other choice but to reduce food consumption, given a lack of savings, liquidity, and credit (Zimmerman and Carter, 2003; World Bank, 2013(b)). Such short-term coping strategies can lead to malnutrition and the degradation of human capital, especially children's, weakening their ability to escape poverty over the long-run.[4] Similarly, poor communities dependent on natural resources for farming and

[4]Grantham-McGregor et al. (2007) estimate that early childhood malnutrition in developing countries reduces individuals' lifetime earnings by 22 percent.

livelihoods may degrade their natural capital in an effort to improve their situation, thereby pushing themselves farther into poverty (Barbier, 2010). Finally, weak infrastructure and limited market access in rural areas pose significant supply-side constraints on the rural poor's ability to escape poverty, suggesting the existence of "fractal poverty traps" (Barrett and Swallow, 2005). In this context of multiple poverty traps, many of which repeat and reinforce themselves at multiple scales (from the household to the community to the region), can cash transfers be an effective development tool?

The many unconditional cash transfer programs currently being implemented in rural Africa offer fertile ground for investigating the impacts of cash transfers beyond protection of children's health and education to include examination of impacts on household agricultural production, market participation, and income generation. These programs also provide an opportunity to critically assess whether cash transfers can work to reduce poverty in the context of potential poverty traps posed by weak market access, natural resource dependence, and climate shocks that threaten food supplies.

This dissertation, composed of three studies, investigates these questions using data from the randomized roll-out of an unconditional cash transfer program currently being implemented in Zambia, the Zambia Child Grant Program.

1.2. Randomized impact evaluation of the Zambia Child Grant Program

The Zambian Child Grant Program is an unconditional cash transfer program being implemented by Zambia's Ministry of Community Development, Mother and Child Health. The goals of the program are to reduce extreme poverty and the intergenerational transmission of poverty to children. To be eligible for the program, households must have a child under the age of five. Enrolled households receive the equivalent of about $12 per month, which is estimated to be the cost of purchasing one meal per day for an average-sized household for a month. The Ministry of Community Development, Mother and Child Health began implementing the program in 2010, in three districts with the highest rates of child mortality and malnutrition in Zambia: Kalabo, Kaputa, and Shongombo. These districts are extremely remote, situated more than two days car travel from the country's capital, Lusaka.

Zambia's Child Grant Program is being rolled out in phases, enabling the program to first conduct a rigorous evaluation of the pilot phase before scaling up. The evaluation employs a multi-site, clustered randomized design. Thirty communities from each of three districts were first randomly assigned to either treatment or control status. All eligible households within treatment communities were then enrolled in the program. Next, 28 households from each control and treatment community were randomly selected to participate in the study. Baseline surveys were administered prior to randomly assigning communities to treatment or control status and the start of the program. In sum, in 2010, baseline data were collected from 2,515 households living in 90 communities (45 control, 45 treatment) across Kaputa, Kalabo, and Shangombo. A second round of data was collected in 2012.

In addition to collecting detailed information on children's health and schooling, households were asked about their consumption, income, assets, agricultural production, and other livelihood activities. Households were also surveyed about their exposure to a long list of potential negative income shocks as well as their specific coping strategies. Households in the sample are quite poor, with 92% living below the poverty line[5] and 90% ranking as severely food insecure. The vast majority are subsistence farmers, farming, on average, less than 1 hectare of land. At baseline, only 22% of households sold crops and only 13% purchased agricultural inputs

[5]Households with total expenditures less than 93.37 kwacha per person per month in 2010 are considered to be severely poor.

(i.e., seeds, fertilizer, or pesticides). On average, households live 19 km from food markets, though there is considerable variation in the study sample.

1.3. Results

1.3.1. Cash transfers and weather shocks

The first chapter of this dissertation situates cash transfers in the specific context of climate change in Africa and the severe risks it poses for development. Climate models predict dramatic disruptions to rainfall patterns in Sub-Saharan Africa, with disastrous consequences for agricultural yields and food security and a potential reversal of gains made in the region's fight against poverty (IPCC, 2014). How the international community chooses to address climate mitigation and adaptation has significant implications for global inequality and intergenerational equity. While crop insurance and "ecosystem-based adaptation" are often cited as important climate adaptation strategies for rural Africa, little attention has been paid to the potential role of unconditional cash transfers. This study is the first to provide econometric evidence of how cash transfers could help households in rural Africa cope with extreme weather events affecting agricultural production.

Between the first and second rounds of data collection for this study, 81% of the sample experienced droughts and floods as well as sharp fluctuations in food and crop prices. A common shock-coping strategy employed by poor, rural households is to simply reduce food consumption, given lack of savings, credit, or other options. Avoiding detrimental coping strategies that degrade households' capabilities, and thus ability to escape poverty, is essential for building resilience to climate change. We find that in the face of shocks, cash empowers poor, rural households to employ coping strategies typically used by the non-poor, such as spending savings, and also enables them to substantially increase their food consumption and overall food security. We also find some evidence that this positive impact of cash on shock-coping is greatest when transfers are received prior to shock exposure, rather than *ex-post*. This evidence demonstrates that extending relatively small cash payments unconditionally and regularly to the rural poor is a powerful policy option for fostering climate-resilient development.

1.3.2. Cash transfers, natural resource use, and market access

The second chapter of this dissertation considers how cash transfers affect the environment and examines whether variation in market access is associated with heterogeneous impacts on natural resource use. The theoretical and empirical ambiguity characterizing poverty-environment relationships motivates this study. Some suggest that reducing poverty could decrease rural households' pressure on natural resources, while others argue poverty reduction increases such pressure by enhancing the poor's ability to clear land and harvest resources. Recent literature, however, suggests this ambiguity may be clarified by more attention to market access when investigating poverty-environment relationships. This is because non-farm livelihood opportunities as well as resource quality and quantity likely vary depending on market access. For example, land resources may be less available and more degraded close to market centers due to the lower transaction costs of bringing agricultural and forest goods to market.

This study is the first to examine the environmental impacts of a cash transfer program in Africa. We look at households' use of fuelwood, charcoal, bushmeat, and land for farming as well as their ownership of non-farm businesses. Based on graphical analysis, we first find that impacts of the cash transfer on natural resources bifurcate around the distance of 10 km to market. We find that households living close to markets are more likely to use the cash transfer to start non-farm businesses as well as consume and/or produce charcoal. Households living far from markets, on the other hand, are more likely to use cash transfers to enter farming or expand their already-existing farms.

1.3.3. Cash transfers, bicycles, and market participation

To date there has been little examination of how cash transfers' effectiveness in remote rural areas may be hindered by supply-side constraints. That is, in areas far from markets dominated by subsistence farming, how will households be able to convert cash transfers into increased consumption and production? We consider this issue of market access and investigate whether bicycle ownership increases the effectiveness of the cash transfers. While there is little in the academic literature regarding the role of bikes in development, there is widespread belief amongst the numerous bicycle initiatives currently being implemented across Africa that bikes can increase poor households' consumption, income, and use of social services (see, for example, the work of World Bicycle Relief, which has a large presence in Zambia).

We examine impacts of the cash transfer as well as bicycle ownership on households' participation in agricultural markets and ownership of non-farm businesses and test for both the independent and multiplicative effects of bikes and cash. While we do not find any evidence of multiplicative effects of bikes and cash (i.e., that impacts are greater for those with bikes amongst the cash transfer beneficiaries), we do find that bikes and cash, separately, have very distinct effects on livelihood strategies. While cash increases the likelihood of selling crops and purchasing agricultural inputs, it has no impact on the volume of crop sales or agricultural input purchases. Bicycle ownership, on the other hand, enables those households already selling crops to increase their crop sales over time and is also associated with an increase in the likelihood of purchasing agricultural inputs (equivalent to the effect size of cash).

1.3.4. Can cash transfers be transformative for household livelihoods?

Taken together, these studies provide evidence that relatively small cash transfers can be transformative for rural African households in numerous ways. First, cash transfers offer a powerful, yet simple, approach for empowering the rural poor to manage the risks climate change poses to their well-being and livelihoods. Second, cash transfers enable households to increase their agricultural production. Households invest the cash grants in their farms and this effect is particularly strong amongst households living far from markets. Third, cash transfers facilitate households' participation in markets. The income effects of cash transfers are powerful enough to shift livelihood strategies. Cash converts subsistence farmers into small-scale farmers that sell some of their production and purchase inputs. Cash also encourages entrepreneurial farmers, particularly those living close to markets, to diversify into non-farm enterprises.

However, there are important nuances in these findings that offer lessons for programs targeting development in rural areas. Development impacts and trajectories will be greatly influenced by market access. And market access is determined not just by absolute distance, but by households' ownership of key assets, such as bicycles, which facilitate market participation. For example, we find that while cash is more transformative than bikes in terms of converting subsistence farmers into small-scale sellers, bicycle ownership can empower households already engaged in agricultural markets to increase their crop sales over time – even in the context of declining crop revenues. This suggests bikes may be an important asset for maintaining growth trajectories in the context of repeated negative shocks that risk trapping households in poverty. The importance of market access in facilitating productive impacts of cash transfers also underscores the need for large-scale development initiatives to improve infrastructure.

Additionally, the impacts of cash transfers on natural resources will vary according to market distance and this heterogeneity has important implications for sustainable development. For example, our study suggests that, in this region, households receiving cash living close to markets will increase their consumption and/or production of charcoal (the number one driver of forest degradation in Zambia) and those living far from markets will enter farming or expand their existing farms. Can cash transfers truly be transformational for development in this context, given the potential for poverty-environment traps? These findings suggest areas for future research as well as the need to pair traditional sector interventions with cash transfer programs. For example, cash transfer programs in ex-urban areas could consider facilitating households' adoption of alternative fuels through market mechanisms. In more remote areas, cash transfers could explore opportunities for expanding agricultural extension services to encourage land-intensive practices as well as the safe handling of pesticides and fertilizers.

In conclusion, these three studies provide evidence that unconditional cash transfers facilitate households' autonomous adaptation and development decisions. For example, households may use cash transfers to expand their farms or to diversify into non-farm businesses, depending on their market distance and personal inclinations. Study households also use these transfers to positively cope with climate shocks that threaten food security. These responses indicate that cash transfers may be preferable to certain traditional development approaches on economic efficiency grounds. By allowing a diversity of livelihood approaches, cash transfers do not risk picking the wrong strategy or flooding markets with one good or service. And because unconditional cash transfers are congruent with both human rights frameworks recognizing the importance of agency as well as adaptation and development approaches emphasizing locally-based solutions, there are strong normative arguments to be made for these transfers as well.

However, cash transfers are likely not an adequate replacement for many traditional development approaches. There are important supply-side constraints on rural households' ability to convert cash transfers into consumption and production, which can only be tackled by large-scale initiatives to improve infrastructure. Bicycle initiatives can also help improve market access, but their efficaciousness in remote communities will likely be limited by absolute distance to market. Traditional development approaches that offer farmers information about safe, sustainable, and improved agricultural techniques as well as alternative cooking technology also have a role to play. Pairing demand-side approaches that increase household incomes via cash transfers and offer information regarding agriculture and other technologies with supply-side approaches that facilitate market access could generate substantial welfare gains for rural communities. Future programming and research should explore these potential synergies between cash transfers and traditional development approaches.

REFERENCES

Attanasio, O.P., V. Oppedisano, M. Vera-Hernandez. 2015. Should cash transfers be conditional? Conditionality, preventive care, and health outcomes. American Economic Journal: Applied Economics 7(2): 35-52.

Baird, S., C. McIntosh, B. Özler. 2011. Cash or Condition? Evidence from a cash transfer experiment. George Washington University, University of California, San Diego and The World Bank.

Banerjee, A., D. Karlan, and J. Zinman. 2015. Six randomized evaluations of microcredit: Introduction and further steps. American Economic Journal: Applied Economics 7(1): 1-21.

Barbier, E.B. 2010. Poverty, environment and development. Environment and Development Economics 15(6): 635-660.

Barrett, C.B., T. Reardon, and P. Webb. 2001. Nonfarm income diversification and household livelihood strategies in rural Africa: concepts, dynamics and policy implications. Food Policy 26: 315–331.

Barrett, C.B. and B.M. Swallow. 2005. Fractal poverty traps. World Development 34(1): 1–15.

Blank, L., S. Devereux, and S. Handa. 2010. The case for social protection for children. Chp 2 in Social Protection for Africa's Children, Handa, S., S. Devereux, and D. Webb (Eds.). Routledge: New York. p. 15-27.

Blattman, C. and P. Niehaus. 2014. Show them the money: Why giving cash helps alleviate poverty. Foreign Affairs (May/June). Available at: http://www.foreignaffairs.com/articles/141214/christopher-blattman-and-paul-niehaus/show-them-the-money

Chen, S. and M. Ravallion. 2007. Absolute poverty measures for the developing world, 1981–2004. PNAS 104(43): 16757–16762.

Dasgupta, P. 1997. Nutritional status, the capacity for work, and poverty traps. Journal of Econometrics 77: 5-37.

Davis, B., M. Gaarder, S. Handa, J. Yablonski. 2012. Evaluating the impact of cash transfer programmes in sub-Saharan Africa: an introduction to the special issue. Journal of Development Effectiveness 4(1): 1-8.

Grantham-McGregor, S., Y.B. Cheung, S. Cueto, P. Glewwe, L. Richter, B. Strupp, and the International Child Development Steering Group. 2007. Development potential in the first 5 years for children in developing countries. The Lancet (369): 60-70.

Handa, S., C.T. Halpern, A. Pettifor, H. Thirumurthy. 2014(a). The Government of Kenya's Cash Transfer Program reduces the risk of sexual debut among young people age 15-25. PLOS One 9(1): e85473. doi:10.1371/journal.pone.0085473

Handa, S., D. Seidenfeld, B. Davis, G. Tembo and the Zambia Cash Transfer Evaluation Team. 2014(b). Are cash transfers a silver bullet? Evidence from the Zambian Child Grant. Innocenti Working Paper no. 2014-08. UNICEF Office of Research: Florence.

IPCC. 2014. Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press: New York.

Journal of Development Effectiveness. 2010. Special Issue: Conditional cash transfer programmes: opening the black box. Vol. 2, Issue 1: 1-157.

Kidd, S. and R. Calder. 2012. The Zomba conditional cash transfer experiment: An assessment of its methodology. Development Pathways Issue Brief No. 6, September. Available at www.developmentpathways.co.uk

Sen, A. 1999. Development as Freedom. Anchor Books: New York.

UNICEF Office of Research-Innocenti. 2014. Improving child outcomes through social protection: Evidence from the transfer project. Presentation for the African Union Expert Consultation on Children and Social Protection Systems in Africa, April. Available at: www.unc.edu/projects/transfer

World Bank. 2013(a). Global Monitoring Report 2013: Rural-Urban Dynamics and the Millennium Development Goals. Washington, DC: World Bank. DOI: 10.1596/978-0-8213-9806-7.

World Bank. 2013(b). World Development Report 2014: Risk and Opportunity – Managing Risk for Development. Washington, DC: World Bank. Doi: 10.1596/978-0-8213-9903-3.

Zimmerman, F. J. and M.R. Carter. 2003. Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. Journal of Development Economics 71: 233-260.

CHAPTER 2:
CASH TRANSFERS ENABLE HOUSEHOLDS TO COPE WITH WEATHER SHOCKS AND AVOID POVERTY TRAPS: EVIDENCE FROM ZAMBIA

2.1. Introduction

Climate change is projected to dramatically disrupt rainfall patterns and agricultural yields in Sub-Saharan Africa (IPCC, 2014). Given the large share of Africa's population living in rural areas (World Bank, 2013(a)) and these communities' dependence on rain-fed agriculture, climate change has the potential to stall and even reverse gains that have been made in the region's fight against poverty (Shepherd et al., 2013). Frequent exposure to failed harvests and other negative income shocks is a reality of life for the world's rural poor and many of these communities have developed strategies for coping with such shocks (Baez et al., 2013). However, some of these coping strategies can lead to poverty traps – the self-reinforcing conditions that cause poverty to persist. For example, coping with shocks by reducing food consumption, pulling children out of school, selling off productive assets, and adopting risk-averse livelihood strategies that discourage growth can negatively affect human capital formation and prospects for escaping poverty in the long run (Dasgupta, 1997; Carter and Barrett, 2006; Wood, 2011). The likelihood of households employing coping strategies that can lead to poverty traps may be greater in the face of weather shocks, given their potential impact on food supplies and livelihoods. Additionally, weather shocks' covariance across a community weakens informal safety nets, such as borrowing, further increasing household vulnerability (Skoufias, 2003; Baez et al., 2013; Boone et al., 2013). Avoiding detrimental coping strategies that degrade households' capabilities (per Sen, 1999), and thus ability to escape poverty, is essential for building resilience to climate change (Barrett and Constas, 2014).

This study investigates whether cash transfers enable households facing weather and other negative income shocks to avoid adverse coping strategies that can lead to poverty traps. To test this hypothesis, we harness data from the impact evaluation of Zambia's Child Grant Program. The Child Grant Program is one of the Government of Zambia's largest social protection programs. The program provides unconditional cash transfers of 60 kwacha (U.S. $12) per month to poor households with children under five years old. A randomized control trial was implemented with 2,515 households to investigate the impact of the program on a range of protective and productive outcomes between 2010 and 2012, with the baseline data collected just prior to program implementation. In addition to containing extensive information on both treatment and control households' consumption, income, assets, and schooling decisions, the study also records the specific types of shocks experienced by respondents as well as their stated coping strategies.

Weather shocks (droughts, floods, and storms) were the most commonly reported negative shock in both survey rounds. These weather shocks increased substantially between rounds, from 42% of the sample reporting such shocks in 2010 to 71% in 2012. Illness and changes in food prices were other commonly experienced shocks (22% and 35% in 2012, respectively), in addition to a multitude of other low-frequency shocks reported by households. Many households experienced multiple shocks and due to the increase in weather shocks over time, only 15% of households reported having completely avoided negative shocks in 2012. We investigate whether the cash transfer program fostered household resilience in the face of these myriad shocks and examine the impacts of cash on both stated and revealed (i.e., behavioral) coping strategies. We also consider how the covariance of shocks across a community affects coping strategies.

Given the preponderance of shocks these households experienced and the knock-on effects of weather shocks in agricultural economies, we first develop a new framework for classifying negative shocks. Because weather shocks can affect not only households' *production* of agricultural goods for both home consumption and market sales, but also the *price* of these goods (due to increased scarcity or increased demand), we group together those shocks affecting agricultural production and prices. Next, we group together all other negative shocks affecting households' assets, labor supply, and other sources of income. In addition to its basis in economic theory, this framework also has the nice property of separating those shocks more likely to be covariate and exogenous to the household (the agricultural production and price shocks) from those more likely to be idiosyncratic and the result of endogenous household choices (the asset, labor, and other income shocks).

We find that amongst households facing agricultural production and price shocks, cash reduces the likelihood of reducing food consumption and increases the likelihood of employing more resilient coping strategies, such as spending savings. This analysis of stated coping strategies is supported by the behavioral data, which show that receiving cash enables households to smooth food consumption in the face of both covariate shocks affecting agricultural production and prices as well as other idiosyncratic shocks affecting households' labor, assets, and income. We also find that amongst those households facing repeated shocks, the covariance of shocks across a community increases the likelihood of being food insecure – but the cash transfer still works to dramatically decrease food insecurity.

However, our analysis suggests that the timing of the transfer may matter. Our data allow us to disentangle the effects of cash on shock coping amongst those (1) shocked only at baseline, prior to program implementation; (2) shocked only after the program began; (3) repeatedly shocked; and (4) never shocked. The effect of cash on group (1) is akin to receiving cash as *ex-post* disaster aid, while the effect of cash on group (2) [and somewhat group (3)] is akin to receiving cash *ex-ante* as part of a proactive, climate-resilient development program. We find that cash has strong, positive impacts on food security when the transfer is received prior to shock exposure, but some evidence that its impact may be weakened when received *ex-post*. But differential out-migration between treatment and control households experiencing weather shocks at baseline limits our ability to make strong causal statements regarding the timing of the cash transfer.

Taken together, these results have significant implications for the design of climate change adaptation programs. While cash transfers are not routinely considered in the policy discourse concerning climate adaptation programming, because *ex-ante* transfers enable households to avoid negative coping strategies and even increase food consumption in the face of covariate weather shocks, cash transfers offer a sound approach for building climate-resilience amongst the world's most vulnerable and facilitating their "autonomous adaptation" to a changing environment (as suggested by Wood, 2011). And because cash also enables households to productively cope with the many other idiosyncratic shocks the rural poor routinely face, cash transfers offer a "no-regrets" approach for climate adaptation programs.

2.2. Poverty traps, shock coping, and cash transfers: Theory and evidence

Evidence shows that the rich are likely to use savings, obtain credit, or work more in response to negative shocks, whereas the poor are more likely to sell off productive assets or reduce consumption (World Bank, 2013(b)). On average, households tend to respond to negative income shocks by employing strategies that allow them to maintain their typical level of consumption (World Bank, 2013(b)). However, poor households often lack access to mechanisms such as insurance and credit that facilitate consumption smoothing – causing the poor to employ a different set of coping strategies than wealthier households (Morduch, 1995; Zimmerman and Carter, 2003; Carter et al., 2007; World Bank, 2013(b)). Moving children from school to the labor force is another coping strategy commonly employed by the poor (Beegle et al., 2004; de Janvry et al., 2006(a) and 2006(b)). The poor may also resort to increased harvesting of common-pool resources (e.g., firewood, bushmeat, etc.) to satisfy consumption and income needs in the face of shocks (Pattanayak and Sills, 2001).

All of these coping strategies commonly used by the poor can weaken their potential for escaping poverty in this generation or the next by reducing household production, hindering the cognitive development of young children via malnutrition, limiting household members' future schooling and work possibilities, or degrading the productivity of natural assets. This theory of 'poverty traps' is articulated most eloquently by Dasgupta (1997) and supported by numerous studies analyzing long-run poverty dynamics (e.g., Glewwe et al., 2000; Carter et al., 2007; Hoddinott et al., 2008; and as summarized by Barrett et al., 2007 and World Bank 2013(b)).

Classical theories of macroeconomic growth – unconditional and conditional convergence – are often applied at the microeconomic level for understanding household welfare trajectories (Carter and Barrett, 2006). These theories posit that all nations/individuals can grow economically along an exponential growth function. However, Barrett and Swallow (2005) and Carter and Barrett (2006) note that an economic growth function may include multiple dynamic equilibria and argue that the concept of poverty traps therefore contradicts classical theories of economic growth. Figure 1 depicts their description of poverty trap dynamics.

In the space of future well-being mapped onto current well-being, welfare dynamics create an S-shaped curve with three equilibrium points as shown. In this figure, W_{PL} marks the poverty line. Those at the middle equilibrium point (W_C) can easily be pushed down into the low-level (poor) equilibrium (W_L) by negative income or asset shocks or easily pushed up to the high-level (non-poor) equilibrium (W_H) by positive shocks. Once households find themselves at either the low- or high-level equilibrium they will tend to converge back to this point, despite small positive or negative income shocks that temporarily knock them off. Those at the low-level equilibrium are thus in a poverty trap; those that move above the middle equilibrium are moving along a self-propelled growth trajectory. This implies that those at the middle equilibrium are at a highly unstable point, which marks an important threshold.

Cash transfer programs aim to help households escape poverty traps by providing cash that can be used to increase consumption of food, schooling, and health services, thereby increasing adults' capacity for work and preventing the intergenerational transmission of poverty to children. Cash transfers should also foster resilience in the face of shocks and enable households to avoid coping strategies that lead to poverty traps (Blank et al., 2010) -- but the relationship between transfers and shock responses has gone relatively unexamined, despite numerous impact evaluations of cash transfer programs (Wood, 2011). Among the studies that have investigated this topic, the focus has been on households' use of child labor as a shock response and impacts on schooling [see studies of cash transfer programs in Mexico by de Janvry et al. (2006(a)) and in Nicaragua by Gitter and Barham (2009) and Maluccio (2005)]. These studies also examine cases in Latin America, with evidence from African countries largely missing. Given greater dependence on subsistence farming, weaker infrastructure and social services, and more severe poverty in Sub-Saharan Africa, results from Latin America are likely not generalizable to the African context.

More research is currently needed to identify interventions that can help poor households avoid coping strategies associated with poverty traps in the face of shocks. Following the theory and evidence it might seem the obvious answer is to make poor households non-poor via cash transfer programs. However, identifying the thresholds that define poverty traps remains a difficult task (Carter and Barrett, 2006; Dercon, 2007) and Carter and Barrett (2006) argue these thresholds may best be identified by measuring assets rather than consumption or income levels, which are the targets of cash transfer programs. This implies that cash transfers may not necessarily help households avoid poverty traps even if the transfer is predicted to push households above a consumption-based poverty line.

The weather-related risks posed by climate change, which will disproportionately affect the poor in developing countries (IPCC, 2014), increase the importance of identifying interventions that can help households living in remote rural areas respond to negative shocks.

2.3. Conceptual framework

We examine whether receiving cash transfers effects households' shock coping and consider the wide range of possible strategies suggested in the literature to be commonly used by the poor. Because we are primarily interested in the relationship between cash transfers and poverty traps, we distinguish between (1) coping strategies hypothesized in the literature to lead to poverty traps, including reducing food consumption, selling assets, sending children away or to work, and doing casual labor for others[6]; and (2) other coping strategies, many of which are

[6] Casual labor for others ("piece work") is often considered a negative coping strategy in this region. Boone et al. (2013) note that in Malawi such casual labor ("*ganyu*") is often a coping strategy of last resort that can lead to

generally considered to be positive, such as starting a business, spending savings, and reducing non-food consumption. Borrowing from the valuation literature on stated and revealed preferences, we examine both households' stated coping strategies as well as their revealed coping strategies (i.e., behavioral responses measured in the data). For the revealed coping strategies, we focus on food consumption, given the centrality of this outcome to avoiding poverty traps and building human capital. We use two measures of this outcome: per capita monthly food consumption and whether a household ranks as severely food insecure, based on their response to a series of questions commonly used to measure food security.[7]

Following Dercon (2002), Carter and Maluccio (2003), Takasaki et al. (2004), and Debela et al. (2012), we distinguish between covariate and idiosyncratic shocks in our analysis, as the available strategy sets for dealing with each type of shock should differ, with covariate shocks posing greater risk of poverty trap coping (Skoufias, 2003). However, such a distinction is not necessarily easy to make. While, extreme weather events and price changes should be covariate shocks; and other negative shocks, such as job loss or illness tend to be idiosyncratic, this does not hold in all cases. For example, in the case of communicable disease, illness can affect a large portion of a community at once and where shocks are self-reported (as they are in our study), some might perceive a weather event as a negative shock while others take no notice of it.[8] The literature reflects various strategies for distinguishing between covariate and idiosyncratic shocks: (1) use of the household-specific community mean (e.g., Debela et al.,

---

poverty traps. This is because the labor on others' farms is very low-wage and typically results in farmers delaying planting time on their own fields, which reduces yields. They argue farmers engage in such a sub-optimal allocation of off-farm labor because farmers in subsistence economies are severely cash-constrained.

[7]Based on the FANTA food security scoring system.

[8]This latter point of course highlights the potential for endogeneity bias with self-reported shock data. We discuss how our estimation strategy addresses potential endogeneity concerns in Section 2.5.2.

2012); (2) use of the general community mean (e.g., de Janvry et al., 2006(a)); or (3) establishing a (somewhat arbitrary) cutoff for what constitutes "covariate" (e.g., Carter and Maluccio, 2003).

A second conceptual challenge for shock coping studies concerns how to identify the impact of a specific shock (such as a weather shock) when households experience multiple shocks at once (e.g., a weather shock, illness, and job loss in the same year). Some choose to only examine one type of shock (e.g., Beegle et al., 2006; Jack and Suri, 2014) or examine shocks separately (e.g., de Janvry et al., 2006), even though households might have experienced multiple shocks. How to classify and group together the numerous specific shocks households experience is another challenge, with no one framework consistently used in the literature. For example, Carter and Maluccio (2003) group together all reported shocks, including illness, job loss, crop failure, and theft, by converting them into monetary values of loss; while Debela et al. (2012) distinguish between labor and non-labor shocks.

We employ the common strategy of using the household-specific community mean, which is the percent of the sample community that experienced a shock, exclusive of the household. This community mean measure is useful for investigating how a marginal increase in shock covariance across a community affects shock coping. But because we are particularly interested in weather shock coping, we also develop a new framework for categorizing shocks that allows us to distinguish the weather-related (and generally more covariate and plausibly exogenous) shocks from the non-weather (and generally more idiosyncratic, possibly endogenous) shocks. Agricultural households in rural developing economies tend to be both sellers and consumers of their own production. Weather shocks can therefore impact not only households' *production* of agricultural goods for both home consumption and market sales, but also the *price* of agricultural goods that might be purchased or sold by affecting their supply and demand. Additionally, weather shocks can increase crops' susceptibility to disease and pests, as well as damage crop storage facilities. For these reasons, we group together all shocks affecting agricultural production and prices. We then group together all other negative shocks affecting households' assets, labor supply, and non-farm income. And because our unique dataset contains households' account of how they coped with each specific shock, we can use this information to investigate the differences between how households cope with the largely covariate agricultural production and price shocks versus the more idiosyncratic asset, labor, and other non-farm income shocks.

We also compare the impacts two policy design options: (1) extension of the cash transfer prior to experiencing a negative income shock and (2) extension of the transfer in the wake of the shock. This allows us to estimate the difference between what an *ex-post* disaster aid cash transfer program might be able to accomplish with one that is focused on building households' climate resilience *ex-ante*.

2.4. Data and descriptive statistics

There were 221 households that migrated out of the study area after the collection of baseline data (see Table 1). Handa et al. (2014) examine the effect this attrition had on the sample and find no differential attrition between the control and treatment groups in terms of rates or their observable household characteristics. These authors also investigate whether out-migration led to overall attrition bias (i.e., whether those that remain in the sample are, on average, different from the overall baseline sample). They find that the sample stays generally the same over time, in terms of observable household characteristics, with the principal difference being that those who remained in the sample were less likely to experience a weather shock at baseline. This follows from the observation that 72% of the households that left the study lived in Kaputa district at baseline, where a lake important for fishing and farming livelihoods is drying up, causing mass migration out of the area. While this out-migration due to weather shocks does not bias our results, it does have implications for external validity.

There was a sharp increase in the percent of households experiencing negative weather shocks (droughts, floods, or storms) between the survey waves – from 42% in 2010 to 71% in 2012 (Table 2). When the shocks to crop production and prices, which are likely knock-on effects of the weather shocks, are factored in, a total of 81% of the sample experienced agricultural production and price shocks in 2012. Shocks to households' assets, labor, and non-farm income show much lower frequency in the sample (experienced by 36% of the sample in 2012) and their prevalence did not increase as sharply over time. Drought (47%), food price change (35%), floods (30%), illness (22%), livestock disease (11%), and crop disease/pests (11%) were the most commonly reported shocks (see Table 3).[9]

We investigate the covariance of each specific shock within communities by calculating the percent of the sample that experienced the shock for each community. Table 4 shows the average of these percentages for each shock. The average covariance levels for communities do not differ much from the averages for the overall sample (Table 3) and indicate that the agricultural production and price shocks are indeed much more covariate than the asset, labor, and other income shocks.

Households employed a wide range of coping strategies for dealing with these shocks. We asked households about their primary as well as secondary coping strategy for each shock they reported. We combine the primary and secondary strategies to compute the tallies in Table 5. All of the principal coping strategies identified in the literature as leading to poverty traps are

[9]In the survey households were asked about 21 specific shocks. If they said they experienced the shock, they were then asked whether the effect was positive or negative. We limit our analysis to those shocks reported by households to have a negative effect.

represented in our dataset. We also classify "doing nothing" as a poverty trap coping strategy based on empirical analysis of household characteristics at baseline, which shows that households who "did nothing" in the wake of a shock had significantly lower food consumption than those who reported a different coping strategy, although they were similar along all other observable characteristics. Reducing food consumption (including "doing nothing") and doing piece work for others are the dominant poverty trap coping strategies in our dataset.

2.5. Estimation strategy

2.5.1. Testing assumptions of the impact estimates' econometric models

Due to random assignment of the program, treatment status should not be correlated with observed or unobserved characteristics of participating households or communities. We confirm whether randomization yielded similar observable characteristics between treatment and control households by testing for their equivalence at baseline. We test for equivalence at baseline in terms of basic characteristics of the recipient/respondent and household, self-reported shocks, and our key outcomes of interest (stated and revealed coping strategies) and report these results in Tables 6 and 7. We restrict our analysis to just the panel of households that remained in the survey for both rounds and cluster robust standard errors at the community-level (and do so for all subsequent models). We examine equivalence at baseline for all variations of the sample used in subsequent impact estimates: the full panel as well as the four shock sub-groups.

For the full panel, we find that randomization succeeded in producing balanced treatment and control groups. We find no significant differences between treatment and control households along observable characteristics, general shock exposure, and our key outcomes of interest – per capita food consumption and overall food security. Households in treatment communities, however, were 7 percentage points less likely to report an agricultural production or price shock at baseline (see Table 7).

We also find some interesting differences between control and treatment households at baseline in terms of stated coping strategies (Table 7). Prior to receiving cash, households in treatment communities were more likely to increase household production or reduce non-food expenses in the wake of agricultural production and price shocks than those residing in control communities. In the face of asset, labor, and other negative income shocks, treatment households were more likely to do piece work for others or participate in a work program and less likely to obtain loans/gifts or "do nothing". These differences in stated shock coping strategies at baseline need to be considered when examining our impact estimates, and draw our focus to examination of just those stated coping strategies balanced at baseline.

Our analysis of revealed coping strategies (food consumption and food security score) breaks the full panel down into four shock sub-groups, based on the temporal trends of shock experience. We therefore test for equivalence at baseline for these four sub-groups as well and find that they are generally balanced in terms of observable characteristics and our key outcomes of interest. This equivalence at baseline allows us to attribute any estimated differences in revealed coping strategies to the cash transfer program. However, for those shocked at round 1 only, the control group has significantly lower per capita food consumption. This suggests that in response to shocks amongst households in the control group, it was the better off households who migrated out of the area and the poorer households who stayed. This lack of equivalence at baseline prevents us from examining the impact of cash on food consumption amongst those shocked only at baseline.

Next, we examine whether treatment and control households are experiencing the same time trend with respect to shock exposure. The time trend could be different due to either (1) differential weather patterns between treatment and control communities over time or (2) actual impacts of cash on the likelihood of experiencing or perceiving a shock (i.e., cash might reduce the likelihood of falling ill by improving nutrition or it might cause one to not notice a change in prices that other perceive as significant). To test for differential time trends, we run a difference-in-difference model, specified in Equation (1) as follows:

(1) $$Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3(Post_{igt}{*}Cash_{ig}) + B_4\boldsymbol{X}_{ig} + B_5\,\boldsymbol{Z}_g + \boldsymbol{W}_g + E_{igt}$$

where Y_{igt} measures whether a shock was reported by household i in district g in period t, $Post_{igt}$ is a dummy variable equal to 1 if the observation is in 2012, $Cash_{ig}$ is a dummy variable equal to 1 if the household is in the treatment group, $\boldsymbol{X}_{ig}$ represents a vector of household and recipient characteristics measured at baseline, $\boldsymbol{Z}_g$, is a vector of baseline prices for food and other important consumption goods, $\boldsymbol{W}_g$ is a district fixed effect, and E_{igt} is the error term. We include controls for baseline characteristics and prices and district fixed effects to increase the precision of our estimates. The coefficient of interest in this model is B_3, which captures the effect of being in a treatment community on self-reported shocks.

The interaction variable (Cash*Post) representing the effect of cash on self-reported negative shocks is not significant for any of the three models presented in Table 8. Control and treatment households therefore appear to be experiencing the same time trends with respect to shock exposure.

2.5.2. Identification strategy for impact estimates

To understand the impact of cash on households' stated coping strategies, we run a series of first difference models using the 2012 survey data and restricted to those who reported a negative shock. This model can be written as:

(2) $Y_{igt} = B_0 + B_1 Cash_{ig} + B_2 \boldsymbol{X}_{ig} + B_3 \boldsymbol{Z}_g + \boldsymbol{W}_g + E_{igt} \mid \text{Shock}_{2012}=1$

where all terms are defined as they were in Equation (1), but now Y_{igt} is a dummy variable coded as 1 if a household reported using the specific coping strategy in question. The identifying assumption for this model is that both the treatment and control groups would have had, on average, similar, shock coping strategies in 2012, had the treatment group not received cash. However, our equivalence at baseline tests shows that this assumption does not hold for certain shock coping strategies. Therefore, we focus our discussion of results on those stated coping strategies balanced at baseline.

To further probe household coping strategies, we use both rounds of data and examine whether cash may have affected households' food consumption and overall food security score. Like Equation (2), these models are conditional on households' shock experience. We run four sets of models, as specified below:

(3) $Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3 (Post_{igt} * Cash_{ig}) + B_4 \boldsymbol{X}_{ig} + B_5 \boldsymbol{Z}_g + \boldsymbol{W}_{gt} + (e_{igt} + \mu_{it} + v_i) \mid \text{Shock2010=1 \& Shock 2012=1}$ {Shocked both rounds}

(4) $Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3 (Post_{igt} * Cash_{ig}) + B_4 \boldsymbol{X}_{ig} + B_5 \boldsymbol{Z}_g + \boldsymbol{W}_{gt} + (e_{igt} + \mu_{it} + v_i) \mid \text{Shock2010=0 \& Shock 2012=0}$ {Never shocked}

(5) $Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3 (Post_{igt} * Cash_{ig}) + B_4 \boldsymbol{X}_{ig} + B_5 \boldsymbol{Z}_g + \boldsymbol{W}_{gt} + (e_{igt} + \mu_{it} + v_i) \mid \text{Shock2010=1 \& Shock 2012=0}$ {Shocked round 1 only}

(6) $Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3 (Post_{igt} * Cash_{ig}) + B_4 \boldsymbol{X}_{ig} + B_5 \boldsymbol{Z}_g + \boldsymbol{W}_{gt} + (e_{igt} + \mu_{it} + v_i) \mid \text{Shock2010=0 \& Shock 2012=1}$ {Shocked round 2 only}

where terms reflect their definitions as described for Equations (1) and (2), though here Y_{igt} is, depending upon the series of models, monthly per capita food consumption or a dummy variable coded as 1 if the household ranks as severely food insecure. For the purposes of transparency, we also decompose the error term here into its various components, with e_{igt} representing truly random error and μ_{it} representing unobserved household characteristics that vary over time and v_i those that are time-invariant. Time-invariant characteristics at the level of the treatment group (i.e., on average) are removed in the differencing. And while, econometrically, unobserved time-varying characteristics at the level of the treatment group remain in the error (as well as μ_{it} and v_i), the randomized research design provides strong assurance that there are no systematic differences between the treatment and control groups along either observed or unobserved characteristics. Therefore, there is little reason to believe that our estimates reported in Tables 11 and 12 are biased by unobserved heterogeneity.

An alternative estimation strategy would be to run triple difference models on the full sample (where Cash is interacted with both Shock and Post) with household fixed effects (to control for unobserved time-invariant characteristics) to identify the effect of both receiving Cash and being shocked on food security. Jack and Suri (2014) take such an approach in their analysis of how Kenya's mobile money system enables households to cope with illness shocks. However, the challenge with these models is that they use only those who switch shock status between rounds to estimate the parameters of interest (i.e., treatment effects). In our dataset, such an analytical approach does not make sense given that many experienced shocks both rounds and amongst those that changed status over time, some went from no shock in 2010 to a shock in 2012, while others experienced the opposite time trend – so any effects of cash would be confounded by these two sub-populations' experiences. From an econometric standpoint, given the shock frequencies in our data and our randomized research design, we believe our sets of difference-in-difference models are more appropriate (and more transparent). Moreover, by disaggregating the analysis according to the temporal experience of shocks, we are able to have a higher degree of external validity and answer an important policy design question: Does it matter whether cash is extended before or after a household experiences a negative shock?

2.6. Results

We find that cash reduces the likelihood of employing negative coping strategies associated with poverty traps and increases the likelihood of employing positive coping strategies. Tables 9 and 10 present the impacts of cash on stated coping. We run two sets of models for each coping strategy: The first restricted to those who experienced agricultural production or price shocks in 2012; the second restricted to those who experienced an asset, labor, or other negative income shock in 2012. We find that amongst those that experienced an agricultural production or price shock, cash reduces the likelihood of reducing food consumption ("doing nothing") by 14 percentage points and increases the likelihood of spending savings by 6 percentage points. Cash also increases the likelihood of using social services (visiting the clinic or seeking help from the government or an NGO) by 2 percentage points in the case of agriculture and price shocks and by 12 percentage points for other shocks. Importantly, all of these stated coping strategies were balanced at baseline, implying that we can confidently attribute the observed differences reported here to the cash transfer program.

These impacts of cash on stated coping strategies are supported by our analysis of the behavioral data, which shows that the program has positive impacts on food consumption and overall food security (Tables 11 and 12).[10] We find that cash increases monthly per capita food expenditures by 31% for those never shocked, by 35% for those shocked only after program implementation (round 2), and by 29% for those shocked both prior to and during the program. [Because food consumption amongst those shocked only prior to the start of the program (round 1) was not balanced at baseline, we can not estimate the impact of cash for this sub-group.]. We see a similar trend with the food security scores. Cash decreases the probability of being severely food insecure by 24 percentage points amongst those never shocked, by 25 percentage points amongst those shocked round 2 only, and by 25 percentage points amongst those shocked both rounds. For those shocked at round 1 only, we do not find evidence that cash has any effect on food security.

We then add a variable measuring shock prevalence in each of the 90 sample communities to our difference-in-difference models to understand the effect of shock covariance on the impact of cash (see Tables 13 and 14). This variable is the percent in each community sample reporting a shock, exclusive of the household. When this variable is added to the difference-in-difference models, the effects of cash on food consumption and food security remain relatively unchanged from the original estimates presented in Tables 11 and 12 – even though a one percentage point increase in community shock prevalence increases the likelihood of being food insecure by 14 percentage points for those shocked both rounds. For these two shock groups we also see that a one percentage point increase in community shock prevalence increases their food consumption by 30 and 33 percent, respectively. This suggests that the

[10]For these difference-in-difference models, we group together agricultural production and price shocks with asset, labor, and other income shocks, since many households experienced both types of shocks and it is not possible to disentangle their effects in the revealed data measuring food consumption and food security.

mechanism by which cash increases food security in the face of covariate shocks is by enabling households to increase food production and/or purchases.

2.7. Conclusions and policy implications

We find that cash transfers enable households to cope with negative shocks in ways that do not increase the likelihood of falling into a poverty trap. Cash empowers the poor, rural households in our study to employ shock-coping strategies commonly used by the non-poor, such as spending savings. The cash transfers provided by Zambia's Child Grant Program are able to increase both food consumption and food security even while the covariance of shocks within a community increases the likelihood of being severely food insecure.

The most recent report from the Intergovernmental Panel on Climate Change (IPCC) states that

> "Throughout the 21st century, climate-change impacts are projected to slow down economic growth, make poverty reduction more difficult, further erode food security, and prolong existing and create new poverty traps (p. 20) …"

Our study provides evidence of a program -- unconditional cash transfers – that can work to help households avoid the poverty traps that climate change threatens to create and entrench. Moreover, we show that a specific program design feature – extending cash to households before severe shocks to agricultural production and prices occur – achieves strong, positive impacts on food consumption and food security.

The international community concerned with climate change has become increasingly focused on developing adaptation strategies in recent years. Crop insurance (Barrett et al., 2007; Baez et al., 2013) and "ecosystem-based adaptation" (FAO and UNEP, 2013) are two potential adaptation strategies that have received a great deal of attention -- and for Africa in particular. However, the concept of using *ex-ante* cash transfer programs (i.e., as opposed to *ex-post* cash or in-kind disaster relief) as an adaptation strategy for rural Africa has received little attention. This may be due to limited interaction between the environmental policy community and the social protection community. There is clearly a need to link these two policy communities and their attendant literatures.

While Wood (2011) argues that cash transfers should be given a greater role in climate adaptation and the recent World Development Report (World Bank, 2013(b)) also highlights the value of cash transfers for risk management and shock-coping in the context of climate change, to date there have been no published evaluations of cash transfer programs that focus on climate and adaptation questions.[11] This study therefore fills an important gap in the literature and offers policy-relevant evidence that should inform the design of climate adaptation programs.

One advantage cash transfers offer over other potential adaptation interventions is their unique ability to address the context of climate change, which is characterized by "deep uncertainty." In their discussion of the economics of risk and uncertainty in the 2014 World Development Report, The World Bank describes problems of deep uncertainty as those where "…experts cannot agree on which models to use…; on the probability distributions of key uncertain parameters…; or on the values of alternative outcomes" (2013(b), p. 93). Climate change is one such problem, because while models converge on predictions of disrupted rainfall patterns in Africa, at the local level models diverge – some predict decreases in rainfall and droughts, others predict increased rainfall and floods. Given that cash transfers have already been demonstrated by numerous studies (Fiszbein and Schady, 2009) to reduce both short-term poverty and its long-term determinants, they therefore offer a "no regrets" (Woods, 2011) strategy for climate-resilient development policy. Further, as also argued by Woods (2011) cash

[11] Asfaw et al. (2011), however, report they are currently studying the impact of Lesotho's cash transfer program on farmers' adaptation strategies, with a particular focus on changes in a series of specific farming practices. The 2014 World Development Report also reports advance results from evaluations of how cash transfer programs in Ethiopia and El Salvador have helped households cope with droughts and natural disasters (World Bank, 2013(b), p. 104-105).

transfers facilitate individuals' autonomous adaptation and development decisions, making them both congruent with a human rights framework that recognizes the importance of agency as well as adaptation frameworks that embrace locally-based and diverse solutions.

REFERENCES

Asfaw, S., B. Davis, and J. Dewbre. 2011. Cash transfer programs in Sub-Saharan Africa: measuring the impact on climate change adaptation. Presented at the 4th meeting of the Wye City Group on Statistics on Rural Development and Agriculture Household Income, Rio de Janeiro, Brazil, 9-11 Nov.

Baez, J.E., D. Kronick, and A.D. Mason. 2013. Rural households in a changing climate. World Bank Working Paper.

Barrett, C.B., and M.A. Constas. 2014. Toward a theory of resilience for international development applications. PNAS www.pnas.org/cgi/doi/10.1073/pnas.1320880111

Barrett, C.B. and B.M. Swallow. 2005. Fractal poverty traps. World Development 34(1): 1–15.

Barrett, C.B., B.J. Barnett, M.R. Carter, S. Chantarat, J.W. Hansen, A.G. Mude, D.E. Osgood, J.R. Skees, C.G. Turvey, and M.N. Ward. 2007. Poverty traps and climate risk: Limitations and opportunities of index-based risk financing. IRI Technical Report 07-02. The International Research Institute for Climate and Society.

Beegle, K., R.H. Dahejia, and R. Gatti. 2006. Child labor and agricultural shocks. Journal of Development Economics 81: 80-96.

Blank, L., S. Devereux, and S. Handa. 2010. The case for social protection for children. Chp 2 in Social Protection for Africa's Children, Handa, S., S. Devereux, and D. Webb (Eds.). Routledge: New York. p. 15-27.

Boone, R., K. Covarrubias, B. Davis, and P. Winters. 2013. Cash transfer programs and agricultural production: the case of Malawi. Agricultural Economics 44: 365-378.

Carter, M.R. and J.A. Maluccio. 2003. Social capital and coping with economic shocks: An analysis of stunting of South African children. World Development 31(7): 1147-1163.

Carter, M.R. and C.B. Barrett. 2006. The economics of poverty traps and persistent poverty: An asset-based approach. Journal of Development Studies 42(2): 187-199.

Carter, M.R., P.D. Little, T. Mogues, and W. Negatu. 2007. Poverty traps and natural disasters in Ethiopia and Honduras. World Development 35(5): 835-856.

Cooper, P.J.M., R.D. Stern, M. Noguer, and J.M. Gathenya. 2013. Climate Change Adaptation Strategies in Sub-Saharan Africa: Foundations for the Future. Chp. 13 Available at: http://dx.doi.org/10.5772/55133

Dasgupta, P. 1997. Nutritional status, the capacity for work, and poverty traps. Journal of Econometrics 77: 5-37.

Davies, M., B. Guenther, J. Leavy, T. Mitchell, and T. Tanner. 2009. Climate change adaptation, disaster risk reduction and social protection: Complementary roles in agriculture and rural growth? IDS Working Paper 320. Institute of Development Studies (IDS): University of Sussex, Brighton, UK.

de Janvry, A., F. Finan, E. Sadoulet, and R. Vakis. 2006(a). Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? Journal of Development Economics 79: 349-373.

de Janvry, A., E. Sadoulet, P. Solomon, and R. Vakis. 2006(b). Uninsured risk and asset protection: Can conditional cash transfer programs serve as safety nets? SP Discussion Paper No. 0604. Social Protection, World Bank: Washington, DC.

Debela, B., G. Shively, A. Angelsen, M Wik. 2012. Economic shocks, diversification, and forest use in Uganda. Land Economics 88(1): 139-154.

Dercon, S. 2002. Income risk, coping strategies, and safety nets. World Bank Research Observer 17(2): 141-66.

Dercon, S. 2007. Comment on poverty traps and social protection policy. Institute of Development Studies (IDS) Bulletin 38(3): 39-42.

FAO and UNEP. 2013. Conference Report: 1st Africa Food Security & Adaptation Conference: Harnessing Ecosystem-based Approaches for Food Security and Adaptation to Climate Change in Africa, Nairobi, 20-21 Aug.

Fiszbein, A. and N. Schady. 2009. Conditional cash transfers: Reducing Present and Future Poverty. The World Bank: Washington, DC.

Gitter, S.R. and B.L. Barham. 2009. Conditional cash transfers, shocks, and school enrolment in Nicaragua. Journal of Development Studies 45(10): 1747-1767.

Glewwe, P., H. Jacoby, and E. King. 2000. Early childhood nutrition and academic achievement: a longitudinal analysis. Journal of Public Economics 81: 345-368.

Handa, S., D. Seidenfeld, B. Davis, G. Tembo and the Zambia Cash Transfer Evaluation Team. 2014. Are cash transfers a silver bullet? Evidence from the Zambian Child Grant. Innocenti Working Paper no. 2014-08. UNICEF Office of Research: Florence.

Hoddinott, J., J.A. Maluccio, J.R. Behrman, R. Flores, and R. Martorell. 2008. Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults. The Lancet 371: 411-416.

IPCC. 2014. Summary for policymakers. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press: New York.

Jack, W. and T. Suri. 2014. Risk sharing and transaction costs: Evidence from Kenya's mobile money revolution. American Economic Review 104(1): 183-223.

Lemos, M. C., A. Agrawal, O. Johns, H. Eakin, D. Nelson, and N. Engle. 2011. Building adaptive capacity to climate change in less developed countries. Working paper.

Maluccio, J.A. 2005. Coping with the 'Coffee Crisis' in Central America: The Role of the Nicaraguan Red de Proteccion Social. Discussion Paper 188. Washington DC: International Food Policy Research Institute, Food Consumption and Nutrition Division.

Morduch, J. 1995. Income smoothing and consumption smoothing. Journal of Economic Perspectives 9(3): 103-114.

Pattanayak, S.K. and E.O. Sills. 2001. Do tropical forests provide natural insurance? The microeconomics of non-timber forest product collection in the Brazilian Amazon. Land Economics 77(4): 595-612.

Sen, A. 1999. Development as Freedom. Anchor Books: New York.

Sheperd, A., T. Mitchell, K. Lewis, A. Lenhardt, L. Jones, L. Scott, and R. Muir-Wood. 2013. The geography of poverty, disasters and climate extremes in 2030. Overseas Development Institute, London.

Skoufias, E. 2003. Economic crises and natural disasters: Coping strategies and policy implications. World Development 31(7): 1087-1102.

Takasaki, Y., B. Barham, O. Coomes. 2004. Risk coping strategies in tropical forests: floods, illnesses, and resource extraction. Environment and Development Economics 9: 203-224.

Wood, R.G. 2011. Is there a role for cash transfers in climate change adaptation? International Conference on Social Protection for Social Justice, Institute of Development Studies, UK, 13-15 April.

World Bank. 2013(a). Global Monitoring Report 2013: Rural-Urban Dynamics and the Millennium Development Goals. Washington, DC: World Bank. DOI: 10.1596/978-0-8213-9806-7.

World Bank. 2013(b). World Development Report 2014: Risk and Opportunity – Managing Risk for Development. Washington, DC: World Bank. Doi: 10.1596/978-0-8213-9903-3.

Zimmerman, F. J. and M.R. Carter. 2003. Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. Journal of Development

Economics 71: 233-260.

CHAPTER 3:
POVERTY-ENVIRONMENT RELATIONSHIPS UNDER MARKET HETEROGENEITY: CASH TRANSFERS AND PRODUCER-CONSUMERS IN ZAMBIA

3.1. Introduction

Poverty alleviation programs in developing countries are typically not concerned with their environmental impacts. Conservation programs in these settings, however, often seek to achieve 'wins-wins' for environment and development, believing these twin goals to be inextricably linked (Wunder, 2001; Angelsen and Atmadja, 2008). Yet poverty-environment relationships in remote rural areas are complex and theoretically ambiguous (Reardon and Vosti, 1995; Scherr, 2000; Wunder, 2001). For example, numerous studies indicate that the poor often cope with income and consumption shocks by increasing their use of natural resources (e.g., Pattanayak and Sills, 2001; Takasaki et al., 2004; McSweeney, 2005; Debela et al., 2012) and there is some limited evidence that positive income shocks can reduce such reliance (Fisher and Shively, 2005). But reducing poverty may not benefit biodiversity conservation in all cases – it likely depends on whether environmental products, such as wild foods, are inferior or normal goods in particular communities. Similarly, impacts on land use may also be variable: reducing poverty may increase households' ability to expand their farms -- thereby increasing pressure on ecosystems -- or it may expand households' ability to participate in markets for off-farm labor, decreasing such pressure.

Poverty-environment relationships should also differ depending on whether one takes a short-run or long-run view, though the directional change over time is not clear. On the one hand, Environmental Kuznets Curve theory posits that societies exploit natural resources to escape poverty and at a certain inflection point of wealth then begin demanding environmental amenities that flow from conserved resources (Koop and Tole, 1999). On the other hand, the environmental impacts of reducing poverty can have important feedback effects for poverty itself: Barbier (2010) argues that the drive to raise incomes through agriculture and resource exploitation can lead to 'poverty-environment traps' if markets for land, off-farm labor, and credit are incomplete. And if reducing poverty increases consumption of wild game, over-exploitation can lead to the collapse of populations that may be an important source of protein for the (future) rural poor.

This theoretical ambiguity may be clarified by more nuanced consideration of heterogeneous access to markets when examining poverty-environment relationships. Research by Ferraro et al. (2011) has shown that the ability of conservation programs to achieve poverty and environment 'win-wins' is moderated by market access, though Alix-Garcia et al. (2013) also note that we are of course only able to observe the full environmental impacts of human behavior where poor transportation networks effectively localize them.

This study explores these themes by examining the short-run impacts of a poverty alleviation program that extends unconditional cash transfers to households in rural Zambia. We investigate impacts on households' consumption of fuelwood, charcoal, and bushmeat, as well as their use of land for farming. We also examine an element of the causal chain hypothesized by Barbier (2010) to be important for avoiding poverty-environment traps: program impacts on off-farm business enterprises. Particular attention is paid to investigating whether impacts vary according to market access. We hypothesize that distance to market significantly affects household decision-making regarding conversion of the transfer into consumption and production.

3.2. Cash transfers, transaction costs, and impact heterogeneity: Theory and evidence

Agricultural households in subsistence economies clearly live in a world characterized by multiple market imperfections. Lack of cash and opportunities for wage labor and loans create liquidity and credit constraints, limiting purchase of productive agricultural inputs. High transaction costs associated with selling crops also hinders specialization and commercial activity -- as does the high uncertainty regarding the purchase price of food, which further encourages self-sufficiency in food production rather than commercial agriculture. All of these points and the importance of considering non-separability when examining cash transfer programs in rural areas have been raised by Handa et al. (2010) and Boone et al. (2013).

But the focus thus far has been on considering agricultural households' shadow value of time (e.g., Handa et al. (2010)) and how cash transfers can help increase agricultural production by relaxing farmers' liquidity and credit constraints (e.g., Boone et al., 2013).

And while the concepts of non-separability and price bands created by transaction costs are generally accepted in the literature, examination of how variable transaction costs moderate households' production and consumption decisions is not routine. And yet, as Lofgren and Robinson (1999) note:

> "The existence of such non-separability indicates the presence of market imperfections or failures that may have important policy implications. For example, depending on the nature of the market imperfections, there may be "threshold" effects whereby policy changes have no effect on household behavior until the change is "large" in some measure. In this environment, policy analysis assuming the existence of perfect markets may badly misstate the impact of policy changes on producer behavior and household welfare" (p. 1).

de Janvry and Sadoulet (2003) also call for more examination of how transaction costs affect rural household behavior. Consideration of how distance to markets affects households' production decisions is receiving increasing attention in the conservation planning and evaluation literature (e.g., Ferraro et al., 2011; Joppa and Pfaff, 2009), but attention to this topic has received comparatively less attention in the development economics and cash transfer literatures. One exception is a study by Alix-Garcia et al. (2013), which examines the ecological impacts of Mexico's Oportunidades program.

In addition to commenting on the importance of understanding market linkages when implementing poverty alleviation programs in rural areas, this study aims to contribute evidence on the heterogeneous impacts of cash transfer programs. Few studies have explored impact heterogeneity in the context of cash transfers and those that do focus on cases from Latin America and health and schooling outcomes. For example, Handa et al. (2010) test for heterogeneous impacts of Progresa in Mexico and whether use of schooling and health services differs between agricultural and non-agricultural households. Dammert (2009) examines heterogeneous impacts of Nicaragua's Red de Proteccion Social program and finds that impacts on schooling and child labor differ according to the age and gender of the child, gender of the household head, and degree of poverty in the community. Galiani and McEwan (2013) look at variation in impacts of the Honduran Programa de Asignacion Familiar (PRAF) and find that the program's positive impacts on children's schooling and labor activity are much larger for the poorest of the poor.

In order to improve the design and success of public policies we often need to understand more than just their average impacts and compare impacts for different sub-populations. For example, if the impacts of cash transfers' are more muted in remote communities, then policymakers should consider how to simultaneously address both supply-side and demand-side factors driving poverty (or perhaps just focus on supply-side factors). As noted by Handa and Davis (2006), cash transfers implicitly assume that the poor consume less schooling and health services due to constraints on their demand – and not that issues of access and quality might pose constraints on the supply-side. Similarly, in remote rural areas, supply-side factors may also constrain basic consumption of food and non-food items as well as agricultural production. Rawlings and Rubio (2005) and Handa and Davis (2006) argue that uncovering heterogeneous impacts and any supply-side constraints are some of the most pressing questions facing the next phase of cash transfer research.

The salience of the question is also reflected in the findings of a recent evaluation by Chetty et al. (2013) of one of the United State's flagship anti-poverty programs (which is essentially a cash transfer program) – the Earned Income Tax Credit (EITC). While the study provides correlational evidence that the EITC has helped children move out of poverty, it also finds that much of the variation in a child's prospects for escaping poverty is explained by community-level variables such as rates of segregation, marriage, religiosity, and inequality. Accompanying qualitative reports hint at the role transactions costs associated with paid work may play as well (see Leonhardt, 2013).

3.3. Conceptual Framework

Following Singh et al. (1986), Sills et al. (2003), and Barbier (2010), we use household production theory to present a model adapted to the specific characteristics of the agricultural household in rural developing economies. In such models, time is the primary input to production and the household consumes most of their own production. From this household production framework we derive equations for estimating household consumption and production. We assume households maximize Utility, which depends on consumption of three goods: those purchased in the market (X), those produced at home (H), and leisure (L). Households consume these goods, conditioned on their preferences (Φ), subject to four constraints: an agricultural and environmental goods production function (the technological constraint), the time constraint, an earned income constraint, and a cash constraint.

The objective function and constraints are defined as follows:

Max $U(X, H, L; \Phi)$

$A = f(T_A, X_A; F_A)$ [Tech Constraint]

$T = L + T_A + T_M$ [Time Constraint]

$E = w^*T_M$ [Earned Income Constraint]

$P_x{}^*X + P_{x_A}{}^*X_A \le p_A(A\text{-}H) + w^*T_M + C$ [Cash Constraint]

Own production of agricultural and environmental goods (A) is a function of time inputs (T_A), purchased inputs (X_A), and the quality of natural resources, including plot fertility (F_A), which is exogenously fixed. Time (T) is composed of leisure time, time in production of agricultural and environmental goods (T_A), and time spent in the market on wage labor (T_M). Earned income (E) is the multiple of any market time and the wage (w). The cash constraint dictates that expenditures on market goods and agricultural inputs must be less than or equal to the sum of the marketed surplus from home production [$p_A(A\text{-}H)$], earned income, and exogenous sources of income (C), such as the cash transfer.

The time, earned income, and cash constraints can be combined into a full income constraint such that the Lagrangian can be written as:

$\ell = U(X,H,L; \Phi) + \lambda_1[f(T_A, X_A; F_A)] + \lambda_2[wT + C + p_A(A\text{-}H) - (p_X X + p_{X_A} X_A + wL + wT_A)]$

The choice variables are consumption of market goods (X), consumption of own produced goods (H), leisure time (L), time in own production (T_A), time in market T_M, own production (A), and agricultural inputs (X_A).

Solving this constrained optimization problem yields first order conditions that reveal households equate marginal costs with marginal benefits when making consumption and production decisions. The shadow values measuring how binding the technological (λ_1) and full income constraints (λ_2) are play key roles in the household's choice of optimal bundles. These shadow values are specific to each household and, like the six choice variables identified in the Lagrangian, are thus endogenous and a function of all exogenous variables in the system.

Where the shadow price for a consumption-production good (functions of the constraint's shadow value and the good's marginal utility) equals the market price for the good, household decisions can be viewed as *separable* (Lofgren and Robinson, 1999). The household first maximizes producer profits and then maximizes their consumption utility according to this income. In such cases markets can be viewed as complete and prices and income are key determinants of household production and consumption in line with standard theory (Sills et al., 2003). But where the shadow and market prices differ, household production and consumption decisions are said to be *non-separable*. As Lofgren and Robinson (1999) state, this non-separability exists "…whenever the household shadow price of at least one producer-consumer good is not given exogenously by the market but instead is determined endogenously by the interaction between household demand and supply" (p.2).

Non-separability arises whenever markets are incomplete (Sills et al., 2003). Lofgren and Robinson (1999) note that farm households in developing economies typically face these market imperfections due to the following circumstances: (1) the market purchased good is not a perfect substitute for the home produced good, (2) the household is not a price-taker, and (3) there are gaps between the sales price and purchase price of a good. Sills et al. (2003) describe how these "price bands" for goods are caused by variable transaction costs facing households, which are influenced both by exogenous sources of market integration (e.g., distance) and endogenous sources, such as connections to traders. These variable transaction costs imply that markets for consumption and production goods may be complete for some but incomplete for others. These insights motivate our adoption of a conceptual framework that explicitly tests how constraints on household's market participation affect their consumption and production decisions.[12]

3.4. Data and descriptive statistics

In-depth information was collected from households' regarding their use of natural resources and establishment of non-farm business enterprises. In the case of fuel and food, we asked households the amounts of resources consumed within the previous four weeks (charcoal and fuelwood) or two weeks (bushmeat); specifically, the amounts purchased at market, received as gifts, and produced/collected themselves. Households reported the price of these amounts (or what the price would have been had it been purchased) and we aggregate these values into one consumption value (expressed in kwacha) for each resource. Additionally, households were surveyed about their agricultural production in the previous season (between October 2011 and September 2012), including the area of land used. In 2012, households also reported whether they owned a non-farm business.

Households in the sample are quite poor, with 92% living below the poverty line and 90% severely food insecure (Table 15). On average, households live between 16 and 22 km from a market. At baseline, roughly 90% of households consumed fuelwood, 5% charcoal, and only

[12]The conceptual model could suggest that there is also a "transaction costs/market participation constraint" that is a function of distance, road quality, etc. as well as endogenous market regime.

2% bushmeat. Households with bushmeat consumption tend to have higher food consumption and be less food insecure than the panel average. We also see that both charcoal and bushmeat consumers are more likely to live in Kaputa. Bushmeat consumption is driven by purchases (87%) whereas fuelwood and charcoal consumption are driven by household's own production (98% and 73%, respectively).

To investigate whether there are heterogeneous impacts of the cash transfer due to a household's distance to market, we split the full panel into two sub-samples using 10 km as a cutoff point. We first explored the data graphically using Lowess-smoothed plots to see if there appear to be differential effects of cash that vary according to market distance (see Figures 2-11).[13] These graphs clearly show that, for the treatment group, impacts bifurcate around the 10km mark for all of our outcomes of interest. Intuitively, the 10km point makes sense when one considers that humans walk, on average, 5 km an hour, and so a one day round-trip to a market more than 10 km away implies more than 4 hours of walking in one day. Households farther from markets may make different consumption and production decisions because they have less access to markets goods; their economic behavior may also differ because the quantity (e.g., fuelwood, bushmeat) or quality (e.g., soil fertility) of natural resources may be greater farther from markets.

Because the graphs show a clear bifurcation around the 10km mark, this indicates that there are threshold effects, which may not be picked up by measuring the effect of distance in a pooled (no market split) triple-difference model using a continuous measure of distance. Additionally, if the effects of market distance and cash are working in opposite directions, trying

[13]We plot Lowess-smoothed graphs to explore whether there are differential impacts of cash that vary according to market distance. To create these graphs we first run triple-difference regressions (and difference-in-difference in the case of non-farm businesses) that interact market distance (logged) with cash, time, and both cash and time. We then plot the predicted results of these regressions for households in 2012. We restrict these graphs to those living within 20 km or less of markets (74% of households).

to capture the interactive effects of cash and distance in a triple-difference model using a binary measure of distance could also miss important threshold effects. For these reasons, we use the 10 km cutoff to split the sample into two sub-groups.

The 10km cutoff splits the sample into 1201 households living more than 10km from a market and 1097 living within 10km from a market. For those living far from markets, average distances range from 20 to 39 km across the natural resource/control-treatment sub-groups. For the sub-groups living close to markets, average distances range from only 2-4 km. Comparing the two market distance sub-samples, we see that the recipient and demographic characteristics tend to be similar. However, somewhat surprisingly, households living closer to markets tend to be poorer, with higher food insecurity and lower food consumption – though they have higher wealth scores (i.e., more assets).

The vast majority of households in the sample – 89% – farmed land in 2012 (Table 18). [We lack baseline data on agricultural production and non-farm businesses and therefore report descriptive statistics for the 2012 data.] Maize, cassava, and rice are the most common crops in the sample, followed by millet, groundpeas, and sorghum. These small-holders farmed, on average, less than one hectare (ha) each. The largest plots measure between 10 and 12 hectares.

Households were asked to name up to three non-farm businesses that they own (Table 19). Of the 885 households (39% of the sample) that own a non-farm business, 73 (8%) own more than one business. We examine whether or not these businesses are based on exploitation of natural resources, which in this sample includes fishing, charcoal production, and haying. Thirteen percent of households own a business based on natural resources, 27% own other types of businesses. The most important non-farm businesses represented in the sample are fishing

(12% of households), home brewery (10%), and petty trader (6%). Only 2% of households produce and sell charcoal.

3.5. Estimation strategy

Because non-separable models of household consumption and production decisions are functions of exogenous household preferences and characteristics they can be estimated using a reduced form approach (de Janvry and Sadoulet, 2003). To estimate the impacts of cash on natural resource use we run a series of difference-in-difference models, which compare the temporal change in the treatment group with the temporal change in the control group. This nets out the effect of any general time trend not associated with the cash transfer on natural resource use in the Kaputa, Kalabo, and Shang'ombo districts.

The key assumptions of our difference-in-difference models are that (1) natural resource use is balanced between the control and treatment groups at baseline and (2) the control and treatment groups would experience the same general time trend with respect to natural resource use in the absence of the cash transfer program. We test that the first assumption holds and while the second assumption is fundamentally unknowable, our research design provides strong assurance that it holds as well. Because the cash transfer program was randomly assigned within and across three districts, treatment status should not be systematically correlated with observed or unobserved characteristics of participating households or communities that vary over time or are time-invariant.

We lack baseline data on land use and non-farm business enterprises and therefore run a series of first-difference models to examine the impact of cash on these outcomes. These models measure the difference between the control and treatment groups in 2012, and therefore assume baseline equivalence between these groups regarding land use and business enterprises.

We consider two measures of natural resource use: whether households used fuelwood, charcoal, bushmeat, or farmland at all; and the amount of the given resource used amongst households consuming it at baseline. Examination of these two trends separately allows us to explore whether the cash transfer is having strong income effects that induce changes in households' livelihood strategies (i.e., moving into or out of farming), dietary patterns, or encourage fuel-switching. It also provides a means of dealing with the high frequency of zeros (i.e., non-users) in the fuelwood, charcoal, and bushmeat data when examining the transfer's impact on overall amounts used.

3.5.1. Testing assumptions of the impact estimates' econometric models

We confirm that randomization yielded similar observable characteristics between treatment and control households by testing for their equivalence at baseline. We test for equivalence at baseline in terms of basic characteristics of the recipient and household and our key outcomes of interest (natural resource use) and report these results in Tables 15-17 & Tables 20-22. We restrict our analysis to just the panel of households that remained in the survey for both rounds and cluster robust standard errors at the community-level (and do so for all subsequent models). Equivalence at baseline tests are run for all variations of the sample used in our impact estimates presented in Section 3.6.

We find charcoal, fuelwood, and bushmeat use to be well balanced between the control and treatment groups at baseline. This equivalence holds for all panel households (Table 20), amongst those living more than 10 km from a market (Table 21), and those within 10 km from a market (Table 22). On average, amongst consumers, fuelwood consumption is roughly equivalent to 14% the value of their food consumption. For charcoal it is about 12%. Bushmeat accounts for roughly 12% of bushmeat consumers' monthly food budget. Similar frequencies and amounts of natural resource use at baseline across the sub-samples suggest remoteness is not associated with different fuelwood, charcoal, or bushmeat consumption patterns in these regions of Zambia.

Control and treatment households are generally equivalent along their observable characteristics at baseline, though there are important differences amongst those with baseline charcoal consumption (n=124) and baseline bushmeat consumption (n=46) (see Table 15). For charcoal users, control households are farther from markets and a greater percentage live below the poverty line while a higher percentage live in Shang'ombo. Amongst bushmeat consumers, the treatment group has a significantly higher percentage living below the poverty line as well as slightly different household size and demographic composition. However, when the 10km cutoff is used to divide the full panel into two sub-samples, any significant differences between the control and treatment groups at baseline disappear (see Tables 16 and 17).

3.5.2. Identification strategy for impact estimates

The difference-in-difference model we use to identify the impacts of cash on natural resource use can be specified as follows:

(7) $$Y_{igt} = B_0 + B_1 Post_{igt} + B_2 Cash_{ig} + B_3 (Post_{igt} * Cash_{ig}) + B_4 \boldsymbol{X}_{ig} + B_5 \boldsymbol{Z}_g + \boldsymbol{W}_g + E_{igt}$$

where Y_{igt} measures whether a household i in district g in period t used the natural resource in question or the per capita amount used, $Post_{igt}$ is a dummy variable equal to 1 if the observation is in 2012, $Cash_{ig}$ is a dummy variable equal to 1 if the household is in the treatment group, $\boldsymbol{X}_{ig}$ represents a vector of household and recipient characteristics measured at baseline, $\boldsymbol{Z}_g$, is a vector of baseline prices for food and other important consumption goods, $\boldsymbol{W}_g$ is a district fixed effect, and E_{igt} is the error term. We include controls for baseline characteristics and prices and district fixed effects to increase the precision of our estimates. The coefficient of interest in this model is B_3, which captures the effect of being in a treatment community on natural resource use.

Because we lack baseline data on land use and non-farm businesses, we run a series of first difference models using the 2012 data to test for the impact of cash. This model is similar to Equation (7) and is written as:

(8) $$Y_{igt} = B_0 + B_1 Cash_{ig} + B_2 \boldsymbol{X}_{ig} + B_3 \boldsymbol{Z}_g + \boldsymbol{W}_g + E_{igt}$$

Here, the treatment effect is captured by B_1.

3.6. Results

We do not find evidence that the cash transfer program significantly affects consumption of fuelwood or bushmeat. Cash does, however, significantly increase both the decision to use charcoal and the amount used amongst those consuming it at baseline. However, these average impacts obscure the heterogeneous effects of distance to market and district. While cash increases the probability of using charcoal by 8 percentage points, on average (Table 23), it has no impact on the decision to use charcoal amongst those more than 10km from a market (Table 28), while increasing this likelihood by 11 percentage points for households within 10km of a market (Table 26). Given that between 68% and 73% of charcoal users (at baseline) live in Kaputa (Table 15) and 25 of the 36 charcoal businesses are located there, we also investigate the impacts of cash on charcoal use in Kaputa district. We find that cash increases the likelihood of charcoal use in Kaputa by 24 percentage points (Table 24).

We also find that impacts of cash on both the decision to farm and the total area of land used vary according to market access. While we do not detect an impact of cash on the decision to farm amongst the full panel (Table 23) or those living within 10km of a market (Table 26), cash significantly increases the likelihood of farming by six percentage points amongst those living more than 10km from markets (Table 28). In terms of land area used, cash increases the area farmed by 21% amongst those within 10km of a market (Table 27) and by 28% for those living more than 10km from a market.

Cash significantly increases the likelihood of owning a non-farm business and these impacts are most pronounced for those living close to markets. For these households, cash increases the likelihood of owning any non-farm business by 23 percentage points; a charcoal, fish, or hay business by 10 percentage points; and all other businesses by 14 percentage points (Table 32). But for households living more than 10km from a market, cash has no impact on natural-resource based businesses and increases the probability of owning a non-farm business in general by only 11 percentage points (Table 31).

We also investigate if cash has differential impacts on land use amongst those with a non-farm business. While we don't find evidence that cash affects the decision to farm for those owning a business, we do find that cash increases the area farmed for these households – though, again, impacts are heterogeneous according to market access. Amongst those close to markets, cash does not appear to affect the area farmed. However, amongst business-owners living far from markets, cash increases the area farmed by 20%.

3.7. Discussion and conclusions

Our findings provide further evidence of the complexity of poverty-environment relationships. We find that, on average, cash increases the likelihood of using charcoal and owning a non-farm business as well as the land area used for farming. Even amongst households owning a non-farm business, cash, on average, increases the area farmed. However, these average impacts mask substantial heterogeneity in resource use, moderated by households' distance to market. For charcoal, we see that cash only increases use amongst those households living within 10km of a market. On the decision to farm, cash only has an impact for those households living far from markets. And the impacts of cash on land area farmed are greater for households more than 10km from a food market. We also see that cash has a higher likelihood of increasing the ownership of non-farm businesses amongst those living closer to markets and has no impact on natural resource-based businesses for those living far from markets. It also appears that non-farm business owners living close to markets do not use the cash to increase the area of their farms, while those living far from markets do.

Taken together, these results show that in this particular region of Zambia, the biggest impacts of a cash transfer program on natural resources – in the short-run – come from charcoal and small-holder farming. Our findings also demonstrate that rural households living close to markets are more likely to use the transfer to diversify their livelihood strategies, which may indicate a transition out of farming to non-farm enterprises.

What are the implications of these findings for policy and programming targeting rural environment and development issues? First, extending cash transfers to households living close to markets may help farmers inclined towards non-farm entrepreneurship to transition out of farming. Second, cash transfers may also cause these same households to increase their consumption and/or production of charcoal. Given that charcoal is the number one driver of deforestation in Zambia (Day et al., 2014) and many other regions of Africa, development programs should consider pairing cash transfers with alternative fuel programs and heightened attention to charcoal supply chains. Third, because households living far from markets will likely use cash to expand their farms, cash transfer programs may wish to consider increasing agricultural extension services in these areas to encourage land-intensive practices and safe use of fertilizers and pesticides.

REFERENCES

Alix-Garcia, J., C. McIntosh, K.R.E. Sims, and J.R. Welch. 2013. The ecological footprint of poverty alleviation: Evidence from Mexico's *Oportunidades* Program. The Review of Economics and Statistics 95(2): 417-435.

Angelsen, A.; Atmadja, S. What is this book about? 2008. In *Moving Ahead with REDD: Issues, Options and Implications*; Angelsen, A., Ed.; CIFOR: Bogor, Indonesia; pp. 1–10.

Barbier, E.B. 2010. Poverty, environment and development. Environment and Development Economics 15(6): 635-660.

Boone, R., K. Covarrubias, B. Davis, and P. Winters. 2013. Cash transfer programs and agricultural production: the case of Malawi. Agricultural Economics 44: 365-378.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2013. The economic impacts of tax expenditures: Evidence from spatial variation across the U.S. Working Paper.

Dammert, A.C. 2009. Heterogeneous impacts of conditional cash transfers: Evidence from Nicaragua. Economic Development and Cultural Change 58(1): 53-83.

Day M, Gumbo D, Moombe KB, Wijaya A and Sunderland T. 2014. Zambia country profile: Monitoring, reporting and verification for REDD+. Occasional Paper 113. Bogor, Indonesia: CIFOR.

Debela, B., G. Shively, A. Angelsen, M Wik. 2012. Economic shocks, diversification, and forest use in Uganda. Land Economics 88(1): 139-154.

de Janvry, A. and E. Sadoulet. 2003. Progress in the Modeling of Rural Households' Behavior under Market Failures. Chp. 8 in Poverty, Inequality and Development: Essays in Honor of Erik Thorbecke (de Janvry, A. and R. Kanbur, Eds.). Kluwer Academic Publishing: Boston.

Ferraro, P.J., M.M. Hanauer, and K.R.E. Sims. 2011. Conditions associated with protected area success in conservation and poverty reduction. PNAS 108(34): 13913-13918.

Fisher, M.M. and G.E. Shively. 2005. Can income programs reduce tropical forest pressure? Income shocks and forest use in Malawi. World Development 37(7): 1115–1128.

Galiani, S. and P.J. McEwan. 2013. The heterogeneous impact of conditional cash transfers. Journal of Public Economics 103: 85-96.

Handa, S. and B. Davis. 2006. The experience of conditional cash transfers in Latin America and the Caribbean. Development Policy Review 24(5): 513-536.

Handa, S., B. Davis, M. Stampini, and P.C. Winters. 2010. Heterogeneous treatment effects in conditional cash transfer programmes: assessing the impact of Progresa on agricultural households. Journal of Development Effectiveness 2(3): 320-335.

Handa, S., D. Seidenfeld, B. Davis, G. Tembo and the Zambia Cash Transfer Evaluation Team. 2014. Are cash transfers a silver bullet? Evidence from the Zambian Child Grant. Innocenti Working Paper no. 2014-08. UNICEF Office of Research: Florence.

Joppa, L.N. and A. Pfaff. 2009. High and far: Biases in the location of protected areas. PLoS ONE 4:e8273.

Koop, G. and L. Tole. 1999. Is there an environmental Kuznets curve for deforestation? Journal of Development Economics 58: 231-244.

Leonhardt, D. 2013. In Climbing Income Ladder, Location Matters. The New York Times. 22 July.

Lofgren, H. and S. Robinson. 1999. To trade or not to trade: Non-separable farm household models in partial and general equilibrium. IFPRI Trade and Macroeconomics Division Discussion Paper No. 37. IFPRI: Washington, D.C.

McSweeney, K. 2005. Natural insurance, forest access, and compounded misfortune: Forest resources in smallholder coping strategies before and after Hurricane Mitch, Northeastern Honduras. World Development 33(9): 1453-1471.

Pattanayak, S.K. and E.O. Sills. 2001. Do tropical forests provide natural insurance? The microeconomics of non-timber forest product collection in the Brazilian Amazon. Land Economics 77(4): 595-612.

Rawlings, L.B. and G.M. Rubio. 2005. Evaluating the impact of conditional cash transfer programs. The World Bank Research Observer 20(1): 29-55.

Reardon, T. and S.A. Vosti. 1995. Links between rural poverty and the environment in developing countries: Asset categories and investment poverty. World Development 23: 1495–1506.

Scherr, S.J. 2000. A downward spiral? Research evidence on the relationship between poverty and natural resource degradation. Food Policy 25: 479–498.

Sills, E.O., S. Lele, T.P. Holmes, and S.K. Pattanayak. 2003. Nontimber Forest Products in the Rural Household Economy. Chapter 15 in Forests in a Market Economy (Sills, E.O. and K.L. Abt, Eds.). Kluwer Academic Publishing: Boston.

Singh, I., L. Squire, and J. Strauss. 1986. A Survey of Agricultural Household Models: Recent Findings and Policy Implications. The World Bank Economic Review 1(1): 149-179. The World Bank: Washington, D.C.

Takasaki, Y., B. Barham, O. Coomes. 2004. Risk coping strategies in tropical forests: floods, illnesses, and resource extraction. Environment and Development Economics 9: 203-224.

Wunder, S. 2001. Poverty alleviation and tropical forests—What scope for synergies? World Development 29: 1817–1833.

CHAPTER 4:
CYCLING OUT OF POVERTY?
THE IMPACTS OF CASH TRANSFERS AND BICYCLES ON MARKET ACTIVITY IN RURAL ZAMBIA

4.1. Introduction

Numerous studies demonstrate the effectiveness of cash transfers in increasing poor households' food consumption, production (agricultural and otherwise), and investments in human capital (e.g., children's schooling, vaccinations, and use of health services). While these general findings hold in both rural and urban areas, there has been little examination of whether the magnitude of results varies according to degree of remoteness and market access. Barrett and Swallow (2005) argue that the poor living in many developing economies' rural areas find themselves in "fractal poverty traps," where the self-reinforcing conditions that cause poverty to persist repeat and reinforce each other at micro (household), meso (community), and macro (nation-state) scales. Such fractal poverty traps are especially hard to break out of because they require simultaneous action at all of these scales. For example, we might expect that in remote rural areas the ability of households to convert cash transfers into consumption, production, and investment is constrained by their limited access to markets, schools, and health clinics. If so, then cash transfer programs operating in remote rural areas should consider whether it is possible to couple payments with complementary steps to increase households' access to markets and public services.

Undertaking major infrastructure projects and expanding transportation networks in rural areas requires significant time and money. Are there other strategies policymakers can adopt in the short-term to increase the rural poor's access to markets? One strategy being promoted by numerous NGOs and social enterprises across Africa and other parts of the developing world is the disbursement and marketing of bicycles (see work of World Bicycle Relief, Bicycle Aid for Africa, and the Village Bicycle Project, among many others). These programs are motivated by the belief that owning a bike enables rural households to send their children to school, make greater use of health clinics, and increase their sales of agricultural products. For example, World Bicycle Relief, which has distributed or sold at least 125,000 bikes and trained more than 800 mechanics across eleven countries in East and Southern Africa, states that their programs in Zambia aim to increase school attendance rates by decreasing travel time and increasing the safety of students (especially girls) while in transit; improve students' test scores by decreasing their time spent traveling, allowing more time for studying; and raise farmers' incomes by decreasing travel time to market, thereby increasing the volume of unspoiled agricultural products they are able to sell (World Bicycle Relief, 2010a and 2010b).

In this study we investigate the third causal pathway – the effect of bikes on participation in agricultural markets in Zambia. We examine households' purchase of agricultural inputs and their sale of agricultural products and the roles of bike ownership and cash transfers in increasing these agricultural inputs and outputs. Building on this investigation of market activity, we also look for impacts of bike and cash on ownership of non-farm businesses. Using a panel dataset from a randomized evaluation of a cash transfer program in Zambia, we test for both independent and multiplicative effects of bikes and cash on our outcomes of interest.

Despite a proliferation of bicycle initiatives across Africa, there have been no academic studies evaluating the impacts of such programs or bicycle ownership itself on African households. This study aims to fill this gap in applied development economics. This paper also seeks to identify options for increasing the effectiveness of cash transfer programs in remote rural areas by investigating whether the impacts of the transfer vary according to bike ownership.

4.2. Cash transfers, supply-side constraints, and poverty traps

Handa and Davis (2006) note there are contradictions in the aim and design of cash transfer programs. On the one hand, these programs often claim they aim to reduce poverty in both the short-term and the long-term. However, the focus of these programs tends to be on human capital accumulation for children – as evidenced by the facts that many transfer programs make payment conditional on children's schooling and health visits and many of the unconditional cash transfer programs target families with young children (as in the Zambia Child Grant program). This emphasis on children may be neglecting opportunities to reduce poverty and foster economic growth in the current generation.

Another contradiction relates to the importance of distinguishing between transitional poverty and chronic poverty and the different strategies that might reduce the incidence of each. Cash transfer programs are often described as "safety-net" programs that can help households cope with negative shocks. But these programs typically use measures of structural poverty to identify beneficiaries and beneficiary communities. This results in programs targeting the chronically poor -- and in ignoring the near-poor, who may be at risk of falling into poverty (either temporarily or permanently) due to a negative shock. Such targeting methods imply that cash transfer programs are trying to lift people out of poverty traps, rather than provide a safety-net for the near-poor and transitional poor. This raises the question: are small, regular cash payments the best policy approach for lifting households above the threshold that characterizes a poverty trap?

The theory of poverty traps suggests that once households fall below some critical threshold of well-being, self-reinforcing conditions will prevent households from escaping poverty. Figure 1 presents poverty trap dynamics, as described and depicted by Barrett and Swallow (2005). In the space of future well-being mapped onto current well-being, welfare dynamics create an S-shaped curve with three equilibrium points as shown in the figure below. In this figure, W_{PL} marks the poverty line. Those at the middle equilibrium point (W_C) can easily be pushed down into the low-level (poor) equilibrium (W_L) by negative income or asset shocks or pushed up to the high-level (non-poor) equilibrium (W_H) by positive shocks. Once households find themselves at either the low- or high-level equilibrium they will tend to converge back to this point, despite small positive or negative income shocks that temporarily knock them off. Those at the low-level equilibrium are thus in a poverty trap; those that move above the middle equilibrium are moving along a self-propelled growth trajectory. This implies that those at the middle equilibrium are at a highly unstable point, which marks an important threshold.

Carter and Barrett (2006) argue that in order to identify poverty trap thresholds we need to examine households' assets, rather than just their consumption levels (the standard approach for measuring welfare and establishing poverty lines). If, they contend, households are above the poverty trap threshold, they can temporarily reduce their consumption or sell off some assets to cope with negative income shocks and then use their (remaining) productive assets to build themselves back up. However, if their assets fall below this threshold, they will lack the means to pull themselves out of poverty and be trapped. These arguments imply that modestly-sized cash transfers may not be enough to push households above the critical threshold – unless they enable households to obtain the right combination or value of assets.

However, as argued by Dercon (2007), measuring such an asset threshold is a nearly impossible task since, empirically, it necessitates collapsing a complex array of assets into a one-dimensional measure – either the value of all assets or the number of a particular type of assets (e.g., livestock, land) held by the household. Moreover, the concept of an asset threshold, he argues, is predicated on the idea that the key constraint households face is a lack of credit markets, which prevents use of intertemporal exchange as a shock-coping strategy. However, financial constraints might not be the defining feature of poverty traps. The threshold may instead be defined by remoteness and limited access to markets. As Dercon (2007) notes:

> "Maybe what we need to do is to make asset thresholds matter less to escape poverty, by making capital accumulation less relevant for escaping poverty. Recent history has taught us that this is how large numbers of the poor have escaped their deep deprivation: by moving out of agriculture and informal activities, where they need capital to move forward, to activities that only involve selling their labour in a context of labour-intensive economic growth" (p. 41-42).

Dercon's argument is in fact congruent with another theory put forward by those arguing the notion of asset-based poverty traps. Barrett and Swallow (2005) theorize the existence of 'fractal poverty traps', which they define as self-reinforcing conditions that cause poverty to persist that repeat and reinforce each other at micro (household), meso (community), and macro (nation-state) scales. Such fractal poverty traps are especially hard to break out of and require, they argue, simultaneous action at multiple scales. The idea can be illustrated with the idea of financial markets, which they argue are often the principal constraint facing households mired in poverty traps. Poor households often lack access to credit and loans because they are poor. At the meso-level, communities in rural areas often lack micro-credit institutions due to weak infrastructure and institutions. At the macro-level, nations' ability to borrow may be hindered by debts owed on existing loans and the fact they are poor. The constraints thus reinforce each other at every level of the poverty trap and these individuals, communities, and countries find themselves in a fractal poverty trap. Rural households may also find themselves in fractal poverty traps because they lack markets for land and non-farm labor and face high transaction costs for getting goods to market due to a lack of infrastructure. Both Dercon's argument and the concept of fractal poverty traps are also consistent with questions that have been raised in the cash transfer literature by Rawlings and Rubio (2005) and Handa and Davis (2006) about the need to investigate whether supply-side constraints are blocking households' ability to escape poverty.

These debates in the literature regarding poverty, assets, and supply-side constraints in remote rural areas motivate our examination of whether bicycle ownership increases the effectiveness of cash transfers. Clearly, bikes are both an asset and a means of increasing one's market access. While we do not explicitly test for the existence of poverty traps defined by a specific asset threshold,[14] our investigation of heterogeneous impacts due to bike ownership may be able to provide support for the validity of this concept. Carter and Barrett (2007) argue that the asset threshold may be identified by either (a) seeing if households' accumulation of assets bifurcates around a specific total value or (b) finding an asset value around which households' behavior bifurcates in response to negative shocks. In this paper, we test if behavior bifurcates around an asset threshold (bike ownership) in response to a *positive* shock. In essence, we are testing if the infusion of cash plus a particular asset is able to move households onto a self-propelled growth trajectory in the context of supply-side constraints.

4.3. Conceptual framework

To investigate whether bicycle ownership yields differential impacts of the cash transfer on participation in agricultural markets and non-farm businesses, we first develop a theory of

[14]As noted by Carter and Barrett (2006), empirical tests for such dynamic asset thresholds require at least three periods of panel data. Qualitative research may also be able to provide evidence for the existence of such thresholds.

change that identifies the various ways bikes could affect the transfer's impacts (see Figure 12). Bikes could moderate impacts of the transfer if their ownership is associated with heterogeneous impacts. Bikes could operate as a moderator and be exogenous to cash, if their ownership is not affected by participation in the cash transfer program; the decision to own a bike could also be endogenous to cash if receiving the transfer causes households to purchase bikes. [Note that regardless of whether bicycle ownership is exogenous or endogenous to cash, owning a bike is still a choice, possibly reflective of other unobserved characteristics, and still needs to be treated as a potential source of endogeneity bias.] For example, bikes sold by the World Bicycle Program in Zambia cost 680 kwacha ($136 in US Dollars), which is roughly equivalent to 11 months of the Child Grant Program's transfers of 60 kwacha per month. Bikes may also mediate the impacts of the cash transfer; that is, much of the effect of the transfer on market activity could be due to households' ownership of bikes.

4.4. Data and descriptive statistics

The Child Grant Program impact evaluation study collected detailed information about households' consumption, income, assets, and livelihood activities. Households were asked about their purchase of agricultural inputs, including seeds, fertilizer, and pesticides, as well as their crop sales during the previous agricultural season (spanning 12 months). They were also asked about the location for these sales and purchases. Households also reported whether or not they owned non-farm businesses. Data on households' ownership of bikes was collected along with ownership information for a long list of assets used to construct household wealth indices.

Overall, bike ownership more than doubled over the two years of the study from 7% in 2010 to 15% in 2012 (Table 35). While bike ownership was balanced at baseline between the cash and control group and the increases over time for both groups are substantial, the increase is sharper for those participating in the cash transfer program.

While randomization of the cash transfer succeeded in creating treatment and control groups that are nearly identical along observable characteristics, bike owners differ from non-owners (as well as the general sample) in numerous ways (see Table 36). Bike owners are more likely to have attended school, be married, have larger households, and live closer to markets. They also have higher food consumption as well as overall consumption. Sixty-eight percent of bike owners live in Kaputa District.

Study households are extremely poor (see Table 36) and most participate in agriculture for subsistence only, with little market activity. The vast majority of households in the sample produce crops (about 80% at baseline) (Handa et al., 2014), but, in 2010, only 22% of households sold crops and only 13% purchased seeds, fertilizer, or pesticides (Table 37). While the value of crop sales was balanced between the cash and control group at baseline (for those with any crop sales), the cash group had significantly higher spending on agricultural inputs in 2010.

Bike owners are more likely to be engaged in agricultural market activity than both non-owners and the overall study sample (Table 38). Twenty percent of bike owners purchased agricultural inputs and 35% sold crops in 2010. However, amongst those with crop sales at baseline, the value of sales is not statistically different between the bike owners and non-bike owners and is similar to the cash group's sales value. While spending on agricultural inputs amongst those with such spending is not statistically significant between bike owners and non-bike owners, bike owners' spending does appear to be much higher and the lack of significance is likely attributable to the small number of those both owning a bike and purchasing agricultural inputs in 2010 (only 84 households).

4.5. Estimation strategy

There is potential endogeneity bias that needs to be thought about carefully when attempting to identify the impact of bikes on economic activity. Because the decision to own a bicycle is a choice, it is possibly reflective of other unobservable characteristics of the owner that might influence our outcomes of interest. For example, bike owners might be more motivated or less risk-averse than non-owners, and thus more likely to own a non-farm business or increase their purchase of agricultural inputs or sale of agricultural outputs over time. This potential endogeneity of bike ownership therefore needs to be explicitly considered in our impact estimates. We address this potential source of bias by including household fixed effects in our econometric models, which sweep out the effect of any time-invariant unobservables.[15]

We consider the following outcomes of interest in our regressions: (1) whether or not households sold any crops, (2) whether or not households purchased agricultural inputs, (3) the value of crops sold amongst those with such sales at baseline, (4) the value of agricultural inputs purchased amongst those with such purchases at baseline, and (5) whether or not households own a non-farm business. We also run series of models that impose no baseline-selling restrictions for the value of crop sales and agricultural input purchases. However, our preferred sets of models distinguish between the decision to engage in market activity and the volumes sold/purchased amongst those already participating in markets. As we will show and discuss in

[15]We also explored the possibility of using an instrumental variables approach in this paper. Instrumenting for bike would address two potential sources of endogeneity bias posed by the bike variable (unobserved time-invariant heterogeneity as well as unobserved time-variant heterogeneity). However, because we have panel data and are testing for the multiplicative effects of bikes and cash, our models include multiple bike interactions. Models with multiple potentially endogenous regressors are beyond the reach of two-stage least squares instrumental variables approaches, which allow for only one endogenous regressor.

Sections 4.6.2 and 4.7, applying this distinction in our models allows for a more nuanced understanding of how cash and bikes impact livelihoods.

4.5.1. Mediation

Testing for mediation helps us unpack the 'black box' of impact estimates and uncover the causal chain linking programs to outcomes. If a variable mediates program impacts, this implies that part of any identified program impact is actually due to the mediating variable. For example, if cash causes households to purchase bikes, and part of any identified impact of cash on increased market activity is actually due to the ownership of bikes, then we would conclude that bikes are a mediator and that part of the success of cash transfers is due to their effect on bike purchases.

To test whether bikes mediate impacts of the cash transfer, we first run a series of difference-in-difference models to examine whether cash in fact is associated with an increase in bike ownership over time. Next, we apply similar models to test for the effect of cash – by itself – on our outcomes of interest. The final step is to then add the bike variable to those models identifying a significant impact of cash and examine whether adding the bike variable reduces the size of the coefficient measuring the impact of cash; if it does, this indicates that bikes mediate the effects of cash. To address the potential bias posed by the endogenous choice to own a bike, our bike measure for these models excludes those who owned a bike at baseline. Another way of addressing this potential bias is to use household fixed-effects models. Therefore, as a further robustness check on our pooled difference-in-difference models, which difference out the average effect for the control group, we also test for mediation using household fixed-effects, which essentially allows each household to serve as a control for itself, giving each it's own intercept and regression line (though all with the same slope).

4.5.2. Moderation

We also investigate whether bikes moderate impacts of the cash transfer; i.e., cause heterogeneous treatment effects. To test for moderation, we run triple-difference models, as specified in Equation (9) below:

$$(9) \quad Y_{igt} = B_0 + B_1 Time_{igt} + B_2 Cash_{ig} + B_3(Time_{igt} * Cash_{ig}) + B_4 Bike_{ig(t)} + B_5(Time_{igt} * Bike_{ig(t)}) + B_6(Cash_{ig} * Bike_{ig(t)}) + B_7(Cash_{ig} * Bike_{ig(t)} * Time_{igt}) + B_8 \boldsymbol{X}_{ig} + B_9 \boldsymbol{Z}_g + \boldsymbol{W}_g + E_{igt}$$

where Y_{igt} measures whether household i in district g in period t purchased/sold agricultural inputs/outputs or the value of the amount purchased/sold, $Time_{igt}$ is a dummy variable equal to 1 if the observation is in 2012, $Cash_{ig}$ is equal to 1 if the household is in the treatment group, and $Bike_{ig(t)}$ is equal to 1 if the household owns a bike. The coefficients of interest in this model are B_3, which captures the effect of cash, B_5, which captures the effect of bicycle ownership, and B_7, which measures the multiplicative effect of cash and bike. To increase the precision of our estimates we include controls for baseline characteristics, baseline prices of food and other important consumption goods, and district fixed effects. Equation (9) represents these time-invariant controls with $\boldsymbol{X}_{ig}$, $\boldsymbol{Z}_g$, and $\boldsymbol{W}_g$, respectively; E_{igt} represents the error term.

We consider two alternative measures of bike ownership: that measured at baseline and that which varies over time. Baseline bike ownership is a "pure" measure of moderation, if we are concerned that cash is affecting bicycle ownership over time. However, the weakness of this measure is that it misses the large increase in bike ownership over the course of the study. The time-varying bike measure assumes that there is not meaningful multicollinearity between bike and cash. That is, it assumes that even if regression estimates identify an "effect" of cash on bike ownership, it assumes any such effect is due to correlation and not causation. For example, bike ownership could have increased in cash villages due to a contemporaneous (and coincidental) expansion of bicycle sales points in these communities.

We run several other specifications of the general model described in Equation (9) as further robustness checks. We examine the effect of bike amongst just the control group and then just the treatment group and then the triple-difference model for just those living in Kaputa (home to 68% of bike owners). We also consider the variation of our outcome variables previously mentioned, which looks at the amounts of agricultural inputs/outputs bought/sold for everyone, with no restrictions for market activity at baseline. Finally, we run all of these model iterations using household fixed effects as well.

4.6. Results

4.6.1. Do bikes mediate the effects of cash?

We first run a series of models to test the hypothesis that bikes mediate impacts of the cash transfer. We begin by investigating whether cash "affects" bicycle ownership and do not find strong evidence that is does. While being in the cash treatment group is associated with a 5 percentage point increase in the likelihood of owning a bike (significant at the 90% level) in the pooled difference-in-difference models, this result is not robust to the inclusion of household fixed-effects. And, as Table 35 highlights, bicycle ownership dramatically increased in the control group between 2010 and 2012 as well.

We next proceed to estimate the impact of cash by itself and then test whether the inclusion of the bike variable in these equations reduces any identified impacts of cash. We find that cash increases the likelihood of purchasing agricultural inputs and selling crops, each by 11 percentage points and each significant at the 99% level. Cash also increases the likelihood of owning a non-farm business by 16 percentage points (significant at 99% level). Inclusion of the bike variable has little impact on these estimates, indicating that bikes do not mediate cash. This pattern of pooled difference-in-difference models results is robust to the inclusion of household fixed effects.[16]

4.6.2. Do bikes moderate the effects of cash?

We estimate several different versions of the model presented in Equation (9) to test for heterogeneous treatment effects, as described in Section 4.5.2. The pattern of results is similar for all model specifications (Kaputa only, control group only, treatment group only, inclusion of household fixed-effects) and provides evidence that while cash increases the likelihood of purchasing agricultural inputs, selling crops, and owning a non-farm business, it does not increase the volumes of inputs purchased or crops sold for those with such market activity at baseline. However, for those with crop sales at baseline, bicycle ownership significantly and substantially increases the value of crops sold. We do not find any evidence of multiplicative effects for bikes and cash combined and therefore cannot reject the null hypothesis that there are no differential effects of cash on market activity for bike owners.

We present here results from our preferred set of models: the pooled triple-difference models (difference-in-difference models in the case of non-farm business outcomes, for which we lack baseline data). The pooled models allow us to explicitly note the various time trends for each group (cash, bike, control) and are thus preferred over the fixed-effects models for exposition purposes. We include results for both measures of bike ownership (ownership at baseline and ownership that varies over time). Regardless of which bike measure is used, cash increases the likelihood of selling crops by 12 percentage points, of purchasing agricultural

[16]We also test for mediation when there is no baseline restriction on crop sales or agricultural input purchases. Here we do find some weak evidence of mediation. Including the bike variable reduces the effect size of cash by about 9 kwacha for crop sales and by less than 1 kwacha for agricultural input purchases. However, these models obscure the fact that while cash is causing more people to engage in market activity, market sales and purchases in fact go down, in general, over time. Therefore, our preferred models estimate effects on values sold and purchased conditional on baseline market activity.

inputs by 11-12 percentage points, and of owning a non-farm business by 14-15 percentage points (Table 39). When the time-varying measure of bikes is used, bikes increase the likelihood of purchasing agricultural inputs by a similar amount (though the effect is less significant than it is for cash). For those with agricultural input purchases at baseline, neither cash nor bikes has a significant effect on the values purchased (Table 40). However, when we apply the time-varying measure of bicycle ownership, we see that bikes significantly increase the value of crops sold for those with crop sales at baseline by 331 kwacha (Table 40). This amount is equivalent to nearly six months of Child Grant Payments or 60% of monthly consumption for a household of average size (6 members) living below the poverty line of 93.37 kwacha per person per month. All of these results are robust to the inclusion of household fixed-effects.

The impact of bikes on crop sale values is perhaps one of the more interesting results in this paper and we examine it in more detail in Table 41. In Table 41 we see that crop sales were balanced at baseline between the cash and control group, between the bike and control group, and between those with bikes in the cash group and those with bikes in the control group. We see that for those in the control group, crop sales significantly decreased over time by 148 kwacha. In the cash treatment group, sales also went down over time, but the decline is not significantly different from that experienced by the control group. Households owning bikes, however, were able to significantly increase their crop sales over time despite the downward trend.

As further robustness checks on the above results, we ran several different model specifications. When we analyze the effects of cash and bikes on crop sales without the condition of baseline market activity using the time-varying measure of bicycle ownership, we find that both bikes and cash (independently) increase the value of sales, though the impact of bikes is nearly triple that of cash. And when we include household fixed-effects, the impact of cash on crop sale volumes is no longer significant, though the positive impact of bikes remains. These results are consistent with the findings from our models that analyze the effect of bikes separately for the control and cash treatment groups. Again using the time-varying measure of bikes, we find that bike ownership increases crop sales by 321.93 kwacha (significant at the 90% level) amongst the control group but has no effect amongst the cash treatment group. This pooled model result is robust to the inclusion of household fixed-effects.

4.6.3. Causal mechanisms

We next considered variations in households' distance to markets and investigated whether there might be heterogeneous effects of bikes according to market distance (i.e., perhaps bikes are more important for market activity for those living farther from markets). We explored this question graphically to test for both marginal and threshold effects but found no graphical indication that market distance moderates the effect of bicycle ownership on any of our outcomes of interest.

Finally, we tried to investigate why it might be that bikes have an impact on crop sale volumes. One likely causal mechanism is that bikes reduce the time to market and therefore allow more market trips and/or access to markets that are farther away and might offer higher prices. In the 2012 survey, households were asked where they purchased agricultural inputs and sold crops (Table 42). Using these data we ran difference-in-difference models to see if bicycle ownership affected whether households sold crops or purchased inputs in their village or in a neighboring village/closest town. We did not find any evidence that bikes affected the location of agricultural market activity. This suggests that bikes may be facilitating higher crop sales because they are allowing for multiple market trips, rather than facilitating access to more distant markets.

4.7. Discussion and conclusions

While we do not find support for our hypothesis that bikes enable households receiving cash transfers to make more productive uses of the transfer by facilitating their market access, we do find evidence that cash and bikes are differentially effective in helping rural households increase their market activity. We find consistent evidence that the income effects of cash transfers are powerful enough to shift livelihood strategies. Cash allows households to diversify their livelihood strategies by increasing the ownership of non-farm businesses. Cash transfers can also convert subsistence farmers into small-scale farmers able to sell some of their agricultural production at markets and purchase seeds, fertilizers, and pesticides to enhance farm productivity. These changes to livelihood strategies have important implications for households' ability to avoid and escape poverty traps, especially in the context of climate change. For example, a recent study of various "climate-smart agricultural practices" in Zambia finds that "Timely access to fertilizer is the most robust determinant of yields and resilience [to weather shocks]" (Arslan et al., 2015, p. v).

We also find consistent evidence that bikes enable those already engaged in agricultural markets to increase their crop sales over time, even in the context of declining crop revenues. This finding provides suggestive evidence that bikes may be an important asset for helping households maintain self-propelled growth trajectories in the context of repeated negative shocks that risk trapping households in poverty. Further research could test this hypothesis more explicitly by using at least three time periods of data and testing whether bicycle ownership marks a critical threshold for how households respond to shocks, in both consumption and production.

Our analysis also leads us to make a methodological conclusion. Our study shows that it is important to distinguish between agricultural market activity, in and of itself, and changes in volumes traded in markets when analyzing the effect of programs in economies dominated by subsistence farming. The transition from growing crops for pure subsistence to growing crops for both consumption and income marks an important shift in the development of rural agricultural economies. This impact of programs can be missed if market participation is not analyzed independently. Additionally, examining just changes in volumes of agricultural goods traded can mask the differential effects of programs on (a) enabling participation in agricultural markets versus (b) increasing trade amongst those already engaged in markets. For example, in our study, agricultural sales went down, in general, over time, but because the cash transfer program increased household's ability to sell crops, analyzing just the effect of cash on the value of sales would fail to identify these two different dynamics and lead to the conclusion that the program increased crop sales (when in fact it just increased the number of sellers).

Finally, it should be noted that this study was powered to test the effects of cash – not the effects of bikes. The number of households owning bikes in our sample is quite small and the inability to detect significant impacts of bikes on outcomes other than crop sales – or multiplicative effects of bikes and cash – can not be taken as definitive.

REFERENCES

Arslan, A., N. McCarthy, L. Lipper, S. Asfaw, A. Cattaneo, and M. Kokwe. 2015. Food security and adaptation impacts of potential climate smart agricultural practices in Zambia. FAO: Rome.

Barrett, C.B. and B.M. Swallow. 2005. Fractal poverty traps. World Development 34(1): 1–15.

Carter, M.R. and C.B. Barrett. 2006. The economics of poverty traps and persistent poverty: An asset-based approach. Journal of Development Studies 42(2): 187-199.

Carter, M.R. and C.B. Barrett. 2007. Asset thresholds and social protection: A ‘think-piece.’ Institute of Development Studies (IDS) Bulletin 38(3): 34-38.

Dercon, S. 2007. Comment on poverty traps and social protection policy. Institute of Development Studies (IDS) Bulletin 38(3): 39-42.

Gitter, S.R. and B.L. Barham. 2009. Conditional cash transfers, shocks, and school enrolment in Nicaragua. Journal of Development Studies 45(10): 1747-1767.

Glewwe, P., H. Jacoby, and E. King. 2000. Early childhood nutrition and academic achievement: a longitudinal analysis. Journal of Public Economics 81: 345-368.

Handa, S. and B. Davis. 2006. The experience of conditional cash transfers in Latin America and the Caribbean. Development Policy Review 24(5): 513-536.

Handa, S., D. Seidenfeld, B. Davis, G. Tembo and the Zambia Cash Transfer Evaluation Team. 2014. Are cash transfers a silver bullet? Evidence from the Zambian Child Grant. Innocenti Working Paper no. 2014-08. UNICEF Office of Research: Florence.

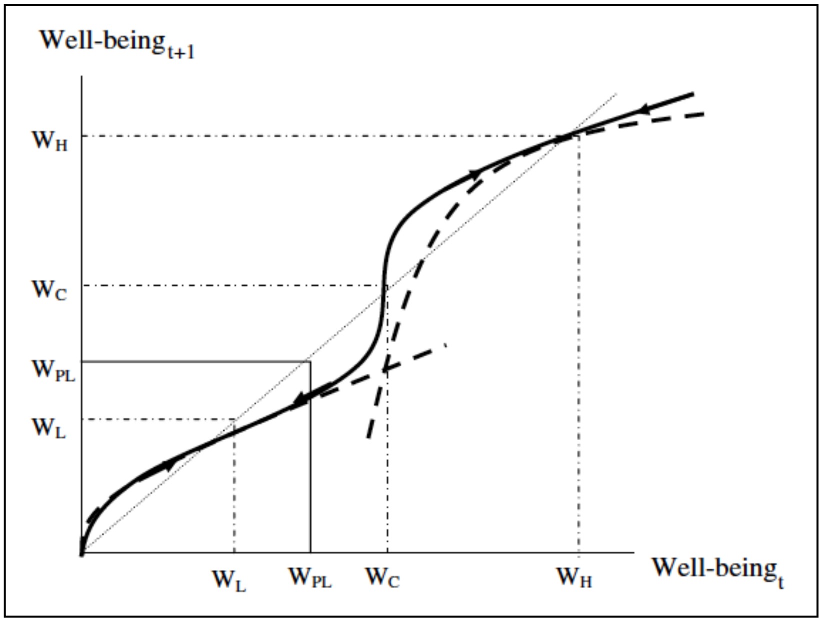
Rawlings, L.B. and G.M. Rubio. 2005. Evaluating the impact of conditional cash transfer programs. The World Bank Research Observer 20(1): 29-55.

World Bicycle Relief. 2010a. Mobility=Education: Report on the *Bicycle for Educational Empowerment Program*. Available at: http://worldbicyclerelief.org/pages/impact

World Bicycle Relief. 2010b. Mobility=Market Access: Smallholder Dairy Farmers in Rural Zambia Report on Using World Bicycle Relief Bicycles to Bring Goods to Market. Available at: http://worldbicyclerelief.org/pages/impact

APPENDIX 1: FIGURES

Figure 1. Welfare dynamics under the poverty trap hypothesis



From Barrett and Swallow (2005), p. 4

Figure 2. Heterogeneous impacts of cash on decision to use fuelwood by market distance in 2012

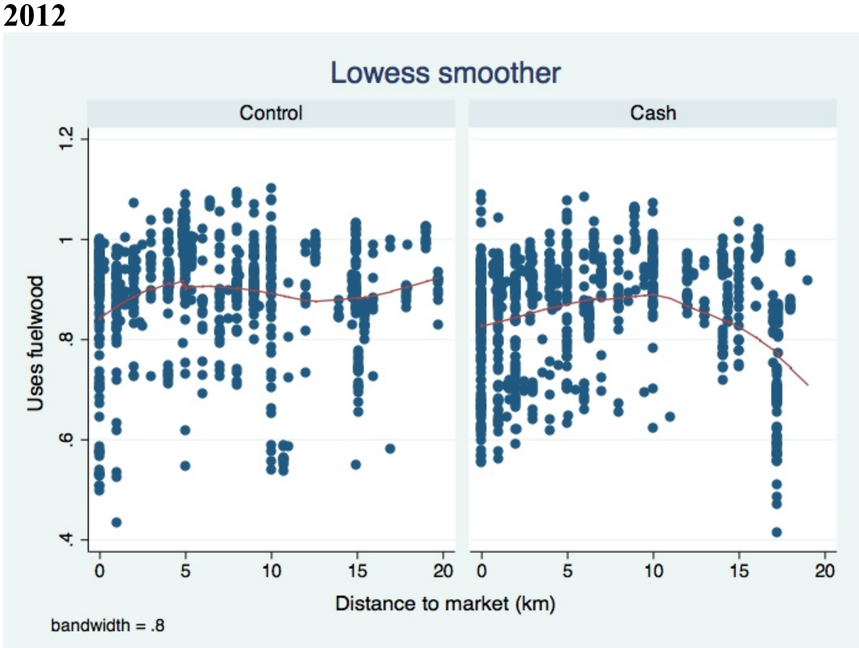


Figure 3. Heterogeneous impacts of cash on per capita fuelwood consumption by market distance in 2012

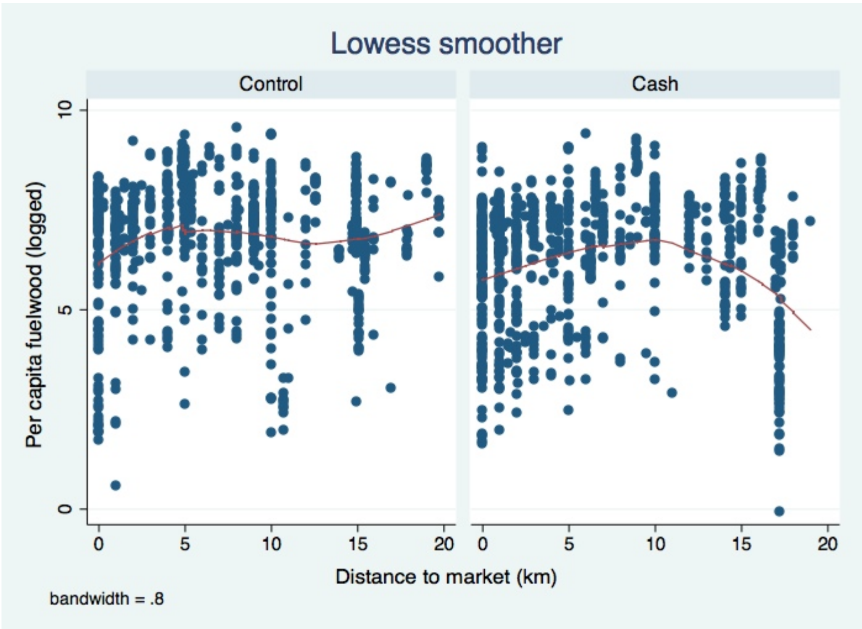


Figure 4. Heterogeneous impacts of cash on decision to use charcoal by market distance in 2012

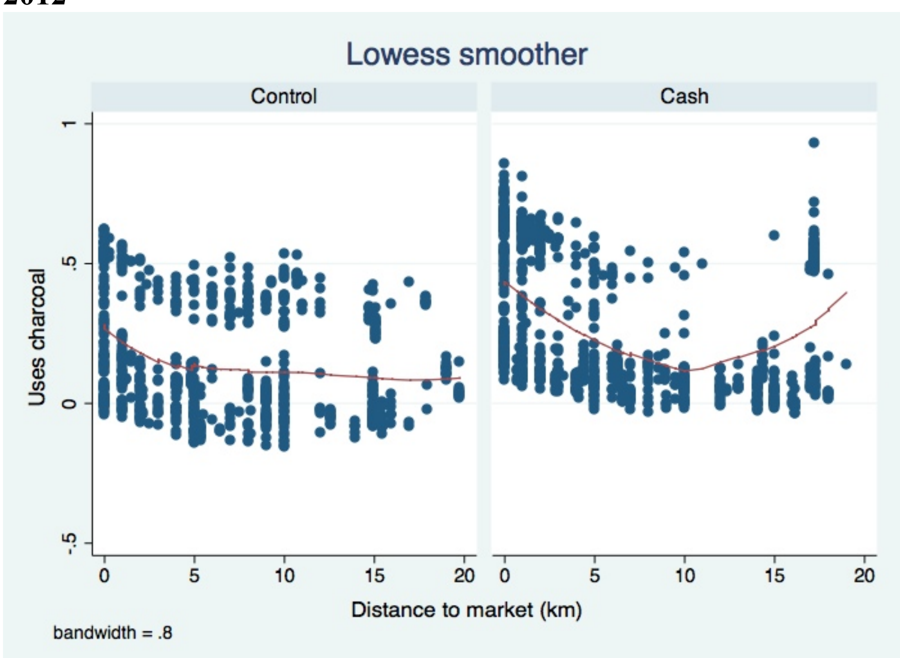


Figure 5. Heterogeneous impacts of cash on per capita charcoal consumption by market distance in 2012

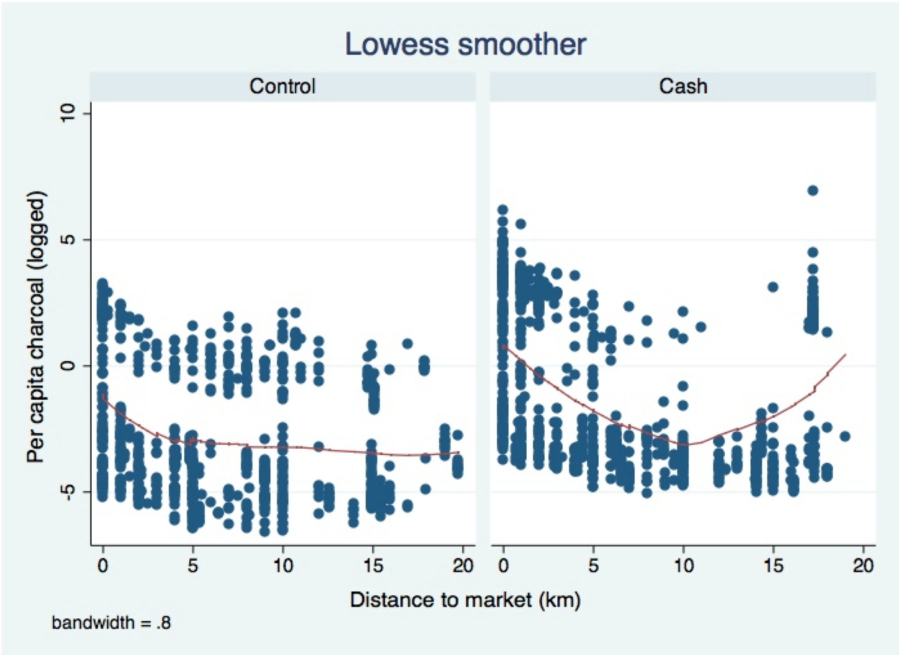


Figure 6. Heterogeneous impacts of cash on decision to consume bushmeat by market distance in 2012

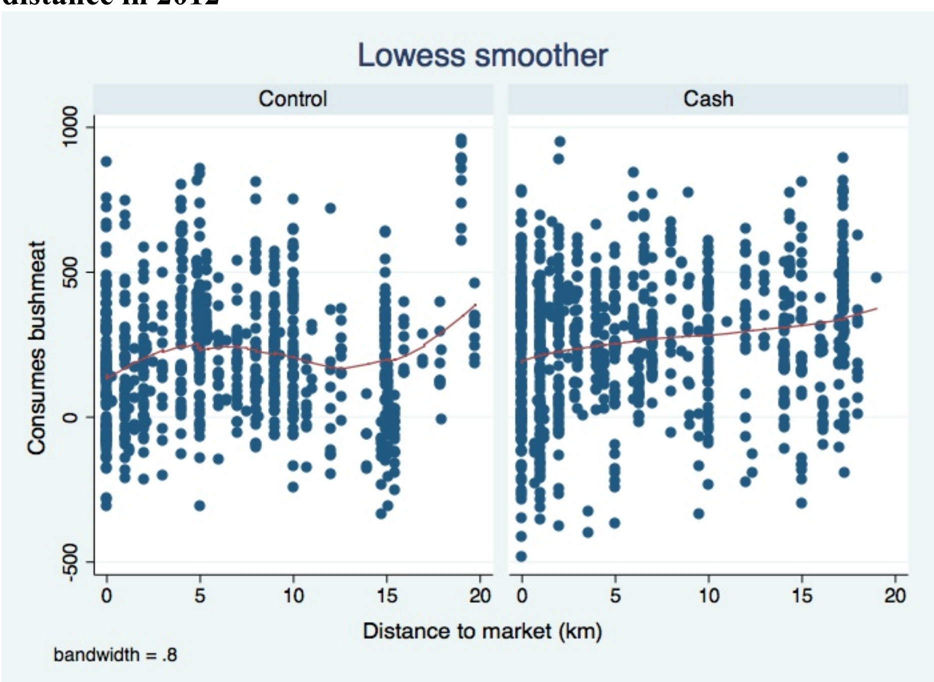


Figure 7. Heterogeneous impacts of cash on per capita bushmeat consumption by market distance in 2012

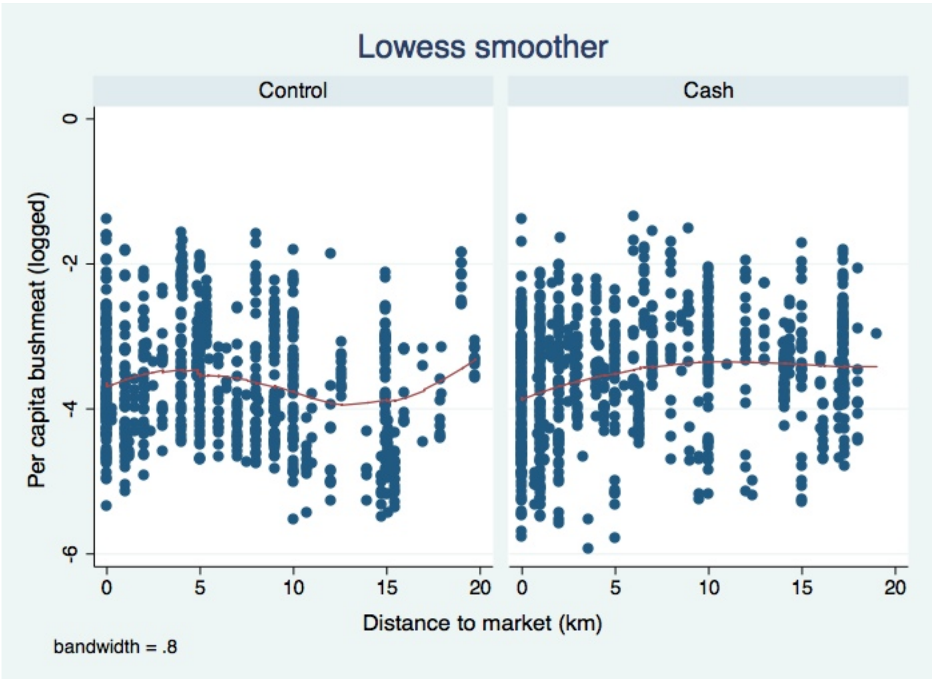


Figure 8. Heterogeneous impacts of cash on decision to farm by market distance in 2012

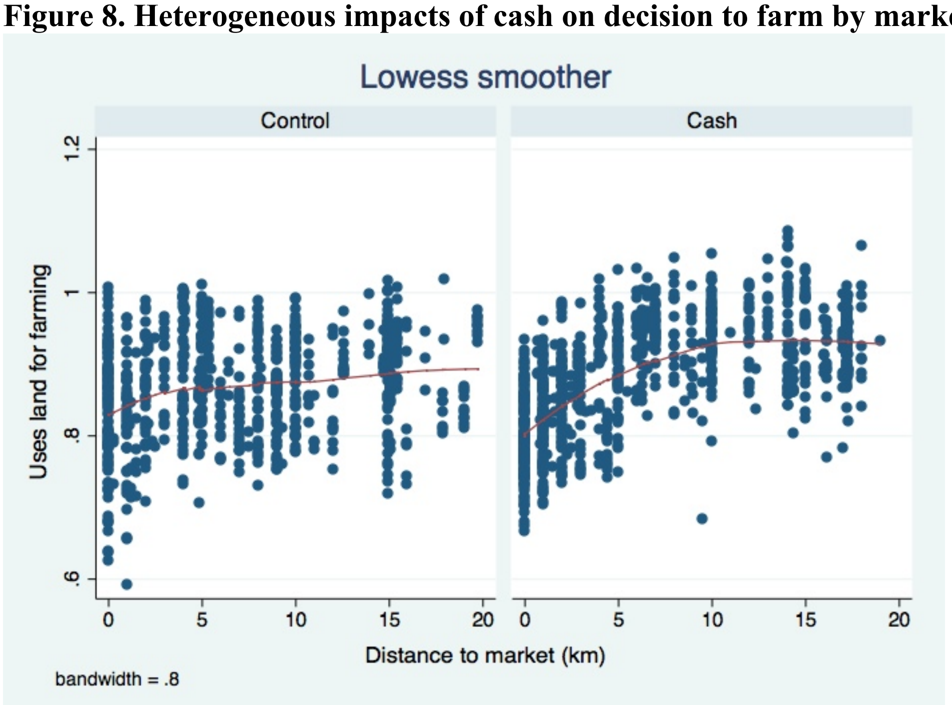


Figure 9. Heterogeneous impacts of cash on per capita area farmed by market distance in 2012

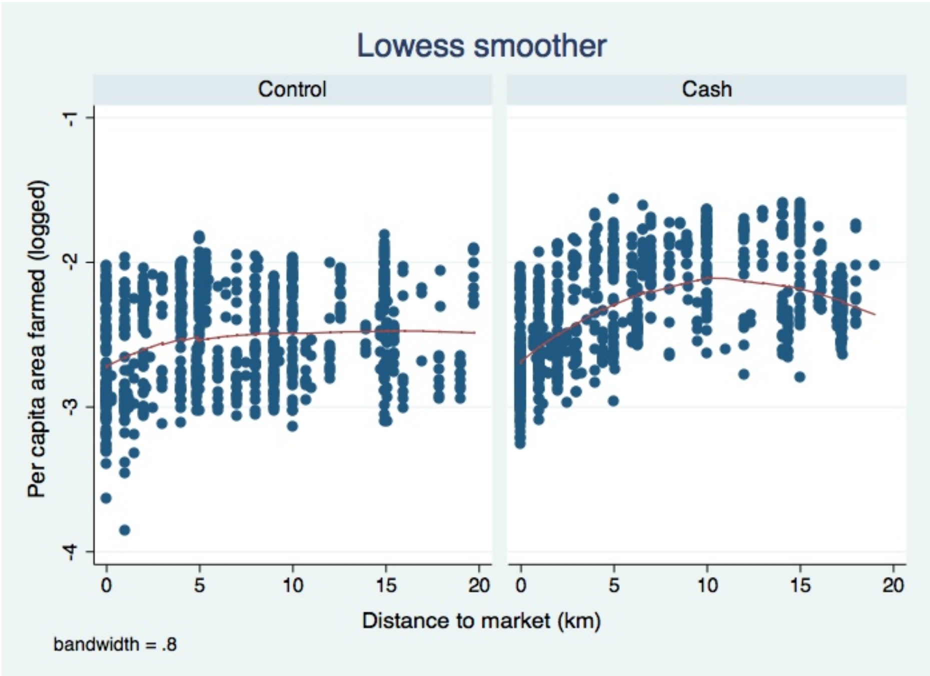


Figure 10. Heterogeneous impacts of cash on per capita area farmed by market distance for non-farm business owners in 2012

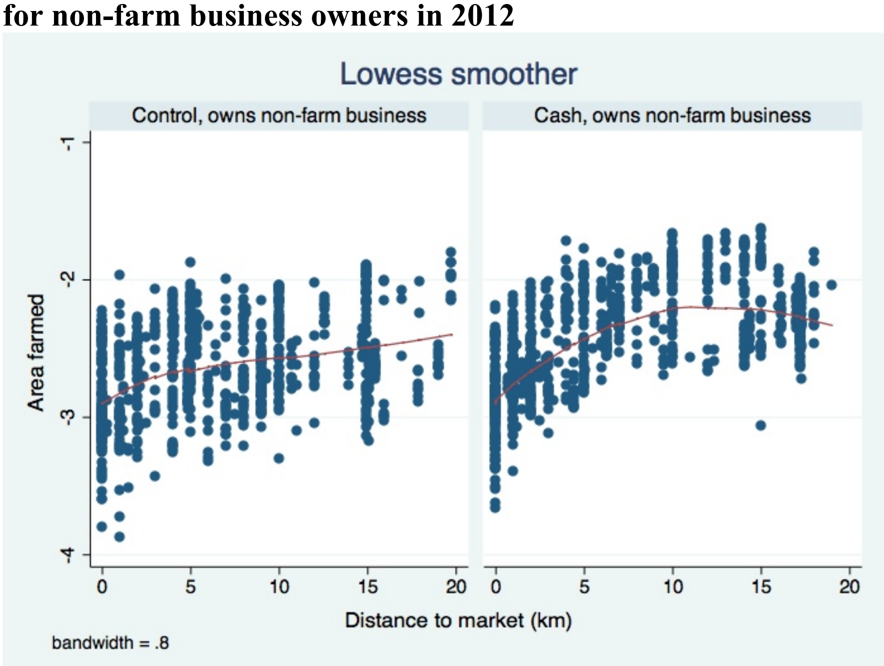


Figure 11. Heterogeneous impacts of cash on ownership of non-farm businesses by market distance in 2012

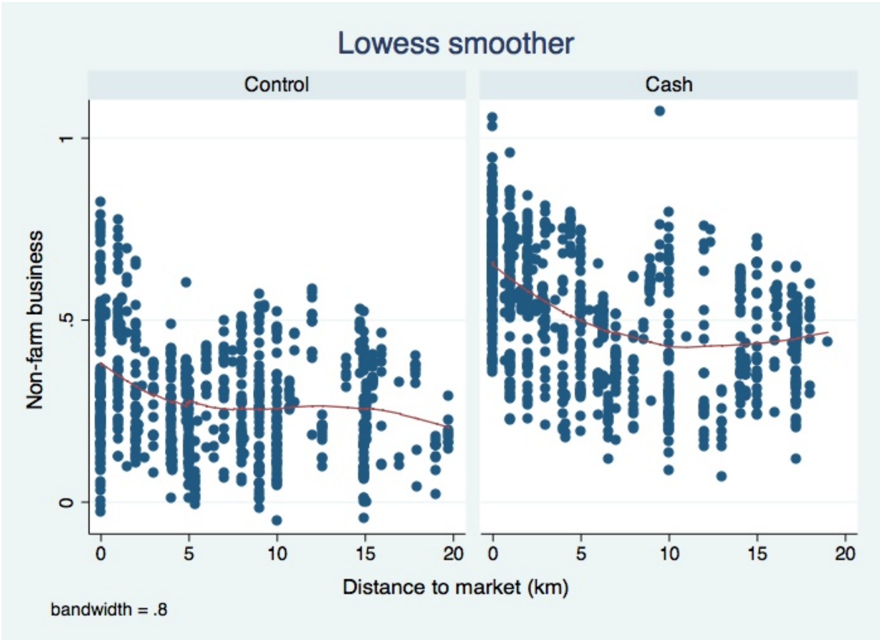
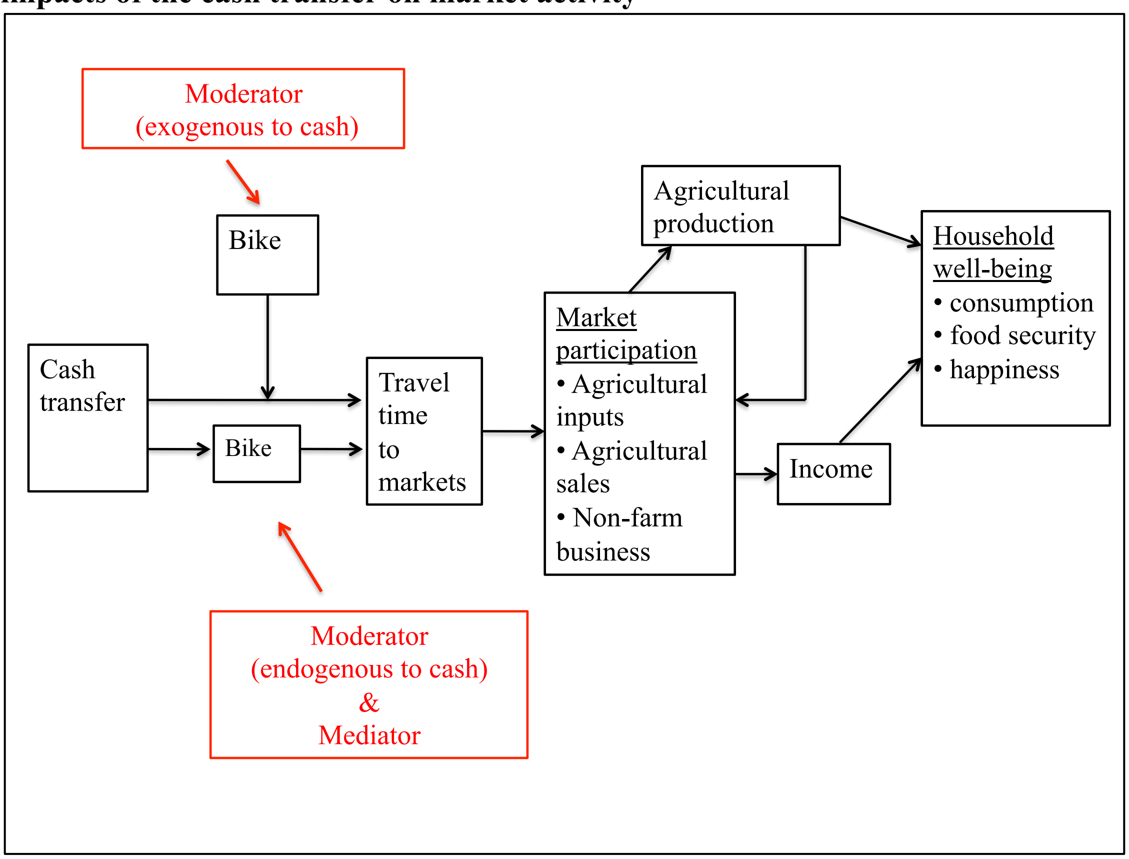


Figure 12. Theory of change: Potential role of bikes in both mediating and moderating impacts of the cash transfer on market activity



APPENDIX 2: TABLES

Table 1. Study sample sizes[1]

	Treatment	Control	Total
2010	1,259	1,260	2,519
2012	1,145	1,153	2,298
Total	2,404	2,413	4,817

[1] 221 households migrated out of the sample

Table 2. Shocks experienced during 12 months prior to collection of baseline data in 2010 and round 2 in 2012

	2010			2012		
	Full sample (n=2,519)	Treatment (n=1,260)	Control (n=1,259)	Full sample (n=2,298)	Treatment (n=1,153)	Control (n=1,145)
No shock	922 (37)%	476 (38)%	446 (35%)	341 (15%)	169 (15%)	172 (15%)
Any shock	1,597 (63%)	784 (62%)	813 (65%)	1,957 (85%)	984 (85%)	973 (85%)
Agricultural production and price shocks	1319 (52%)	614 (49%)	705 (56%)	1852 (81%)	939 (81%)	913 (80%)
Weather shocks	1058 (42%)	484 (38%)	574 (46%)	1632 (71%)	828 (72%)	804 (70%)
Crop and price shocks	740 (29%)	352 (28%)	388 (31%)	1404 (61%)	681 (59%)	723 (63%)
Asset, labor, and other income shocks	694 (28%)	357 (28%)	337 (27%)	822 (36%)	380 (33%)	442 (39%)

Table 3. Specific shocks experienced

	2010			2012		
Negative Shocks	Full sample (n=2,519)	Treatment (n=1,260)	Control (n=1,259)	Full sample (n=2,298)	Treatment (n=1,153)	Control (n=1,145)
Agricultural production and price shocks						
Flood	851	375	476	690	382	308
	(34%)	(30%)	(38%)	(30%)	(33%)	(27%)
Food price change	368	180	188	813	401	412
	(15%)	(14%)	(15%)	(35%)	(35%)	(36%)
Drought	318	160	158	1080	536	544
	(13%)	(13%)	(13%)	(47%)	(46%)	(48%)
Crop disease/pests	172	88	84	244	115	129
	(7%)	(7%)	(7%)	(11%)	(10%)	(11%)
Storms	95	43	52	63	17	46
	(4%)	(3%)	(4%)	(3%)	(1%)	(4%)
Crop price change	78	25	53	174	80	94
	(3%)	(2%)	(4%)	(8%)	(7%)	(8%)
Crops damaged in storage	62	30	32	59	27	32
	(2%)	(2%)	(3%)	(3%)	(2%)	(3%)
Input price change	60	29	31	114	58	56
	(2%)	(2%)	(2%)	(5%)	(5%)	(5%)
Asset, labor, and other income shocks						
Illness	468	243	225	504	210	294
	(19%)	(19%)	(18%)	(22%)	(18%)	(26%)
Business collapse	97	50	47	37	22	15
	(4%)	(4%)	(4%)	(2%)	(2%)	(1%)
Death other member	74	36	38	107	55	52
	(3%)	(3%)	(3%)	(5%)	(5%)	(5%)
Death household head	65	30	35	30	15	15
	(3%)	(2%)	(3%)	(1%)	(1%)	(1%)
Livestock disease	51	23	28	250	119	131
	(2%)	(2%)	(2%)	(11%)	(10%)	(11%)
Person joined household	39	21	18	50	24	26
	(2%)	(2%)	(1%)	(2%)	(2%)	(2%)
Injury	37	20	17	13	6	7
	(1%)	(2%)	(1%)	(1%)	(1%)	(1%)
Inability to pay back loan	19	10	9	4	3	1
	(1%)	(1%)	(1%)	(<1%)	(<1%)	(<1%)
Less loans/gifts	11	6	5	9	4	5
	(<1%)	(<1%)	(<1%)	(<1%)	(<1%)	(<1%)
Job loss	9	6	3	11	6	5
	(<1%)	(<1%)	(<1%)	(<1%)	(1%)	(<1%)
Conflict	8	1	7	18	12	6
	(<1%)	(<1%)	(1%)	(1%)	(1%)	(1%)

Table 4. Covariance of shocks: Average percent reporting the shock within a community cluster, averaged across communities

	2010			2012		
Negative shocks	Full sample (n=90)	Treatment (n=45)	Control (n=45)	Full sample (n=90)	Treatment (n=45)	Control (n=45)
Any shock	63%	62%	65%	85%	85%	85%
Agricultural production and price shocks						
Flood	34%	30%	38%	29%	32%	26%
Food price change	15%	14%	15%	36%	35%	36%
Drought	13%	13%	13%	47%	47%	47%
Crop disease/pests	7%	7%	7%	10%	10%	11%
Storms	4%	3%	4%	3%	2%	4%
Crop price change	3%	2%	4%	8%	7%	8%
Crops damaged in storage	2%	2%	3%	3%	2%	3%
Input price change	2%	2%	2%	5%	5%	5%
Asset, labor, and other income shocks						
Illness	19%	20%	18%	22%	18%	26%
Business collapse	4%	4%	4%	2%	2%	1%
Death other member	3%	3%	3%	5%	5%	5%
Death household head	3%	2%	3%	1%	1%	1%
Livestock disease	2%	2%	2%	11%	11%	12%
Person joined household	2%	2%	1%	2%	2%	3%
Injury	1%	2%	1%	1%	1%	1%
Inability to pay back loan	1%	1%	1%	<1%	<1%	<1%
Less loans/gifts	<1%	<1%	<1%	<1%	<1%	<1%
Job loss	<1%	<1%	<1%	<1%	1%	<1%
Conflict	<1%	<1%	<1%	<1%	<1%	<1%

Table 5. Coping strategies employed by households experiencing negative shocks

Coping strategy	2010 Full sample (n=1,597)	2010 Treatment (n=784)	2010 Control (n=813)	2012 Full sample (n=1,957)	2012 Treatment (n=984)	2012 Control (n=973)
Coping strategies associated with poverty traps						
Did nothing	664 (42%)	288 (37%)	376 (46%)	988 (62%)	457 (46%)	531 (55%)
Piece work for others (farm or non-farm)	642 (40%)	313 (40%)	329 (40%)	645 (33%)	314 (32%)	331 (34%)
Reduced food consumption	228 (14%)	113 (14%)	115 (14%)	223 (11%)	93 (9%)	130 (13%)
Sold assets	40 (3%)	20 (3%)	20 (2%)	64 (3%)	26 (3%)	38 (4%)
Sent kids to relatives/friends	26 (2%)	14 (2%)	12 (1%)	18 (1%)	9 (1%)	9 (1%)
Sent kids to work/sell	5 (<1%)	2 (<1%)	3 (<1%)	0	0	0
Other coping strategies						
Loans/gifts from family, friends, or lender	394 (25%)	174 (22%)	220 (27%)	274 (14%)	131 (13%)	143 (15%)
Worked more hours, grew/sold more crops, or started a business	325 (20%)	175 (22%)	150 (18%)	371 (19%)	208 (21%)	163 (17%)
Sought help from government, NGO, or clinic	244 (15%)	129 (16%)	115 (14%)	235 (12%)	95 (10%)	140 (14%)
Spent savings	185 (12%)	83 (11%)	102 (13%)	275 (14%)	169 (17%)	105 (11%)
Work-for-food or Work-for-assets program	140 (9%)	64 (8%)	76 (9%)	72 (4%)	40 (4%)	32 (3%)
Reduced non-food expenses	136 (9%)	74 (10%)	62 (8%)	291 (15%)	160 (16%)	131 (13%)
Migrated for work or moved house/field	47 (3%)	16 (2%)	31 (4%)	16 (1%)	10 (1%)	6 (1%)
Used cash transfer	0	0	0	0	25 (3%)	0

Table 6. Mean characteristics and equivalence at baseline tests for full panel as well as four shock sub-group panels in 2010[1]

	Full Panel		No shock either round		Shock round 1 only		Shock round 2 only		Shocked both rounds	
	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
Sample size	(1,153)	(1,145)	(55)	(67)	(114)	(105)	(373)	(337)	(611)	(636)
Recipient characteristics										
Age	30	30	28	30	31	30	30	29	30	30
Attended school	73%	70%	78%*	62%*	72%	76%	71%	66%	75%	72%
Married	74%	71%	71%	64%	74%	66%	79%	75%	71%	71%
Male	1.2%	0.5%	0%	0%	3%*	0%*	1%*	0%*	1%	1%
Household characteristics										
Wealth index	0.002	-0.04	-0.12	-0.04	0.08	-0.06	0.05	-0.06	-0.03	-0.02
Below 2010 poverty line	92%	92%	93%	96%	85%	89%	94%	94%	92%	91%
Household size	6	6	6	5	6	6	6	6	6	6
Members age 0-5	2	2	2	2	2	2	2	2	2	2
Members age 6-12	1	1	1	1	1	1	1	1	1	1
Members age 13-18	1	1	1	0	1	1	1	1	1	1
Members age 19-35	1	1	1	1	1	1	1	1	1	1
Members age 36-55	1	1	0	0	1	1	1	1	1	1
Members age 56-79	0	0	0	0	0	0	0	0	0	0
Members 70+	0	0	0	0	0	0	0	0	0	0
Kilometers to food market	16	22	23	34	20	30	14*	23*	16	19
Percent from each district										
Kaputa	30%	29%	33%	48%	24%	38%	39%	39%	25%	21%
Kalabo	35%	35%	29%	36%	50%	44%	23%	25%	41%	39%
Shang'ombo	35%	35%	38%	16%	26%	18%	39%	36%	34%	40%
Revealed coping strategies										
Monthly per capita food consumption (kwacha)	30.16	28.50	24.03	24.89	40.73***	32.57***	26.61	26.58	31.71	29.60
Severely food insecure	90%	90%	96%	88%	87%	92%	91%	90%	89%	90%

[1]All samples restricted to those who remain in the panel survey in 2012. Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Revealed coping strategy regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size and demographic composition, distance to food market), district fixed effects and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significantly different from control group at the 99% level, ** at the 95% level, and * at the 90% level

Table 7. Equivalence at baseline tests for full panel's exposure to shocks and stated coping strategies in 2010[1,2]

	Significantly different for treatment households
Shocks	
Agricultural production or price shock	7 percentage points less likely*
Asset, labor, and other income shock	
Any shock	
Stated coping strategies associated with poverty traps	
Did nothing	9 percentage points less likely** (Other Shocks)
Piece work for others (farm or non-farm)	9 percentage points more likely* (Other Shocks)
Reduced food consumption	
Other stated coping strategies	
Loans/gifts from family, friends, or lender	10 percentage points less likely** (Other Shocks)
Worked more hours, grew/sold more crops, or started a business	5 percentage points more likely* (Ag/Price Shocks)
Sought help from government, NGO, or clinic	
Spent savings	
Work-for-food or Work-for-assets program	3 percentage points more likely* (Other Shocks)
Reduced non-food expenses	3 percentage points more likely* (Ag/Price Shocks)

[1]Sample restricted to those who remain in the panel survey in 2012. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size and demographic composition, distance to food market), district fixed effects and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). Robust standard errors are clustered at the community level to account for the clustered randomized design. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Analysis restricted to those coping strategies employed by 5% or more of households in at least one of the four time/treat sub-groups (i.e., 2010 control group that experienced shock, 2010 treatment group that experienced shock, etc.).

Table 8. Equivalent time trends between treatment and control households with respect to shock exposure[1]

	Dependent variables (1/0 – Linear probability models)		
	Agricultural production or price shock	*Asset, labor, and other income shock*	*Any shock*
Constant	0.54***	0.12	0.57***
	(0.13)	(0.12)	(0.12)
Time	0.24***	0.12***	0.20***
	(0.04)	(0.05)	(0.03)
Treatment household	-0.08**	0.002	-0.04
	(0.04)	(0.03)	(0.04)
Treatment household * Time	0.08	-0.07	-0.02
	(0.05)	(0.06)	(0.05)
Recipient characteristics			
Age	0.001	0.002*	0.002
	(0.001)	(0.001)	(0.001)
Attended school	0.05***	0.03	0.05***
	(0.02)	(0.02)	(0.01)
Married	0.03	-0.02	0.001
	(0.02)	(0.02)	(0.02)
Household characteristics			
Wealth index	-0.01	0.03***	0.003
	(0.01)	(0.01)	(0.01)
Household size	0.002	-0.03	0.003
	(0.02)	(0.02)	(0.02)
Members age 0-5	0.0002	0.03	-0.003
	(0.02)	(0.02)	(0.02)
Members age 6-12	-0.01	0.05**	-0.002
	(0.02)	(0.02)	(0.02)
Members age 13-18	-0.01	0.02	-0.02
	(0.02)	(0.03)	(0.02)
Members age 19-35	-0.01	0.01	-0.005
	(0.02)	(0.02)	(0.02)
Members age 36-55	0.02	0.005	0.02
	(0.02)	(0.02)	(0.02)
Kilometers to food market (logged)	-0.02*	-0.03**	-0.02**
	(0.01)	(0.01)	(0.01)
Regional characteristics			
Kaputa District	-0.22***	-0.01	-0.16***
	(0.04)	(0.04)	(0.04)
Shangombo District	-0.03	0.05	0.005
	(0.04)	(0.05)	(0.04)
N	4518	4518	4518

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

Table 9. The impact of cash on coping strategies associated with poverty traps amongst households experiencing negative income shocks in the 12 months prior to collection of round 2 data in 2012[1,2]

Dependent variable: coping strategy employed (1) – Linear probability model

	Did Nothing	*Piece work for others*	*Reduced food consumption*
	Ag/Price	Ag/Price	Ag/Price
Constant	0.87***	0.19	0.03
	(0.18)	(0.14)	(0.15)
Cash	**-0.14*** **	0.01	-0.03
	(0.04)	(0.03)	(0.03)
Recipient characteristics			
Age	-0.001	-0.001	0.002
	(0.002)	(0.001)	(0.001)
Attended school	0.01	-0.04*	0.007
	(0.02)	(0.02)	(0.02)
Married	-0.02	0.02	0.02
	(0.03)	(0.02)	(0.02)
Household characteristics			
Wealth index	-0.01	-0.02*	-0.01*
	(0.01)	(0.01)	(0.01)
Household size	-0.04	0.04	-0.03
	(0.04)	(0.03)	(0.02)
Members age 0-5	0.05	-0.05	0.04
	(0.04)	(0.03)	(0.02)
Members age 6-12	0.05	-0.03	0.03
	(0.04)	(0.03)	(0.02)
Members age 13-18	0.04	-0.04	0.04
	(0.04)	(0.03)	(0.03)
Members age 19-35	0.05	-0.04	0.03
	(0.04)	(0.03)	(0.03)
Members age 36-55	0.05	-0.04	0.02
	(0.04)	(0.04)	(0.03)
Kilometers to food market (logged)	0.004	-0.001	0.02**
	(0.01)	(0.01)	(0.01)
Regional characteristics			
Kaputa	0.15**	-0.11***	-0.10*
	(0.06)	(0.03)	(0.05)
Shangombo	-0.49***	0.45***	0.02
	(0.06)	(0.05)	(0.05)
N	1823	1823	1823

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

[2]Analysis restricted to those coping strategies (1) employed by 5% or more of households in at least one of the four time/treat sub-groups (i.e., 2010 control group that experienced shock, 2010 treatment group that experienced shock, etc.) and (2) balanced at baseline. No coping strategies associated with poverty traps met these criteria in the case of non-agricultural/price shocks.

Table 10. The impact of cash on coping strategies not associated with poverty traps amongst households experiencing negative income shocks in the 12 months prior to collection of round 2 data in 2012[1,2]

Dependent variable: coping strategy employed (1) – Linear probability model

	Loans or gifts	*Grew/sold additional crops, worked more, started business*	*Sought help from government or NGO*		*Spent savings*		*Work-for-food/ Work-for-assets*
	Ag/Price	Other	Ag/Price	Other	Ag/Price	Other	Ag/Price
Constant	0.005	-0.04	0.02	0.15	-0.02	0.04	-0.03
	(0.10)	(0.12)	(0.02)	(0.21)	(0.09)	(0.17)	(0.08)
Cash	0.002	0.03	**0.02****	**0.12****	**0.06*****	0.04	0.0004
	(0.02)	(0.03)	(0.01)	(0.06)	(0.02)	(0.04)	(0.01)
Recipient characteristics							
Age	0.002**	0.002	0.003	0.0002	0.0001	0.0003	-0.001
	(0.001)	(0.002)	(0.0003)	(0.002)	(0.001)	(0.002)	(0.001)
Attended school	0.02	0.03	0.004	-0.07**	-0.003	-0.03	0.01
	(0.02)	(0.02)	(0.007)	(0.03)	(0.02)	(0.03)	(0.01)
Married	-0.01	-0.08***	-0.003	0.06	-0.001	0.04	-0.01
	(0.02)	(0.03)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
Household characteristics							
Wealth index	0.0002	0.0003	-0.002	-0.02	0.03***	0.02*	-0.01*
	(0.005)	(0.01)	(0.001)	(0.02)	(0.01)	(0.01)	(0.003)
Household size	-0.03	-0.02	-0.01*	-0.07**	-0.002	0.001	0.01
	(0.02)	(0.03)	(0.004)	(0.03)	(0.03)	(0.03)	(0.01)
Members age 0-5	0.03	-0.002	0.004	0.08**	-0.01	-0.01	-0.004
	(0.02)	(0.03)	(0.004)	(0.03)	(0.03)	(0.04)	(0.01)
Members age 6-12	0.02	0.03	0.006*	0.08**	0.01	0.0002	-0.02
	(0.02)	(0.03)	(0.003)	(0.04)	(0.03)	(0.04)	(0.01)
Members age 13-18	0.03	0.03	0.01	0.08**	-0.001	0.002	-0.01
	(0.02)	(0.04)	(0.005)	(0.03)	(0.03)	(0.04)	(0.01)
Members age 19-35	0.02	0.04	0.01*	0.04	-0.01	0.01	-0.01
	(0.02)	(0.04)	(0.01)	(0.03)	(0.03)	(0.04)	(0.02)
Members age 36-55	0.01	0.04	0.01*	0.0001	-0.01	-0.004	-0.0002
	(0.02)	(0.04)	(0.004)	(0.03)	(0.03)	(0.04)	(0.01)
Kilometers to food market (logged)	-0.01	0.01	0.003	-0.03	0.02***	-0.01	0.002
	(0.01)	(0.01)	(0.002)	(0.02)	(0.01)	(0.02)	(0.004)
Regional characteristics							
Kaputa	-0.05*	-0.04	-0.003	-0.20***	-0.01	-0.06	-0.001
	(0.03)	(0.04)	(0.005)	(0.07)	(0.03)	(0.06)	(0.01)

Shangombo	-0.01	0.14**	0.01	0.09	0.02	-0.10*	0.08***
	(0.04)	(0.06)	(0.01)	(0.08)	(0.03)	(0.06)	(0.02)
N	1823	809	1823	809	1823	809	1823

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

[2]Analysis restricted to those coping strategies (1) employed by 5% or more of households in at least one of the four time/treat sub-groups (i.e., 2010 control group that experienced shock, 2010 treatment group that experienced shock, etc.) and (2) balanced at baseline.

Table 11. The impact of cash on food consumption amongst households experiencing and avoiding negative income shocks[1,2]

Dependent variable: Per capita food consumption (logged)

	No shock either round	*Shock round 2 only*	*Shock both rounds*
Constant	10.5***	10.4***	10.7***
	(0.49)	(0.25)	(0.22)
Time	0.39***	0.26***	0.10
	(0.09)	(0.08)	(0.06)
Cash	0.07	-0.03	0.04
	(0.17)	(0.06)	(0.06)
Cash*Time	**0.31***	**0.35*****	**0.29*****
	(0.17)	(0.10)	(0.09)
Recipient characteristics			
Age	0.01	0.005*	0.0004
	(0.01)	(0.002)	(0.002)
Attended school	0.06	0.08**	0.11***
	(0.11)	(0.04)	(0.04)
Married	-0.10	-0.01	0.05
	(0.09)	(0.05)	(0.04)
Household characteristics			
Wealth index	0.11	0.15***	0.16***
	(0.07)	(0.02)	(0.02)
Household size	-0.12	-0.01	-0.05
	(0.12)	(0.05)	(0.04)
Members age 0-5	-0.08	-0.11*	-0.10**
	(0.12)	(0.06)	(0.05)
Members age 6-12	-0.05	-0.11*	-0.08*
	(0.12)	(0.06)	(0.04)
Members age 13-18	0.04	-0.01	-0.05
	(0.14)	(0.06)	(0.05)
Members age 19-35	0.18	-0.03	-0.06
	(0.13)	(0.06)	(0.05)
Members age 36-55	0.15	-0.03	-0.01
	(0.11)	(0.06)	(0.05)
Kilometers to food market	-0.02	0.02	0.03*
(logged)	(0.04)	(0.02)	(0.02)
Regional characteristics			
Kaputa	-0.38**	-0.22***	-0.20***
	(0.16)	(0.08)	(0.07)
Shangombo	-0.45***	-0.31***	-0.24***
	(0.12)	(0.06)	(0.07)
N	240	1393	2455

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

[2]Analysis restricted to those shock groups balanced at baseline along per capita food consumption.

Table 12. The impact of cash on food security amongst households experiencing and avoiding negative income shocks[1]

Dependent variable: Severely food insecure (1) – Linear Probability Model				
	No shock either round	*Shock round 1 only*	*Shock round 2 only*	*Shock both rounds*
Constant	1.40***	1.0***	0.94***	1.17***
	(0.25)	(0.18)	(0.10)	(0.11)
Time	-0.05	-0.08	-0.04	-0.07**
	(0.08)	(0.05)	(0.03)	(0.03)
Cash	0.05	-0.01	0.03	0.01
	(0.07)	(0.05)	(0.03)	(0.04)
Cash*Time	**-0.24****	-0.0004	**-0.25*****	**-0.20*****
	(0.11)	(0.07)	(0.04)	(0.04)
Recipient characteristics				
Age	-0.004	0.002	0.004***	0.0005
	(0.004)	(0.002)	(0.001)	(0.001)
Attended school	0.05	-0.01	-0.001	-0.05**
	(0.07)	(0.04)	(0.02)	(0.02)
Married	-0.03	0.004	-0.05*	-0.03*
	(0.05)	(0.05)	(0.03)	(0.02)
Household characteristics				
Wealth index	-0.04	-0.04**	-0.03***	-0.04***
	(0.02)	(0.02)	(0.01)	(0.01)
Household size	0.05	0.05	-0.01	-0.01
	(0.09)	(0.04)	(0.04)	(0.03)
Members age 0-5	-0.12	-0.02	0.04	0.06**
	(0.09)	(0.04)	(0.04)	(0.03)
Members age 6-12	-0.03	-0.02	0.02	0.02
	(0.09)	(0.05)	(0.03)	(0.03)
Members age 13-18	-0.09	-0.07	0.01	0.04
	(0.11)	(0.05)	(0.04)	(0.03)
Members age 19-35	-0.05	-0.07	0.04	-0.003
	(0.10)	(0.05)	(0.04)	(0.03)
Members age 36-55	-0.03	-0.05	0.004	-0.02
	(0.08)	(0.04)	(0.04)	(0.03)
Kilometers to food market (logged)	-0.04*	-0.003	-0.001	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)
Community characteristics				
Kaputa	0.09	0.01	0.01	-0.01
	(0.10)	(0.06)	(0.04)	(0.04)
Shangombo	-0.04	-0.15*	-0.02	-0.13***
	(0.09)	(0.09)	(0.06)	(0.04)
N	240	428	1385	2445

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

Table 13. The impact of cash on food consumption amongst households experiencing and avoiding negative income shocks, controlling for the effect of shock covariance[1,2]

Dependent variable: Per capita food consumption (logged)	*No shock either round*	*Shock round 2 only*	*Shock both rounds*
Constant	10.3***	10.2***	10.5***
	(0.50)	(0.27)	(0.22)
Time	0.35***	0.16**	0.05
	(0.09)	(0.08)	(0.06)
Cash	0.06	-0.03	0.06
	(0.16)	(0.06)	(0.06)
Cash*Time	**0.31***	**0.34*****	**0.28*****
	(0.17)	(0.10)	(0.08)
Community shock covariance	0.25	**0.34****	**0.29****
(fraction excluding household)	(0.24)	(0.14)	(0.14)
Recipient characteristics			
Age	0.01	0.005*	0.0002
	(0.01)	(0.002)	(0.002)
Attended school	0.06	0.08**	0.11***
	(0.11)	(0.04)	(0.04)
Married	-0.10	-0.01	0.05
	(0.09)	(0.05)	(0.04)
Household characteristics			
Wealth index	0.10	0.15***	0.16***
	(0.07)	(0.02)	(0.02)
Household size	-0.11	-0.01	-0.04
	(0.12)	(0.05)	(0.04)
Members age 0-5	-0.09	-0.11*	-0.10**
	(0.12)	(0.06)	(0.05)
Members age 6-12	-0.06	-0.11*	-0.08*
	(0.12)	(0.06)	(0.04)
Members age 13-18	0.03	-0.01	-0.05
	(0.14)	(0.06)	(0.05)
Members age 19-35	0.17	-0.02	-0.06
	(0.13)	(0.06)	(0.05)
Members age 36-55	0.14	-0.03	-0.01
	(0.11)	(0.06)	(0.05)
Kilometers to food market (logged)	-0.02	0.02	0.04**
	(0.04)	(0.02)	(0.02)
Regional characteristics			
Kaputa	-0.33*	-0.19**	-0.16**
	(0.18)	(0.08)	(0.07)
Shangombo	-0.45***	-0.34***	-0.22***
	(0.12)	(0.07)	(0.07)
N	240	1393	2455

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

[2]Analysis restricted to those shock groups balanced at baseline along per capita food consumption.

Table 14. The impact of cash on food security amongst households experiencing and avoiding negative income shocks, controlling for the effect of shock covariance[1]

Dependent variable: Severely food insecure (1) – Linear Probability Model				
	No shock either round	*Shock round 1 only*	*Shock round 2 only*	*Shock both rounds*
Constant	1.30***	1.23***	0.85***	1.08***
	(0.28)	(0.18)	(0.13)	(0.13)
Time	-0.08	-0.05	-0.08**	-0.10***
	(0.08)	(0.04)	(0.04)	(0.03)
Cash	0.04	-0.01	0.03	0.01
	(0.07)	(0.05)	(0.03)	(0.04)
Cash*Time	**-0.24****	-0.01	**-0.26*****	**-0.20*****
	(0.10)	(0.06)	(0.04)	(0.04)
Community shock covariance	0.21	**-0.33*****	0.15	**0.14***
(fraction excluding household)	(0.20)	(0.11)	(0.09)	(0.07)
Recipient characteristics				
Age	-0.004	0.002	0.004***	0.0004
	(0.004)	(0.002)	(0.001)	(0.001)
Attended school	0.05	-0.002	-0.004	-0.05**
	(0.07)	(0.04)	(0.02)	(0.02)
Married	-0.03	0.01	-0.05**	-0.03*
	(0.05)	(0.05)	(0.03)	(0.02)
Household characteristics				
Wealth index	-0.04*	-0.04*	-0.04***	-0.04***
	(0.03)	(0.02)	(0.01)	(0.01)
Household size	0.06	0.06	-0.01	-0.01
	(0.09)	(0.04)	(0.04)	(0.03)
Members age 0-5	-0.12	-0.04	0.04	0.06**
	(0.09)	(0.04)	(0.04)	(0.03)
Members age 6-12	-0.04	-0.04	0.02	0.02
	(0.09)	(0.05)	(0.03)	(0.03)
Members age 13-18	-0.09	-0.09*	0.02	0.04
	(0.11)	(0.05)	(0.04)	(0.03)
Members age 19-35	-0.06	-0.08	0.04	-0.01
	(0.09)	(0.06)	(0.04)	(0.03)
Members age 36-55	-0.04	-0.05	0.004	-0.02
	(0.08)	(0.05)	(0.04)	(0.03)
Kilometers to food market	-0.04	-0.01	0.002	-0.01
(logged)	(0.02)	(0.02)	(0.01)	(0.01)
Community characteristics				
Kaputa	0.14	-0.03	0.03	0.01
	(0.11)	(0.07)	(0.04)	(0.04)
Shangombo	-0.04	-0.15*	-0.03	-0.12***
	(0.10)	(0.08)	(0.05)	(0.04)
N	240	428	1385	2445

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. Kalabo district omitted. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

Table 15. Mean characteristics and tests for equivalence between control and treatment groups at 2010 baseline[1]

	Panel households, all		Panel households, 2010 fuelwood >0		Panel households, 2010 charcoal >0		Panel households, 2010 bushmeat >0	
	Treatment (n=1,153)	Control (n=1,145)	Treatment (n=1,044)	Control (n=1,033)	Treatment (n=76)	Control (n=48)	Treatment (n=24)	Control (n=22)
Recipient characteristics								
Age	30	30	30	29	32	31	29	28
Attended school	73%	70%	73%	69%	91%	81%	88%	77%
Married	74%	71%	74%	71%	70%	73%	83%	82%
Male	1.2%	<1%	<1%	<1%	<1%	<1%	<1%	<1%
Household characteristics								
Wealth index	0.002	-0.04	-0.08	-0.07	1.20	0.67	0.47	-0.04
Below 2010 poverty line	92%	92%	92%	91%	89%**	100%**	92%**	68%**
Monthly per capita food consumption (kwacha)	30.16	28.50	35.91	34.48	38.96	28.76	53.82	64.42
Severely food insecure	90%	90%	89%	89%	93%	94%	65%	77%
Household size	6	6	6	6	7	6	6**	5**
Members age 0-5	2	2	2	2	2	2	2	2
Members age 6-12	1	1	1	1	2	2	1**	1**
Members age 13-18	1	1	1	1	1	1	1	0
Members age 19-35	1	1	1	1	1	1	1	1
Members age 36-55	1	1	1	1	1	1	1	0
Members age 56-69	0	0	0	0	0	0	0	0
Members 70+	0	0	0	0	0	0	0	0
Kilometers to market	16	22	17	21	8*	22*	16	24
Percent from each district								
Kaputa	30%	30%	26%	25%	73%	68%	50%	50%
Kalabo	35%	35%	38%	37%	1%	17%	4%	23%
Shang'ombo	35%	35%	36%	38%	26%*	15%*	46%	27%

[1]All samples restricted to those who remain in the panel survey in 2012. Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Monthly per capita food consumption and food security regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 16. Mean characteristics and tests for equivalence between control and treatment groups at 2010 baseline amongst households more than 10km from a market[1]

	Panel households, all		Panel households, 2010 fuelwood >0		Panel households, 2010 charcoal >0	
	Treatment (n=578)	Control (n=623)	Treatment (n=523)	Control (n=562)	Treatment (n=27)	Control (n=25)
Recipient characteristics						
Age	29	30	29	30	33	29
Attended school	75%	70%	74%	70%	96%	76%
Married	77%	68%	76%	67%	78%	80%
Male	<1%	<1%	<1%	<1%	4%	<1%
Household characteristics						
Wealth index	-0.18	-0.17	-0.26	-0.20	0.84	0.35
Below 2010 poverty line	90%	90%	90%	89%	93%	100%
Monthly per capita food consumption (kwacha)	40.46	38.69	40.60	38.74	38.62	31.31
Severely food insecure	87%	87%	86%	86%	92%	96%
Household size	6	5	6	5	7	6
Members age 0-5	2	2	2	2	2	2
Members age 6-12	1	1	1	1	1	1
Members age 13-18	1*	0*	1	0	1	1
Members age 19-35	1*	1*	1	1	1	1
Members age 36-55	1	1	1	1	1	1
Members age 56-69	0	0	0	0	0	0
Members 70+	0	0	0	0	0	0
Kilometers to food market	29	37	30	36	20	39
Percent from each district						
Kaputa	20%	29%	15%	25%	74%	60%
Kalabo	44%	46%	46%	49%	26%	24%
Shang'ombo	36%	25%	39%	26%	<1%	16%

[1]All samples restricted to those who remain in the panel survey in 2012. Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Monthly per capita food consumption and food security regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 17. Mean characteristics and tests for equivalence between control and treatment groups at 2010 baseline amongst households within 10km of a market [1]

	Panel households, all		Panel households, 2010 fuelwood >0		Panel households, 2010 charcoal >0	
	Treatment (n=575)	Control (n=522)	Treatment (n=521)	Control (n=471)	Treatment (n=49)	Control (n=23)
Recipient characteristics						
Age	30	29	30	29	32	32
Attended school	72%	70%	72%	69%	88%	87%
Married	71%	74%	72%	76%	65%	65%
Male	<1%	<1%	<1%	<1%	6%	<1%
Household characteristics						
Wealth index	0.19	0.12	0.09	0.09	1.39	1.02
Below 2010 poverty line	93%	94%	93%	94%	88%	100%
Monthly per capita food consumption (kwacha)	32.34	29.54	31.54	29.51	40.95	28.28
Severely food insecure	93%	93%	93%	93%	94%	91%
Household size	6	6	6	6	7	7
Members age 0-5	2	2	2	2	2	2
Members age 6-12	1	1	1	1	2	2
Members age 13-18	1	1	1	1	1	1
Members age 19-35	1	1	1	1	1	1
Members age 36-55	1	1	1	1	1	0
Members age 56-69	0	0	0	0	0	0
Members 70+	0	0	0	0	0	0
Kilometers to food market	3	4	3	4	2	4
Percent from each district						
Kaputa	39%	30%	36%	27%	71%	78%
Kalabo	27%	23%	27%	22%	27%	4%
Shang'ombo	34%	48%	36%	51%	2%	17%

[1] All samples restricted to those who remain in the panel survey in 2012. Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Monthly per capita food consumption and food security regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 18. The decision to farm and land area used in 2012

	Treatment (n=1,153)	Control (n=1,145)
Used land for farming	1,042 (90%)	995 (87%)
Total area farmed (ha)		
Mean	0.85	0.63
Maximum	10.4	11.5

Table 19. Types of non-farm businesses owned in 2012

	Treatment (n=1,153)	Control (n=1,145)
Own a non-farm business	541 (47%)	344 (30%)
Own a natural resource-based business	189 (16%)	119 (10%)
Fishing	167 (14%)	102 (9%)
Charcoal	23 (2%)	13 (1%)
Hay	4 (<1%)	4 (<1%)
Own a business not based on natural resources	377 (33%)	233 (20%)
Home brewery	135 (12%)	95 (8%)
Petty trader	83 (7%)	49 (4%)
Food preparation	27 (2%)	14 (1%)
Crafts	19 (2%)	21 (2%)
Grocery store	11 (<1%)	3 (<1%)
Carpentry	7 (<1%)	6 (1%)
Other	121 (10%)	57 (5%)

Table 20. Natural resource use at 2010 baseline: Means and tests for equivalence between control and treatment groups[1]

	Panel households, all		Fuelwood consumption >0		Charcoal consumption >0		Bushmeat consumption >0	
	Treatment (n=1,135)	Control (n=1,124)	Treatment (n=1,031)	Control (n=1,014)	Treatment (n=73)	Control (n=48)	Treatment (n=23)	Control (n=22)
Fuelwood								
Percent consuming	91%	90%	-	-	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	5.36	5.12	-	-	-	-
Charcoal								
Percent consuming	6%	4%	-	-	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	-	-	3.59	3.50	-	-
Bushmeat								
Percent consuming	2%	2%	-	-	-	-	-	-
2 weeks per capita consumption (kwacha)	-	-	-	-	-	-	2.81	4.67

[1]Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 21. Natural resource use at 2010 baseline: Means and tests for equivalence between control and treatment groups amongst households more than 10km from a market[1]

	Panel households, all		Fuelwood consumption >0		Charcoal consumption >0	
	Treatment (n=566)	Control (n=613)	Treatment (n=513)	Control (n=552)	Treatment (n=25)	Control (n=25)
Fuelwood						
Percent consuming	91%	90%	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	5.13	5.00	-	-
Charcoal						
Percent consuming	4%	4%	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	-	-	3.98	3.89

[1]Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 22. Natural resource use at 2010 baseline: Means and tests for equivalence between control and treatment groups amongst households within 10km of a market[1]

	Panel households, all		Fuelwood consumption >0		Charcoal consumption >0	
	Treatment (n=569)	Control (n=511)	Treatment (n=518)	Control (n=462)	Treatment (n=48)	Control (n=23)
Fuelwood						
Percent consuming	91%	90%	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	5.61	5.31	-	-
Charcoal						
Percent consuming	8%	5%	-	-	-	-
Monthly per capita consumption (kwacha)	-	-	-	-	3.61	3.55

[1]Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (wealth, household size, and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.

Table 23. The impact of cash on use of fuelwood, charcoal, bushmeat and land for farming[1,2]

Dependent variable: Consumed resource (1) – Linear Probability Model				
	Used fuelwood	*Used charcoal*	*Used bushmeat*	*Used land for farming*
Constant	1.08***	-0.14*	-0.16***	0.59***
	(0.08)	(0.08)	(0.05)	(0.09)
Time	-0.01	0.07***	0.05***	--
	(0.02)	(0.02)	(0.01)	
Cash	0.01	0.01	-0.005	0.03
	(0.02)	(0.02)	(0.01)	(0.02)
Cash*Time	-0.04	**0.08***	0.02	--
	(0.02)	(0.04)	(0.02)	
Recipient characteristics				
Age	-0.001	-0.0001	0.0002	0.003***
	(0.001)	(0.0006)	(0.0004)	(0.001)
Attended school	0.01	-0.01	2.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Married	0.04	-0.02**	0.018	0.04**
	(0.02)	(0.01)	(0.01)	(0.02)
Household characteristics				
Wealth index	-0.03***	0.05***	0.01	-0.02**
	(0.01)	(0.01)	(0.004)	(0.01)
Household size	-0.001	-0.01	0.003	-0.04
	(0.01)	(0.01)	(0.01)	(0.02)
Members age 0-5	0.01	-0.005	0.001	0.05**
	(0.01)	(0.01)	(0.01)	(0.02)
Members age 6-12	0.01	0.01	-0.01	0.04*
	(0.01)	(0.01)	(0.01)	(0.02)
Members age 13-18	0.01	0.01	0.004	0.05*
	(0.02)	(0.01)	(0.01)	(0.03)
Members age 19-35	-0.01	0.02*	-0.01	0.04*
	(0.01)	(0.01)	(0.01)	(0.03)
Members age 36-55	-0.003	0.02	-0.01	0.04*
	(0.01)	(0.01)	(0.01)	(0.02)
Community characteristics				
Kaputa	-0.14***	0.22***	0.01	0.002
	(0.03)	(0.03)	(0.02)	(0.04)
Shangombo	0.03*	-0.01	0.05	0.08***
	(0.02)	(0.02)	(0.02)	(0.03)
N	4518	4518	4518	2259

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 24. The impact of cash on charcoal and bushmeat consumption in Kaputa district[1,2]

Dependent variable: Consumed resource (1) – Linear Probability Model

	Used charcoal	*Used bushmeat*
Constant	0.01	-0.20*
	(0.20)	(0.10)
Time	0.22***	0.01
	(.05)	(0.01)
Cash	0.01	-0.01
	(0.05)	(0.03)
Cash*Time	**0.24*** **	0.02
	(0.08)	(0.04)
Recipient characteristics		
Age	-0.001	0.00002
	(0.002)	(0.001)
Attended school	-0.02	0.03***
	(0.04)	(0.01)
Married	-0.03	0.02
	(0.03)	(0.01)
Household characteristics		
Wealth index	0.10***	0.0002
	(0.02)	(0.01)
Household size	0.01	0.01
	(0.04)	(0.02)
Members age 0-5	-0.04	0.001
	(0.04)	(0.02)
Members age 6-12	0.002	-0.02
	(0.04)	(0.02)
Members age 13-18	-0.01	-0.01
	(0.04)	(0.02)
Members age 19-35	0.01	-0.02
	(0.04)	(0.02)
Members age 36-55	0.02	-0.02
	(0.03)	(0.02)
N	1314	1314

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Sub-samples balanced at baseline (regression results not shown).

Table 25. The impact of cash on consumption of fuelwood, charcoal, and land amongst households with consumption at baseline (fuelwood, charcoal) or in 2012 (land)[1,2]

Dependent variable: Per capita consumption (logged)			
	Fuelwood, monthly (kwacha)	*Charcoal, monthly* (kwacha)	*Land used for farming* (hectares)
Constant	9.59***	2.40	-2.76***
	(0.61)	(2.97)	(0.35)
Time	-1.10***	-7.94***	
	(0.22)	(1.32)	-
Cash	0.00003	-0.68	**0.27*****
	(0.12)	(0.95)	(0.08)
Cash*Time	-0.35	2.02	-
	(0.30)	(1.67)	
Recipient characteristics			
Age	-0.01	0.005	0.01**
	(0.008)	(0.04)	(0.003)
Attended school	0.05	0.39	0.18***
	(0.11)	(0.68)	(0.05)
Married	0.15	-0.18	0.09*
	(0.15)	(0.69)	(0.05)
Household characteristics			
Wealth index	-0.13*	0.43**	-0.01
	(0.06)	(0.17)	(0.03)
Household size	-0.09	-0.003	-0.08
	(0.19)	(0.90)	(0.07)
Members age 0-5	-0.02	-0.28	0.002
	(0.19)	(0.84)	(0.08)
Members age 6-12	-0.09	-0.003	0.01
	(.19)	(0.84)	(0.08)
Members age 13-18	-0.001	0.17	0.06
	(0.20)	(0.91)	(0.08)
Members age 19-35	-0.12	0.47	-0.01
	(0.19)	(1.08)	(0.08)
Members age 36-55	0.06	-0.06	0.05
	(0.18)	(0.98)	(0.07)
Community characteristics			
Kaputa	-1.07***	0.66	0.06
	(0.29)	(1.10)	(0.13)
Shangombo	0.04	-1.05	0.57***
	(0.17)	(1.08)	(0.10)
N	4076	240	2259

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 26. The impact of cash on use of fuelwood, charcoal, and land within 10km of a market[1,2]

Dependent variable: Consumed resource (1) – Linear Probability Model			
	Used fuelwood	*Used charcoal*	*Used land for farming*
Constant	0.99***	-0.19	0.47***
	(0.13)	(0.11)	(0.14)
Time	-0.01	0.10***	--
	(0.02)	0.04	
Cash	0.01	(0.01)	0.001
	(0.03)	0.04	(0.03)
Cash*Time	-0.05	**0.11***	--
	(0.03)	(0.07)	
Recipient characteristics			
Age	-0.001	-0.0004	0.002
	(0.001)	(0.001)	(0.001)
Attended school	0.01	0.01	0.05**
	(0.01)	(0.02)	(0.02)
Married	0.05**	-0.02	-0.001
	(0.02)	(0.01)	(0.03)
Household characteristics			
Wealth index	-0.04***	0.05***	-0.02*
	(0.01)	(0.01)	(0.01)
Household size	0.002	0.001	-0.03
	(0.02)	(0.02)	(0.03)
Members age 0-5	-0.02	-0.02	0.05
	(0.02)	(0.02)	(0.03)
Members age 6-12	-0.004	0.01	0.04
	(0.02)	(0.02)	(0.03)
Members age 13-18	-0.003	-0.01	0.04
	(0.02)	(0.02)	(0.04)
Members age 19-35	-0.01	0.02	0.04
	(0.02)	(0.02)	(0.04)
Members age 36-55	0.01	0.001	0.05
	(0.02)	(0.02)	(0.03)
Community characteristics			
Kaputa	-0.08**	0.23***	0.03
	(0.04)	(0.04)	(0.05)
Shangombo	0.06*	-0.01	0.11**
	(0.03)	(0.03)	(0.05)
N	2160	2160	1080

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 27. The impact of cash on consumption of fuelwood and land amongst households with consumption at baseline (fuelwood) or 2012 (land) within 10km of a market[1,2]

Dependent variable: Per capita consumption (logged)		
	Fuelwood, monthly (kwacha)	*Land used for farming* (hectares)
Constant	8.98***	-2.03***
	(1.11)	(0.41)
Time	-1.07***	--
	(0.29)	
Cash	0.15	**0.21*****
	(0.14)	(0.07)
Cash*Time	-0.63	--
	(0.39)	
Recipient characteristics		
Age	-0.01	0.0004
	(0.01)	(0.003)
Attended school	0.06	0.17***
	(0.16)	(0.05)
Married	0.17	-0.02
	(0.22)	(0.05)
Household characteristics		
Wealth index	-0.20**	0.07***
	(0.08)	(0.03)
Household size	-0.02	0.01
	(0.28)	(0.08)
Members age 0-5	-0.21	-0.17*
	(0.29)	(0.09)
Members age 6-12	-0.24	-0.09
	(0.28)	(0.09)
Members age 13-18	-0.14	-0.06
	(0.30)	(0.09)
Members age 19-35	-0.25	-0.14
	(0.28)	(0.09)
Members age 36-55	0.18	-0.09
	(0.25)	(0.09)
Community characteristics		
Kaputa	-0.80**	0.18
	(0.32)	(0.12)
Shangombo	0.20	0.48***
	(0.28)	(0.11)
N	1953	925

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 28. The impact of cash on use of fuelwood, charcoal, and land more than 10km from a market[1,2]

Dependent variable: Consumed resource (1) – Linear Probability Model			
	Used fuelwood	*Used charcoal*	*Used land for farming*
Constant	1.16***	-0.19*	0.72***
	(0.11)	(0.10)	(0.11)
Time	-.011	0.05**	--
	(0.03)	(0.03)	
Cash	0.002	0.01	**0.06*****
	(0.03)	(0.02)	(0.02)
Cash*Time	-0.03	0.04	--
	(0.03)	(0.05)	
Recipient characteristics			
Age	-0.0002	0.001	0.003***
	(0.001)	(0.001)	(0.001)
Attended school	-0.001	-0.01	-0.01
	(0.01)	(0.01)	(0.02)
Married	0.02	-0.01	0.06***
	(0.02)	(0.01)	(0.02)
Household characteristics			
Wealth index	-0.02	0.03***	-0.01
	(0.01)	(0.01)	(0.01)
Household size	-0.01	-0.02	-0.03
	(0.02)	(0.01)	(0.03)
Members age 0-5	0.03	0.01	0.03
	(0.02)	(0.01)	(0.03)
Members age 6-12	0.01	0.02	0.03
	(0.02)	(0.01)	(0.03)
Members age 13-18	0.01	0.03**	0.04
	(0.02)	(0.01)	(0.03)
Members age 19-35	-0.01	0.03**	0.03
	(0.02)	(0.01)	(0.03)
Members age 36-55	-0.02	0.04**	0.02
	(0.02)	(0.02)	(0.03)
Community characteristics			
Kaputa	-0.21***	0.22***	0.01
	(0.05)	(0.03)	(0.03)
Shangombo	0.004	-0.01	0.10***
	(0.02)	(0.02)	(0.02)
N	2358	2358	1179

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 29. The impact of cash on consumption of fuelwood and land amongst households with consumption at baseline (fuelwood) or 2012 (land) more than 10km from a market[1,2]

Dependent variable: Per capita consumption (logged)		
	Fuelwood, monthly (kwacha)	*Land used for farming* (hectares)
Constant	9.98***	-1.32***
	(0.86)	(0.31)
Time	-1.12***	--
	(0.28)	
Cash	-0.03	**0.28*****
	(0.18)	(0.08)
Cash*Time	-0.07	--
	(0.43)	
Recipient characteristics		
Age	-0.002	0.001
	(0.01)	(0.002)
Attended school	-0.02	0.09*
	(0.16)	(0.05)
Married	0.11	-0.04
	(0.15)	(0.06)
Household characteristics		
Wealth index	0.10	0.08*
	(0.08)	(0.04)
Household size	-0.16	-0.02
	(0.21)	(0.06)
Members age 0-5	0.15	-0.07
	(0.21)	(0.06)
Members age 6-12	0.02	-0.08
	(0.22)	(0.06)
Members age 13-18	0.14	-0.03
	(0.21)	(0.06)
Members age 19-35	0.04	-0.09
	(0.23)	(0.07)
Members age 36-55	-0.04	-0.02
	(0.24)	(0.06)
Community characteristics		
Kaputa	-1.44***	-0.01
	(0.40)	(0.09)
Shangombo	-0.17	0.44***
	(0.19)	(0.12)
N	2123	1078

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level
[2]Baseline data for land use not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 30. The impact of cash on household ownership of non-farm businesses[1,2]

Dependent variable: Own business (1) – Linear Probability Model

	Any non-farm business	*Charcoal, fish, or hay business*	*All other businesses*
Constant	0.77***	0.18*	0.64***
	(0.13)	(0.10)	(0.10)
Cash	**0.17*****	**0.05****	**0.13*****
	(0.03)	(0.02)	(0.03)
Recipient characteristics			
Age	-0.004***	-0.0003	-0.004***
	(0.001)	(0.001)	(0.001)
Attended school	0.065**	0.04***	0.03
	(0.023)	(0.02)	(0.03)
Married	-0.03	0.02	-0.04*
	(0.03)	(0.02)	(0.03)
Household characteristics			
Wealth index	0.03***	-0.01	0.04***
	(0.01)	(0.01)	(0.01)
Household size	-0.03	-0.01	-0.01
	(0.03)	(0.02)	(0.03)
Members age 0-5	0.06*	0.03	0.02
	(0.03)	(0.02)	(0.03)
Members age 6-12	0.05	0.03	0.01
	(0.03)	(0.02)	(0.03)
Members age 13-18	0.04	0.003	0.03
	(0.03)	(0.02)	(0.03)
Members age 19-35	0.03	.01	0.01
	(0.04)	(0.02)	(0.04)
Members age 36-55	0.03	.01	0.02
	(0.04)	(0.02)	(0.03)
Community characteristics			
Kaputa	-0.04	0.06	-0.11***
	(0.04)	(0.04)	(0.04)
Shangombo	-0.19***	-0.12***	-0.08**
	(0.04)	(0.04)	(0.03)
N	2252	2252	2252

[1]Sample restricted to 2012 data; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

[2]Baseline business enterprise data not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 31. The impact of cash on ownership of non-farm businesses more than 10km from a market

Dependent variable: Own business (1) – Linear Probability Model			
	Any non-farm business	*Charcoal, fish, or hay business*	*All other businesses*
Constant	0.81***	0.16	0.69***
	(0.14)	(0.12)	(0.12)
Cash	**0.11*****	0.02	**0.11*****
	(0.03)	(0.02)	(0.03)
Recipient characteristics			
Age	-0.004**	0.00004	-0.004**
	(0.002)	(0.002)	(0.002)
Attended school	0.02	0.05***	-0.02
	(0.03)	(0.02)	(0.03)
Married	-0.03	0.03	-0.06
	(0.04)	(0.02)	(0.04)
Household characteristics			
Wealth index	0.03	0.02	0.03
	(0.02)	(0.01)	(0.02)
Household size	-0.04	-0.03	0.01
	(0.05)	(0.03)	(0.05)
Members age 0-5	0.06	0.05	-0.01
	(0.05)	(0.04)	(0.05)
Members age 6-12	0.06	0.04	0.003
	(0.05)	(0.03)	(0.05)
Members age 13-18	0.05	0.02	0.01
	(0.05)	(0.03)	(0.05)
Members age 19-35	0.02	0.01	-0.01
	(0.05)	(0.03)	(0.05)
Members age 36-55	0.02	0.01	0.005
	(0.05)	(0.03)	(0.05)
Community characteristics			
Kaputa	-0.12**	0.005	-0.16***
	(0.05)	(0.04)	(0.04)
Shangombo	-0.25***	-0.14***	-0.14***
	(0.04)	(0.03)	(0.04)
N	1175	1175	1175

[1]Sample restricted to 2012 data; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline business enterprise data not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 32. The impact of cash on ownership of non-farm businesses within 10km of a market[1,2]

Dependent variable: Own business (1) – Linear Probability Model			
	Any non-farm business	*Charcoal, fish, or hay business*	*All other businesses*
Constant	0.62**	0.27	0.43**
	(0.24)	(0.19)	(0.20)
Cash	**0.23*** **	**0.10** **	**0.14*** **
	(0.05)	(0.04)	(0.04)
Recipient characteristics			
Age	-0.004**	-0.001	-0.003**
	(0.002)	(0.002)	(0.002)
Attended school	0.11***	0.04	0.08**
	(0.04)	(0.02)	(0.04)
Married	-0.03	0.02	-0.01
	(0.03)	(0.03)	(0.03)
Household characteristics			
Wealth index	0.03***	-0.02**	0.05***
	(0.01)	(0.01)	(0.01)
Household size	-0.02	0.01	-0.03
	(0.05)	(0.03)	(0.04)
Members age 0-5	0.05	0.01	0.04
	(0.05)	(0.03)	(0.04)
Members age 6-12	0.03	0.01	0.02
	(0.05)	(0.03)	(0.04)
Members age 13-18	0.03	-0.02	0.04
	(0.05)	(0.04)	(0.05)
Members age 19-35	0.03	0.001	0.03
	(0.05)	(0.03)	(0.05)
Members age 36-55	0.04	0.01	0.03
	(0.06)	(0.03)	(0.05)
Community characteristics			
Kaputa	0.03	0.11**	-0.09
	(0.07)	(0.05)	(0.07)
Shangombo	-0.11	-0.10	-0.03
	(0.08)	(0.06)	(0.07)
N	1077	1077	1077

[1]Sample restricted to 2012 data; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline business enterprise data not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 33. The impact of cash on the decision to farm, amongst households with a non-farm business[1,2]

Dependent variable: Used land for farming (1) – Linear Probability Model

	All 2012 households	Households more than 10km from a market	Households within 10km of a market
Constant	0.50***	0.74***	0.30
	(0.17)	(0.19)	(0.31)
Cash	0.03	0.03	0.05
	(0.04)	(0.04)	(0.05)
Recipient characteristics			
Age	0.0003	0.002	-0.001
	(0.002)	(0.003)	(0.003)
Attended school	-0.02	-0.04	-0.0003
	(0.03)	(0.03)	(0.06)
Married	0.06*	0.03	0.08
	(0.03)	(0.04)	(0.05)
Household characteristics			
Wealth index	-0.01	0.003	0.01
	(0.01)	(0.02)	(0.02)
Household size	-0.02	-0.02	0.01
	(0.04)	(0.04)	(0.07)
Members age 0-5	0.04	0.01	0.08
	(0.04)	(0.05)	(0.05)
Members age 6-12	0.02	0.01	0.005
	(0.04)	(0.04)	(0.07)
Members age 13-18	0.02	0.02	-0.01
	(0.05)	(0.06)	(0.08)
Members age 19-35	0.03	0.03	-0.002
	(0.04)	(0.05)	(0.07)
Members age 36-55	0.04	0.04	0.04
	(0.05)	(0.06)	(0.07)
Community characteristics			
Kaputa	0.01	-0.01	0.05
	(0.05)	(0.06)	(0.07)
Shangombo	0.03	0.06	0.08
	(0.05)	(0.05)	(0.09)
N	870	413	457

[1]Sample restricted to 2012 data; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline business enterprise data not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 34. The impact of cash on the area farmed, amongst farming households with a non-farm business[1,2]

Dependent variable: Hectares farmed (Logged, per capita)			
	All 2012 households	Households more than 10km from a market	Households within 10km of a market
Constant	-1.73***	-1.62***	-1.85***
	(0.30)	(0.43)	(0.60)
Cash	**0.13***	**0.20***	0.04
	(0.07)	(0.12)	(0.09)
Recipient characteristics			
Age	-0.005	-0.004	-0.01
	(0.004)	(0.01)	(0.005)
Attended school	0.03	0.004	0.03
	(0.06)	(0.08)	(0.09)
Married	0.01	0.05	-0.05
	(0.06)	(0.10)	(0.08)
Household characteristics			
Wealth index	0.03	0.04	0.04
	(0.03)	(0.05)	(0.03)
Household size	0.14	0.16	0.16
	(0.13)	(0.20)	(0.15)
Members age 0-5	-0.23*	-0.31*	-0.19
	(0.12)	(0.18)	(0.14)
Members age 6-12	-0.26**	-0.26	-0.31*
	(0.12)	(0.16)	(0.16)
Members age 13-18	-0.16	-0.16	-0.21
	(0.13)	(0.19)	(0.17)
Members age 19-35	-0.28**	-0.33*	-0.30**
	(0.12)	(0.17)	(0.15)
Members age 36-55	-0.19*	-0.30*	-0.14
	(0.11)	(0.17)	(0.14)
Community characteristics			
Kaputa	0.08	-0.13	0.33**
	(0.12)	(0.13)	(0.14)
Shangombo	0.53***	0.48***	0.71***
	(0.11)	(0.15)	(0.16)
N	721	366	355

[1]Sample restricted to 2012 households with farmed area greater than zero; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline business enterprise data not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 35. Bike ownership trends[1]

	Cash (n=1,153)	Control (n=1,145)
2010	80 (7%)	87 (8%)
2012	195 (17%)	144 (13%)

[1] Restricted to households that remain in the panel

Table 36. Mean characteristics and tests for equivalence at 2010 baseline between (a) those ever owning a bike and those never owning a bike and (b) the cash transfer group and the control group[1,2]

	Cash vs. Control		Bike ever vs. Bike never	
	Cash (n=1,153)	Control (n=1,145)	Bike ever (n=430)	Bike never (n=1868)
Recipient characteristics				
Age	30	30	31**	30**
Attended school	73%	70%	84%***	69%***
Married	74%	71%	86%**	69%**
Male	1.2%	<1%	<1%**	2%**
Household characteristics				
Monthly per capita consumption (kwacha)	48.11	46.09	49.38***	46.57***
Monthly per capita food consumption (kwacha)	30.16	28.50	36.30**	35.13**
Below 2010 poverty line	92%	92%	90%	92%
Severely food insecure	90%	90%	89%	90%
Household size	6	6	7***	5***
Members age 0-5	2	2	2***	2***
Members age 6-12	1	1	2***	1***
Members age 13-18	1	1	1***	1***
Members age 19-35	1	1	1*	*1
Members age 36-55	1	1	1***	0***
Members age 56-69	0	0	0	0
Members 70+	0	0	0	0
Kilometers to market	16	22	14**	20**
Percent from each district				
Kaputa	30%	30%	68%***	21%***
Kalabo	35%	35%	19%***	40%***
Shang'ombo	35%	35%	13%***	39%***

[1]All samples restricted to those who remain in the panel survey in 2012. Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Consumption and food security regressions include controls for recipient characteristics (age, education, marital status), household characteristics (household size and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Monthly per capita consumption does not include spending on agricultural inputs.

Table 37. Agricultural market activity at 2010 baseline: Means and tests for equivalence between the cash and control group[1,2]

	Panel households, all		Agricultural input spending > 0		Crop Sales > 0	
	Cash (n=1,153)	Control (n=1,145)	Cash (n=157)	Control (n=150)	Cash (n=227)	Control (n=275)
Agricultural inputs						
Percent consuming	14%	13%	-	-	-	-
Spending during prior agricultural season/year (kwacha)	-	-	53.06*	49.19*	-	-
Crop sales						
Percent selling	20%	24%	-	-	-	-
Value of sales during prior agricultural season/year (kwacha)	-	-	-	-	326.04	271.03

[1]Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (household size and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Agricultural inputs include seeds, fertilizer, and pesticides.

Table 38. Agricultural market activity at 2010 baseline: Means and tests for equivalence between those ever owning bikes and those never owning bikes[1,2]

	Panel households, all		Agricultural input spending > 0		Crop Sales > 0	
	Bike ever (n=430)	Bike never (n=1,868)	Bike ever (n=84)	Bike never (n=223)	Bike ever (n=149)	Bike never (n=353)
Agricultural inputs						
Percent consuming	20%*	12%*	-	-	-	-
Spending during prior agricultural season/year (kwacha)	-	-	70.89	44.01	-	-
Crop sales						
Percent selling	35%**	19%**	-	-	-	-
Value of sales during prior agricultural season/year (kwacha)	-	-	-	-	327.48	282.93

[1]Means and tests for significant difference are regression-adjusted to account for clustered randomized design. Regressions include controls for recipient characteristics (age, education, marital status), household characteristics (household size and demographic composition), district fixed effects, and a vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap). *** indicates significant differences between the treatment and control groups at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Agricultural inputs include seeds, fertilizer, and pesticides.

Table 39. The impact of cash and bikes on engagement in agricultural markets and non-farm business[1,2]

Dependent variable: Engaged in market activity (1) – Linear Probability Model

	Sold crops		*Purchased agricultural inputs*		*Owned non-farm business*	
	Baseline bike	Time-varying bike	Baseline bike	Time-varying bike	Baseline bike	Time-varying bike
Constant	0.13	0.13	0.24***	0.24***	0.82***	0.82***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.12)	(0.12)
Time	-0.01	-0.01	0.06**	0.04*	-	-
	(0.03)	(0.03)	(0.03)	(0.02)		
Cash	-0.03	-0.03	0.01	0.01	**0.15*** **	**0.14*** **
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Cash*Time	**0.12*** **	**0.12*** **	**0.11*** **	**0.12*** **	-	-
	(0.04)	(0.04)	(0.04)	(0.04)		
Bike	0.14**	0.14**	0.02	0.02	-0.05	-0.02
	(0.06)	(0.06)	(0.04)	(0.04)	(0.05)	(0.05)
Bike*Time	0.01	-0.01	0.02	**0.12***	-	-
	(0.07)	(0.06)	(0.06)	(0.07)		
Bike*Cash	-0.06	-0.06	-0.03	-0.03	0.11	0.09
	(0.08)	(0.08)	(0.06)	(0.06)	(0.08)	(0.07)
Bike*Cash*Time	-0.10	-0.02	0.05	-0.05	-	-
	(0.11)	(0.08)	(0.09)	(0.09)		
Recipient characteristics						
Age	0.001	0.001	0.0002	0.0003	-0.004***	0.06*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.03)
Attended school	0.08***	0.08***	0.02*	0.02	0.06**	0.06**
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)
Married	0.04**	0.04**	0.06***	0.05***	-0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Household characteristics						
Household size	0.02	0.01	-0.03	-0.03*	-0.03	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Members age 0-5	-0.01	-0.01	0.02	0.03	0.06*	0.06*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
Members age 6-12	-0.02	-0.016	0.03	0.03	0.04	0.04
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Members age 13-18	-0.002	-0.001	0.04**	0.05**	0.04	0.04
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)

Members age 19-35	-0.02	-0.01	0.03	0.04*	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Members age 36-55	-0.02	-0.02	0.05**	0.05**	0.03	0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)
Kilometers to market (logged)	0.03**	0.03**	0.01	0.01	-0.03*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Community characteristics						
Kaputa	0.04	0.03	0.02	0.01	-0.03	-0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Shangombo	-0.07**	-0.07**	-0.06**	-0.06**	-0.21***	-0.21***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
N	4584	4584	4584	4584	2284	2284

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.
[2]Baseline data for non-farm business not available; first difference regressions using just 2012 data assume equivalence at baseline.

Table 40. The impact of cash and bikes on crop sales and agricultural input purchases, amongst those with such activity at baseline[1]

Dependent variable: Value sold/purchased during prior agricultural season/year (kwacha)				
	Value of crops sold, amongst those with sales at baseline		*Value of agricultural inputs purchased, amongst those with spending at baseline*	
	Baseline bike	Time-varying bike	Baseline bike	Time-varying bike
Constant	141.09	137.89	46.58	41.19
	(120.23)	(122.17)	(35.53)	(35.64)
Time	-105.1**	-147.41***	-27.64***	-30.96***
	(440.94)	(35.13)	(8.42)	(8.31)
Cash	313.20	32.20	-9.14	-9.34
	(85.71)	(85.61)	(7.78)	(7.67)
Cash*Time	31.19	18.41	19.17	11.38
	(97.34)	(79.90)	(12.18)	(10.34)
Bike	55.64	69.17	2.65	5.90
	(106.34)	(108.84)	(16.59)	(16.63)
Bike*Time	251.86	**331.26****	17.69	25.14
	(159.45)	(164.32)	(29.59)	(31.72)
Bike*Cash	62.11	69.41	77.11*	76.31*
	(212.89)	(209.09)	(42.73)	(41.91)
Bike*Cash*Time	-127.78	-146.53	-50.30	-43.43
	(248.11)	(309.47)	(52.66)	(53.92)
Recipient characteristics				
Age	-20.72	-1.78	-0.093	14.51
	(76.64)	(2.40)	(0.41)	(0.42)
Attended school	113.04**	99.36**	16.52*	14.88*
	(44.25)	(41.02)	(9.67)	(8.76)
Married	73.40	61.08	2572	2.34
	(67.47)	(69.93)	(9.64)	(9.46)
Household characteristics				
Household size	44.73	36.39	17.94	18.15
	(76.01)	(70.73)	(20.15)	(19.97)
Members age 0-5	-20.72	-10.73	-15.02	-13.22
	(76.64)	(71.19)	(21.03)	(20.66)
Members age 6-12	4.21	5.08	-17.44	-17.42
	(84.97)	(80.58)	(20.77)	(20.51)
Members age 13-18	20.52	24.13	-12.23	-14.20
	(75.71)	(70.61)	(22.07)	(21.63)
Members age 19-35	3.619	14.46	-16.34	-17.70
	(67.64)	(68.59)	(21.20)	(21.27)
Members age 36-55	33.730	40.20	-11.42	-13.25
	(63.12)	(63.18)	(19.66)	(19.78)
Kilometers to market (logged)	-10.35	-2.44	-1.77	-1.13
	(159.12)	(17.14)	(2.96)	(3.04)
Community characteristics				
Kaputa	-78.89	-110.84	19.74	10.84
	(72.28)	(70.87)	(14.33)	(13.04)
Shangombo	-16.66	-10.44	6.17	5.07
	(126.26)	(126.95)	(9.64)	(9.27)

N	1000	1000	612	612

[1]Sample restricted to those who remain in the panel survey in 2012; robust standard errors are clustered at the community level to account for the clustered randomized design and included in parentheses below coefficients. Parameter estimates for vector of baselines prices (maize/grain, rice, beans, fish, oil, sugar, salt, hand soap, liquid soap) not shown. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

Table 41. Impact of bikes and cash on crop sales (kwacha): triple-difference model using time-varying measure of bike ownership[1]

	2010 (n=500)	**2012** (n=500)	**1st difference (2012-2010)**
Cash (n=226 in 2010; 226 in 2012)	(B_0 + Cash) 170.09 (169.69)	(B_0 + Cash + Time + CashTime) 41.10 (127.77)	(Time + CashTime) **-128.10*** (71.63)
Bike (n=63 in 2010; 117 in 2012)	(B_0 + Bike) 207.06 (155.57)	(B_0 + Bike + Time + BikeTime) **390.91*** (199.87)	(Time + BikeTime) 183.85 (168.96)
Control (no cash, no bike) (n=237 in 2010; 216 in 2012)	(B_0) 137.89 (122.17)	(B_0 + Time) -9.52 (124.24)	(Time) **-147.41***** (35.13)
1st difference (cash-control)	DIFFERENCES AT BASELINE (Cash) 32.20 (85.61)	(Cash + CashTime) 50.62 (44.29)	**EFFECT OF CASH** (CashTime) 18.41 (79.90)
1st difference (bike-control)	DIFFERENCES AT BASELINE (Bike) 69.17 (108.84)	(Bike + BikeTime) **400.43**** (164.45)	**EFFECT OF BIKE** (BikeTime) **331.26**** (164.32)
Triple difference (bike & cash – control)	DIFFERENCES AT BASELINE (BikeCash) 69.41 (209.09)	(BikeCash + BikeCashTime) -77.12 (219.10)	**MULTIPLICATIVE EFFECT OF CASH AND BIKE** (BikeCashTime) -146.53 (309.47)

[1]Clustered robust standard errors in parentheses below coefficients. *** indicates significant differences at the 99% level, ** at the 95% level, and * at the 90% level.

Table 42. Location of agricultural market activity in 2012

	Cash	Control	Bike	No bike
Location of crop sales				
Village of residence	217	166	79	304
	(64%)	(68%)	(60%)	(68%)
Neighboring village or closest town	121	77	52	146
	(36%)	(32%)	(40%)	(32%)
Total	*338*	*243*	*131*	*450*
Location of agricultural input purchases				
Village of residence	182	124	68	238
	(54%)	(57%)	(54%)	(56%)
Neighboring village or closest town	154	93	58	189
	(46%)	(43%)	(46%)	(44%)
Total	*336*	*217*	*126*	*427*