A Replication Study Proposal for

3ie's Replication Window 4: Financial Services for the Poor

on

"The Short-term Impact of Unconditional Cash Transfers to the Poor: Evidence from Kenya"

By Johannes Haushofer and Jeremy Shapiro

Principal Investigator:

Hongmei Wang, Ph.D.

Assistant Professor

Department of Health Services Research and Administration

University of Nebraska Medical Center

984350 Nebraska Medical Center

Omaha, Nebraska, USA

Tel: (402)559-9413

Email: hongmeiwang@unmc.edu

Co- principal investigator:

Jiangtao Luo, Ph. D.

Assistant Professor

Department of Biostatistics

University of Nebraska Medical Center

984375 Nebraska Medical Center

Omaha, Nebraska, USA

Tel: (402)559-1976

Email: jiangtao.luon@unmc.edu

Replicated Article:

Haushofer, J and Shapiro J. The Short-term Impact of Unconditional Cash Transfers to the Poor: Evidence from Kenya. Quarterly Journal of Economics. 2016. Forthcoming

Financial services to the poor

Poverty remains a global problem in spite of the efforts and half of the world population lives on less than $2.5 a day.[1] The fight against poverty requires innovative ways to alleviate issues related to poverty including water and sanitation, hunger, health, and education to break the vicious cycle. Financial services for the poor have become a priority to tackle the poverty problem for these underserved populations. The essence of most of these financial services is to provide assistance through social transfer interventions. Studies have shown that financial services for the poor are associated with the improved consumption, savings, and welfare gain.[2,3,4] The diverse forms and designs of transfer may incur different implementation costs and lead to various degree of success in behavior change, consumption increase, and welfare gain. Compared to in-kind transfers, cash transfers is not distortionary, can meet heterogeneous needs for welfare improvement, have psychological benefits by allowing choices, and have lower delivery costs.[5] Compared to conditional cash transfer (CCT), unconditional cash transfer (UCT) is cheaper to implement but it may be inferior in improving outcomes related to conditions but superior in improving other outcomes.[5] On the other hand, UCT might be spent on temptation goods and decrease welfare in the long run and its income effects could reduce labor supply. [6]

In Kenya, studies have shown that UCTs have positive effects on economic outcomes and psychological wellbeing for recipients.[7,8] The positive effects of UCT include increased consumption, food consumption, food diversity, reduced poverty, increased health expenditure and improved performance at school, with no inflation overtime nor reduced labor supply.[5] Studies have also suggested that UCT leads to improved psychosocial wellbeing for participants.[8] A recent study examines various cash transfer methods and finds that mobile money technology is particularly effective in Kenya.[9] Recently studies increasingly adopted randomized experimental design that allows the examination of such differences to inform policy and program design in developing countries.

Study for Replication

The Haushofer and Shaprio 2016 study, "*The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya*", uses a randomized controlled trial to examine the effects of a large unconditional cash transfer (UCT) on economic outcomes and psychological wellbeing of poor households in rural Kenya. The study design also allows the examination of the differential impacts between transferring cash to husband versus wife, monthly transfers versus lump sum transfers, and large versus small transfer size.

The main analyses included examination of overall effects of cash transfers and the differential effects of treatment arms on indices in eight domains including assets, revenue, expenditure, food security, health, education, psychological well-being, and female empowerment. When estimating the main impacts of the cash transfer, Haushofer and Shaprio adopted a one-variate ANCOVA model that controls for village fixed effects and household-level correlation of the error terms. To address the multiple inference issues related to the multiple outcomes, the authors computed corrected p-values using Familywise Error Rate (FWER).[10] Additionally, the authors estimated equations jointly using seemingly unrelated regression (SUR) and reported the joint significance of the treatment coefficient using Wald tests. The authors also examined impacts of cash transfers and the recipient gender, transfer frequency, and transfer magnitude on individual component measures of psychological wellbeing, consumption, assets, and income indices. The authors examined the validity of the main analyses by checking (1) baseline differences in index variables (between treatment and spillover groups) and (2) the spillover effects of the index variables (comparing spillover group to pure control groups). The authors conducted robustness checks on the spillover effects by estimating lee bounds and Horowitz-

Manski Bounds.[11,12] These analysis results suggested that the spillover effects were small and unlikely to distort the treatment effects identified.

The authors reported statistically significant and economically meaningful impacts of cash transfers on economic outcomes and psychological wellbeing in the poor households in Kenya. Households received UCT reported significantly higher household consumption, asset holdings, monthly income, food security index, and psychological wellbeing index, but no significant improvement in health, education, or female empowerment index. The results comparing different treatment arms suggested that monthly payments were more likely than lump-sum transfers to increase food security while lump-sum transfers lead to higher levels of asset holdings. Compared to small cash transfers, larger transfers increased asset holdings and improved the psychological wellbeing of household members. There was little evidence that providing cash transfers to women vs. men differentially affects outcomes.

Haushofer and Shapiro's study provides evidence of the short-term impacts of UCT on increasing consumption, asset holding, income, and psychological wellbeing in rural Kenya. The insights gained from the study shed light on the specific mobile money technology used and the transfer design in terms of recipient gender, magnitude, and frequencies that fit the developing world. The study also made a unique contribution to the health literature by examining the impact of UCT on health and psychological wellbeing of the recipients. A replication of this study will help verify these important findings and provide policy makers with solid evidence to select most effective and efficient policies to fight poverty.

Replication Plan

The investigators propose to conduct a replication study with three objectives: (1) conduct a push-button replication and pure replication, (2) conduct measurement and estimation analysis including conducting a statistical replication of study using different modeling methods and techniques and then (3) conduct theory of change analysis using multivariate linear model methods.

Aim 1: Push-button replication and Pure Replication

Aim 1.1. Push-button replication. Upon approval of the application, we'll start push-button replication by requesting data and codes from the authors of the original study and regenerating main study findings using same data, measures, and codes from the authors.

Aim 1.2. Pure Replication. Pure replication will focus on replication of the overall treatment effects and the impacts of different treatment arms. We'll follow the same regression methods and measures used by the authors to examine the impacts of the cash transfers. We plan to use SAS for the pure replication and expect to see similar results founds in the original study. If some results in the original paper cannot be generated we will conduct the authors and find reasons to ensure the key findings on the impact of UCT are reproducible.

a) Replication of the overall impacts of cash transfers and the differential impacts of recipient gender, transfer frequency, and transfer size on the indices of *assets, income, consumption, food security, health, education, psychological wellbeing, and female empowerment*. Same regression models will be run on all eight outcome indices and to obtain key results reported in Tables II. We'll also examine baseline balance and the spillover effects and recreate Table I and III in the original article.

b) Replication of the overall impacts of cash transfers and the differential impacts of recipient gender, transfer frequency, and transfer size on individual outcome measures that composed of the indices of *assets, income, consumption, and psychological wellbeing*. We'll run the same models to obtain key results reported in Tables IV-VI in the original article.

Aim 2: Measurement and Estimation Analysis

After the verification of the original analysis results, we will examine the robustness of the findings through additional analysis. The authors specified a pre-analysis plan and conducted rigorous data analysis including extensive robust checks on methods and measures. The study design was fairly convincing as well as the analysis presented. We propose to examine the study results by exploring alternative estimation methods, model specifications, outcome measurements, and sample inclusion criteria.

2.1 Alternative Estimation Method

The authors chose the ANCOVA model with village level fixed effects based on McKenzie 2012.[13] ANCOVA estimates are preferable to Difference-In-Difference (DID) estimates for outcome measures with the high variability and low autocorrelation. While ANCOVA fits estimating economic outcomes such as income and expenditure that are subject to high variability and low autocorrelation, the DID model is suitable for studying highly autocorrelated and relative precisely measured outcomes in health and education domains.[13] The authors applied ANCOVA on both economic outcomes and health and psychological wellbeing outcomes and identified effects on consumption and income but failed to find significant treatment effects on health and education outcomes. We propose to examine the two conditions for ANCOVA, the high variability and low autocorrelation, to validate the adoption of ANCOVA. We also propose to conduct DID analysis for outcome variables shows high autocorrelation.

The study used clustered randomized sampling method where randomization took in household and village level which entailed correlation of the error terms within these clusters. The authors modeled village-level fixed effects and controlled household-level correlation for individual level outcome measures. An alternative method for estimation of this type of data is generalized linear mixed models (GLMM), also known as hierarchical or multi-level models.[14] This model allows for estimation of error terms that correlated in two levels of clusters and increase efficiency of estimation.[14] We propose to conduct multi-level modelling at both the household and village level for psychological wellbeing indicators as it takes consideration of the nested structure of the data collected.

We propose to examine estimation method by the following steps:

a. Validation of the ANCOVA used in the main analysis.

   The model validation will focus on the examination of two features pertinent to ANCOVA, autocorrelation and variability, for eight indices.

   We will also check model assumptions for all models used in the analyses, especially, the normality of the data and equal variance assumption. If these conditions are not satisfied then will transform the data and redo the analyses. In addition, we will check the validity of using dummy indicator for missing variables in baseline.

b. Conduct DID models for outcome measures with high autocorrelation. It is hypothesized that health, food security, and psychological wellbeing measures in these poor households in Kenya have relatively large autocorrelation. We will use a cut-point of 0.5 for autocorrelation coefficient (ρ) as when ρ is smaller than this value ANCOVA is preferred to DID model.[13] We then will compare results from DID models to the authors' to examine the robustness of the treatment effects.

c. Use multi-level modeling to take into consideration of household and village-level correlations when examining the treatment effects. As the experiment follows a clustered randomized design at the village level and at the household level, we propose to use the multi-level modelling methods that controls for the correlation at the household and village level for the difference in outcome measures. SAS procedure PROC GLIMMIX will be used for modelling.

2.2. Alternative model specification

The authors did not consider potential interaction effects of village to treatment effects and the interaction effects between recipient gender and transfer frequencies. Some underlying village features may moderate the impacts of cash transfers and adding the interaction terms in the model allows estimation of such effects. In addition recipient gender may be related to the effects of UCT as wife and husband may play different roles in making household decisions. We propose to examine two interaction effects, gender with treatment and village with treatment, in the model and test if these interaction terms are significantly related to the outcomes of interest.

2.3. Alternative measures of health, food security, and psychological wellbeing.

The study measured short term impacts of cash transfers on the outcomes of interests. The lack of significance of impacts of UCT on health, food security, or psychological wellbeing could be explained if these measures are expected to change only in a longer term. Alternatively, the lack of significant impacts may be due to the fact that the short-term relationship is not linear. For example, we do not expect that a one-time cash transfer increase the BMI values of the children linearly. Rather, it may change the likelihood of the children being in the normal range of BMI through increased access to food and nutrition.[15] Thus, categorizing certain individual outcome measures in health, education, and psychological wellbeing may better capture the impacts. For health indicators, we are particularly interested in examining the treatment effects on BMI categories of children in the treatment households.

In addition, the authors used standardized indices in eight domains to reduce the number of outcome variables for estimation. While this practice is reasonable for conventional economic measures such as consumption, income, and asset holdings, it may not capture the underlying structure for complex measures of health, food security, and psychological wellbeing. We propose to conduct Principle Component Analysis(PCA) on certain variables in health, food security, and psychological wellbeing measures separately and identifying the underlying factors for examination.[16-18] The main applications of the PCA analytic techniques are to reduce the number of variables and to detect structure in the relationships between variables.[16-18] When there are a number of variables that measure similar underlying factors, the application of PCA will help identify the underlying factors (often fewer than the total number of variables) and suggest logarithms to calculate weighted index values of the factors based on raw observed data of the variables. We will conduct PCA by using SAS procedure PROC PRINCOMP. Based on PCA results we will define the principal components of measures in health, food security, and psychological wellbeing and compose new indices. We will also run ANCOVA or DID model on these new indices to examine the treatment effects based on the autocorrelation and variability of these new outcome measures.

Aim 3: Theory of Change Analysis

The paper is modelling the outcome measured after intervention using one variable ANCOVA or regression with adjustment of baseline measurements. The authors addressed the multiple inference issues by examining index measures of economic and health outcomes to reduce total number of regressions conducted and by applying FWER to control for the 'false positive' rate. As these outcome measures are potentially correlated, the authors also run SUR on the eight estimation equations and reported the joint significance. We propose to extend the study by conducting Multivariate Analysis on the eight indices and on the individual measures in each domain.

The multivariate analysis fits a simultaneous regression to multiple outcomes that are correlated. This methodology allows for the complete modeling of all data in one analysis, testing correlations between multiple outcomes, and directly estimating the difference in the association between treatment effects on multiple outcomes.[16,19] By employing a multivariate model, it is possible to gain precision compared to estimating separate models for each outcome. We propose to conduct Multivariate Analysis of Variance (MANOVA) to examine the differential treatment effects on the correlated multiple outcomes including asset holdings, consumption, income, and the health and psychological wellbeing. SAS procedure Proc GLM with multivariate setting will be used with adjustment for treatment effects. We plan to:

(1) Examine the treatment effects on the indices using multivariate analysis. As the index measures in each domain are expected to be correlated, the use of multivariate regression analyses or MANOVA allows tests for differential impacts of cash transfers on the economic and health outcomes.

(2) Examine the treatment effects on the individual outcome measures that composed the indices of assets, income, consumption, and psychological wellbeing. As the individual measures in each domain are expected to be correlated, the use of multivariate regression analyses or MANOVA allows tests for differential impacts of cash transfers on the individual outcomes in each of the four domains.

Conclusion

This replication study aims to validate the findings of Haushofer and Shaprio 2016 study on the impacts of UCT on income, consumption, and wellbeing of poor households in rural Kenya. The push-button replication and a pure replication will regenerate the results and validate key findings in the original paper. The alternative methodologies, model specifications, measurements, and sample inclusion criteria proposed in MEA help us understand the robustness of the impacts of UCT in rural Kenya. The MEA can potentially help us identify effects not addressed in the original study by using more efficient multi-level modeling technique and examining the potential interaction effects. Additionally, the multivariate analysis allows us to test the differential impacts of cash transfers in economic and health outcomes to inform policy decisions. All proposed MEA and Theory of Change analysis are not part of the analysis plan of the original authors. The proposed replication study plan is developed with no interactions with the data or code from the original study.

Tentative replication study timeline

Task	Months 1-2	Months 3-6	Months 7-8	Months 8-9	Months 10-11	Month 12
Preparation: Data acquisition and management	x					
Aim1. Conduct push-button and pure replication and regenerate tables I-VI		x				
Aim2. MEA_ Model validation and run DID models			x			
Aim2: MEA_ Explore alternative measures, model specifications, and sample inclusion criteria				x		
Aim3: Conduct multivariate Analysis of indices and individual outcome					x	
Draft and finalize replication report and write manuscripts						x

Research team

Our research team will consist of Dr. Hongmei Wang, Ph.D. and health economist, Assistant Professor of Health Services Research and Administration (PI), at University of Nebraska Medical Center (UNMC). Dr. Jiangtao Luo, Ph.D. and statistician, Assistant Professor of Biostatistics at UNMC (Co-PI). Dr. Wang has extensive experience in conducting evaluation and economic evaluations of health and medical interventions. Dr. Wang will contact the original study authors for data and be responsible to carry out the replication study plan and complete the study reports. Dr. Luo has expertise in the area of statistical methodology and modeling and had experience with replication study for 3ie. Dr. Luo will guide the research team in replication study design and conduct statistical analyses.

References

1. Shah A. *Poverty Facts and Stats.* 2013. http://www.globalissues.org/article/26/poverty-facts-and-stats. Accessed July 30 2016.
2. Hidrobo M, Peterman A, Hoddinott J, Margolies A, Moreira V. Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador. *J. of Dev. Econ.* 2014. 107:144-156.
3. Brune L, Gine X, Goldberg J, and Yang D. Facilitating savings for agriculture: field experimental evidence from Malawi. *Economic Development and Cultural Change*. 2016. 64(2):187-220.
4. Hoynes HW, Schanzenbach DW. Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. *Am. Econ. J. Appl. Econ.* 2009. 109-139.
5. Baird S, McIntosh C, Özler B. 2011. “Cash or condition? Evidence from a cash transfer experiment.” *The Quarterly Journal of Economics* 126 (4): 1709–1753.
6. Cesarini D, Lindqvist E, Notowidigdo MJ, Östling R. 2015, November.“The Effect of Wealth on Individual and Household Labor Supply: Evidence from Swedish Lotteries.” Working Paper 21762, National Bureau of Economic Research.
7. Merttens F, Hurrell A, Marzi M, Attah R, Farhat M, Kardan A, MacAuslan I. *Kenya Hunger Safety Net Programme Monitoring and Evaluation Component. Impact Evaluation Final Report: 2009 to 2012.* 2013.
8. Attah R, Barca V, Kardan A, MacAuslan I, Merttens F, Pellerano L. Can Social Protection Affect Psychosocial Wellbeing and Why Does This Matter? Lessons from Cash Transfers in Sub-Saharan Africa, *The Journal of Development Studies*, 2016. 52:8, 1115-1131.
9. Barca V, Hurrell A, MacAuslan I, Visram A, Willis J. Paying attention to detail: how to transfer cash in cash transfers, *Enterprise Development and Microfinance* 2013. 24(1).
10. Anderson, Michael. 2008. “Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects.” *Journal of the American Statistical Association* 103 (484): 1481-1495.
11. Lee DS. Training, wages, and sample selection: Estimating sharp bounds on treatment effects. *Rev. Econ. Stud.* 2009. 76(3):1071-1102
12. Horowitz, Joel L., and Charles F. Manski. 1995. “Identification and robustness with contaminated and corrupted data.” *Econometrica* 63 (2): 281–302.
13. McKenzie D. Beyond baseline and follow-up: the case for more T in experiments. *J. Dev. Econ.* 2012. 99(2):210-221.
14. Jacob Cohen, Patricia Cohen, Stephen G. West, Leona S. Aiken. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences.* 3rd Edition, Mahwah, New Jersey. Lawrence Erlbaum.
15. Ogden, C. L., Lamb, M. M., Carroll, M. D. & Flegal, K. M. Obesity and socioeconomic status in adults: United States, 2005–2008. *NCHS Data Brief* 50, 1–8 (2010).

16. Anderson TW. 2003. *An introduction to multivariate statistical analysis*. 3rd Edition, John Wiley & Sons, New York.
17. Abdi H, Williams LJ. Principal component analysis. Wiley interdisciplinary reviews: *computational statistics*. 2010 Jul 1;2(4):433-59.
18. Vyas S, Kumaranayake L. Constructing socio-economic status indices: how to use principal components analysis. *Health policy and planning*. 2006 Nov 1;21(6):459-68
19. Johnson RA and Wichern DW. 2007. *Applied Multivariate Statistical Analysis*. 6th Edition, Pearson Prentice Hall, New Jersey.