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HAPPINESS AND ALLEVIATION OF INCOME POVERTY: IMPACTS OF AN UNCONDITIONAL CASH TRANSFER PROGRAM USING A SUBJECTIVE WELL-BEING APPROACH

Kelly Kilburn, PhD[a], Sudhanshu Handa, PhD[a], Gustavo Angeles, PhD[b],

a Department of Public Policy, University of North Carolina, Chapel Hill, North Carolina
b Department of Maternal and Child Health, Gillings School of Global Public Health, University of North Carolina, Chapel Hill, North Carolina

Abstract

This study analyzes the impact of an exogenous, positive income shock on caregivers' subjective well-being in Malawi using panel data from 3,365 households targeted to receive Malawi's Social Cash Transfer Program that provides unconditional cash to ultra-poor, labor constrained households. The study consists of a cluster-randomized, longitudinal design. After the baseline survey, half of these village clusters were randomly selected to receive the transfer and a follow-up was conducted 17 months later. Utilizing econometric analysis and panel data methods, we find that household income increases from the cash transfer can have substantial subjective well-being gains among caregivers. Households use the cash to improve their families' livelihoods, ensuring provision of their basics needs including food, shelter, and clothing. Reduction of these daily stresses makes caregivers happy about their current situations and gives them hope that the future will continue to get better.

CHAPTER 2: HAPPINESS AND ALLEVIATION OF INCOME POVERTY: IMPACTS OF AN UNCONDITIONAL CASH TRANSFER PROGRAM ON WELLBEING USING A SUBJECTIVE APPROACH

Introduction

The importance of income for individual subjective well-being, often described as "happiness" or "life satisfaction", has been debated for decades (see for example: Easterlin, 1974; Fritjters, Haisken-DeNew, & Shields, 2004; Stevenson & Wolfers, 2008; Easterlin et al., 2010). Most evidence comes from examining correlations between average subjective well-being and national income in cross-sectional data. In richer, more developed countries income is positively correlated with happiness but with diminishing returns (Frey & Stutzer, 2002). At lower levels of income and in low-income countries however, there is a stronger linear relationship implying that income is an important determinant of happiness when it corresponds to a better quality of life in the sense of satisfying basic needs (Deaton, 2008; Graham & Behrman, 2009). The relationship between low-income and happiness suggests that poverty alleviation programs that have direct impacts on income may have the potential to increase subjective well-being. Nevertheless, little is known about the subjective well-being impacts of income increases for the poor, especially by means of specific policy.

This paper revisits the relationship between income and happiness and estimates the impact of an unconditional social cash transfer program on individual subjective well-being. Social cash transfer programs provide consistent cash payments to targeted, poor households. Unconditional cash transfers distribute payments regardless of recipient behaviors as opposed to conditional transfers such as those in Latin America that tie receipt to certain conditions. Limited evidence exists on the relationship between cash transfers and happiness, but a study in Mexico found a dissonance on objective and subjective

welfare; the reduction of income poverty for households in the Mexican Oportunidades program did not translate into a greater sense of well-being (Rojas, 2008).

While an interesting relationship to explore on its own, there is increasing attention in the measurement and use of subjective well-being as a means of informing policy design (Dolan & Peasgood, 2008). Mounting evidence has shown that subjective well-being metrics can capture individual emotional states and predict other measures of individual well-being such as health outcomes (Kahneman & Kruger, 2006). They also have the potential to predict behavior across other domains such as work life and relationships (Lyubomirsky, King, & Diener, 2005). Incorporating subjective welfare indicators into social policy evaluations can thus complement existing objective measures and provide a deeper understanding of how policies affect livelihoods across more dimensions than the economic one.

This paper uses data from an experimental study of Malawi's Social Cash Transfer Program to explore measures of subjective well-being that capture concepts of life satisfaction, relative wealth, and future expectations amongst household caregivers. The study collected longitudinal household data with a baseline survey in 2013 and a 17-month follow-up survey at the end of 2014. The households for this study were randomly assigned to either the treatment and control group after the baseline survey. While income is generally taken to be endogenous to both individual well-being and determinants such as health status and personality, the random assignment to treatment provides exogenous variation in income that allows us to identify the impact of such increases on subjective well-being. As a starting point, our empirical specification models subjective well-being traditionally as an additive function of individual determinants. We then use panel data methods to control for time trends and unobserved individual characteristics to elicit a casual impact of income.

This investigation finds that household income increases from the cash transfer can have substantial subjective well-being gains among caregivers. We find large, significant effects of treatment on both life satisfaction and future outlooks, which are robust across empirical specifications and additional controls. Specifically, after about a year's worth of transfers, caregivers in beneficiary households score 0.50 SD

higher on the Quality of Life scale and are over 20 percentage points more likely to believe in better future in two years using panel data specifications.

Background

Subjective well-being is defined by Diener, Lucas, and Oishi (2009) as an individual's evaluation of his or her life from both emotional and cognitive perspectives. Therefore, high subjective well-being can include the recurrent experience of positive affect (and low negative affect) as well as high life satisfaction. In practice, surveys such as the Gallup World Poll tend to capture more of the cognitive aspect of subjective well-being with questions about how an individual assesses their quality of life. Economists have traditionally been critical of these quality of life measures though because self-reports are assumed to be unreliable signals for individuals' underlying preferences and constraints that affect actual behavior. Instead, they have relied on revealed preference analysis, examining observable consumption and investment behavior with the underlying assumption that these measurable choices better reflect the set of unobservable trade-offs of preferences and constraints (Graham & Behrman, 2009).

Regularly, however, people's choices are not aligned with their own happiness. Literature from behavioral economics and psychology finds that people habitually make inconsistent choices, departing from the standard model of the rational economic agent (Kahneman, 2003). Evidence from developing country contexts finds that people repeat the same mistakes, fail to participate in market opportunities, and make myopic decisions that fail to take account of their long-term welfare such borrowing at very high interest rates (Anderson & Stamoulis, 2006; Banerjee & Duflo, 2004, Banerjee & Mullainthan, 2010). Revealed preference analysis is therefore limited in providing explanation of other factors influencing important choices, such as self-control problems and constraints like poverty that might result in perverse choices (Graham & Behrman, 2009). Moreover, personal psychological states have been clearly linked to individual economic and social behaviors. Decision-makers with positive life outlooks are expected to make better choices for themselves and their household such as seeking preventive care or

investing in human capital because happiness increases decision-makers' cognitive flexibility and self-control to carefully assess their future (Isen 2008; Lyubomirsky, King, & Diener, 2005).

In theory, collecting subjective data allows researchers to test fundamental economic assumptions because subjective data directly captures well-being (Frey & Stutzer, 2002). While the assumption that income is a basic determinant of subjective well-being has been tested and affirmed, supporters of the subjective approach do not condone using income to exclusively evaluate welfare for the risk of overvaluing policy impacts. There are other human needs and values that cannot be directly bought or enriched with income such as emotional support and personal relationships as well as autonomy and human development. Moreover, focusing solely on income neglects the fact that income may not be used efficiently and that well-being could depend more on relative rather than absolute consumption (Rojas, 2007). Alleviation of income poverty might not be enough to increase individual's overall sense of well-being if other dimensions of their life are going poorly. As Rojas (2009, 2015) describes in his 'subjective well-being approach', the goals of poverty alleviation programs may be compromised if dissonances emerge between subjective and objective measures. Policies that cannot improve people's lives across more dimensions than absolute income may not lead to successful transitions out of intergenerational poverty since well-being involves other aspects such as work, relationships, and communities. Thus, including subjective well-being measures within evaluations of social programs can complement objective measures to provide a better picture on the effect of policies across more dimensions than the economic one.

Though subjective well-being analysis may be useful in policy evaluation, it is important to point out that individuals' perception of well-being are not easily comparable between people. Even if subjective questions can appropriately capture individual well-being, researchers expect that individuals have different interpretations of subjective questions, which will bias interpersonal comparisons (Beegle, Himelein, & Ravallion, 2012). Nonetheless, econometric techniques that control for unobserved heterogeneity among individual responses makes the use of subjective survey data more acceptable for

policy analysis (Graham & Behrman, 2009). Moreover, recent findings indicate that differences in individual viewpoints present little bias in relative well-being data (Beegle et al., 2012), and measures of life satisfaction have been validated as a good correlate across other measures of well-being including economic, psychological, physiological ones (Dolan, Peasgood, & White, 2008; Kahneman & Kruger, 2006).

Therefore, subjective well-being measures have become increasingly popular among economists and policy analysts for the purpose of measuring individual and social welfare (e.g. Kahneman & Kruger, 2006; Mullainathan, 2005; Rojas, 2008; Rojas, 2009; Fafchamps & Shilpi, 2009; Di Tella & MacCulloch; 2006). However, despite the growing use and acceptance subjective well-being data, literature on well-being and income rarely makes causal claims because survey data is usually missing the exact timing of changes in income and happiness, raising concerns about reverse causality. A few studies, however, have been able to test this causality by utilizing natural exogenous variations in income. For instance, Frijters, Haisken-DeNew, and Shields (2004) use the reunification of Germany to show that income gains for East Germans resulted in lasting gains on individual life satisfaction. Gardner and Oswald (2007) use data on lottery winners in Britain, to show that mid-size wins result in better psychosocial health for winners compared both to those with no wins or smaller wins. Experimental data, however, is missing because as Gardner and Oswald (2007) point out "…it is not possible to run giant experiments where, in the name of science, different amounts of government-funded research cash are randomly allocated to treatment and control groups (p 50)."

This paper fills this important gap by exploiting the randomized study design to measure the causal impact of income increases on subjective well-being. Evaluations of unconditional cash transfer programs have just recently started to measure subjective well-being. In Kenya, Give Directly, an NGO that gives one-time unconditional cash payments to poor households, found that the program had strong positive effects on happiness and life satisfaction measures (Haushofer & Shapiro, 2013), however, there were larger negative spillover effects for neighbors that did not receive the transfer (Haushofer, Reisinger, &

Shapiro, 2015). Another working paper by Handa and company (2014) also uses subjective data from Kenya. The paper examines the country's large-scale government-run unconditional program (CT-OVC) and shows that subjective measures performed well and correlated to expected material well-being and demographic measures. The evidence from Kenya's CT-OVC program, however, is limited to cross-section analysis. This study uses longitudinal data from Malawi and thus improves upon this evidence by controlling for ex-ante well-being and any unobserved individual heterogeneity in survey responses. Additionally, comprehensive survey data allows us to control for individual and household determinants of subjective well-being including baseline consumption.

Study Setting and Design

Location

Malawi is a small, landlocked country in southern Africa. The majority of the nation's population (51 percent of 16.7 million) lived below the poverty line in 2014 and the vast majority of the population reside in rural areas, living as subsistence farmers. The country is one of the poorest in Africa; Malawi's 2014 GNI per capita figure of $790 (PPP, current international $) is less than 25 percent of the SSA average of $3382 (World Bank, 2014). According to the same data source, gross enrollment in secondary school was a low 37 percent in 2013, and unemployment was high at 14.8 percent for women and 12.6 percent for men aged 15-24 years in 2014.

The Malawi SCTP program

The Government of Malawi's (GoM's) Social Cash Transfer Program (SCTP) is an unconditional cash transfer program targeted to ultra-poor, labor constrained households in Malawi. The main objectives of the program are to alleviate hunger and poverty among households and to improve children's well-being and human capital through education, nutrition, health, and household productivity. The program began as a pilot in the Mchinji district in 2006 and since that time, the program has expanded to 18 districts and reached approximately 175,000 as of January 2016.

SCTP beneficiary selection is made through a community-based approach with oversight provided by local and national government. Appointed community members are responsible for identifying households that meet the eligibility criteria of being ultra-poor and labor constrained. After further screening of identified households by the GoM, including a proxy means test to meet the ultra-poor eligibility condition, the recipient list is generated. The program's goal is that these lists target the bottom 10 percent of each community (Malawi SCTP Evaluation Team, 2015). An early evaluation of the Malawi SCTP in Mchinji confirms that recipient households live in extreme poverty and have higher dependency ratios than other poor households (Miller, Tsoka, & Reichert, 2010). Additionally, household heads tend to be older (above 60) and upwards of 80 percent of households are missing at least one prime-age adult, highlighting their particular vulnerability to the impacts of HIV/AIDS (Handa et al., 2013).

The SCTP provides a monthly unconditional cash transfer to eligible households, which vary depending upon the number and school status of members in the household. Table 2.1 shows transfer amounts in Malawi Kwacha (MWK) that were in use at time of follow-up data collection (first column, 'Prior to May 2015') and the new transfer levels that were increased in May 2015.

Table 2.1. Structure and level of transfers (current MWK)

	Prior to May 2015	After May 2015
1 Member	1,000	1,700
2 Members	1,500	2,200
3 Members	1,950	2,900
4+ Members	2,400	3,700
Each primary school child[1]	300	500
Each secondary school member[2]	600	1,000

[1]Provided for household residents age 21 or below in primary school. [2] Provided for household residents age 30 or below in secondary.
Source: Malawi Social Cash Transfer Program Midline Impact Evaluation Report (2015)

The 'rule of thumb' among policy experts is that size of the transfer should amount to at least 20 percent of baseline consumption in order to have measurable impacts (Davis & Handa, 2015). Before the increase in transfer amounts in May 2015, the majority of beneficiaries in this study's sample had a share below this 20 percent threshold. The average share was 18 percent and 50 percent of beneficiaries had a share below 15 percent.

Study Design

Data comes from the impact evaluation of Malawi's SCTP undertaken by UNC-Chapel Hill's Carolina Population Center and University of Malawi's Center for Social Research. The design consists of a cluster-randomized longitudinal study with a baseline survey and two follow-up surveys. This study only uses the baseline survey conducted mid-2013 and the first follow-up survey conducted in late 2014 through early 2015. The household survey is the main survey instrument covering a comprehensive list of topics including household composition, consumption, economic activity, education, health, time use, and subjective welfare among others. A qualitative component also includes in-depth individual interviews with the caregiver and one youth from 16 treatment households selected using a stratified sampling approach. This study has IRB approval from both the University of North Carolina (IRB Study No. 14-1933) and Malawi's National Commission for Science and Technology (IRB Study No. RTT/2/20).

The evaluation was designed around the GoM's plans to extend and expand coverage of the SCTP within in Malawi over three years starting in 2013. In order to integrate the impact evaluation with early expansion plans in 2013, two districts, Salima and Mangochi, were chosen for this study. Random selection was included at all possible levels, including the two smaller levels within these districts, Traditional Authorities (TAs) and Village Clusters (VCs). First, two TAs in each district were first randomly selected to participate in the evaluation study and then eligible beneficiary lists from each VC within these four TAs were generated following normal program operating guidelines described above. In the second stage, VCs were randomly selected to arrive at a necessary sample size of 3,500 based on power calculations for key program outcomes. In Salima, all eligible households were selected in the VCs. In Mangochi, 125 eligible households per VC were randomly selected in each selected VC. The final sample for the study was drawn from 29 VCs and comprises 3,531 households, approximately 47 percent of all eligible households from the four TAs.

The quantitative baseline survey was administered over several months from June to September 2013 to the study sample of 3,531 households (1,678 treatment and 1,853 control). Households were not

assigned to treatment (T) and control (C) status until after the baseline survey in order to maintain objectivity during data collection. Half of the VCs in each TA were randomly assigned the treatment group to start receiving the cash transfer right away. The other half of the VCs was assigned to the delayed-entry control group and entered the program in late 2015. This cluster randomization approach is preferable to household randomization in this study because it reduces concerns that treatment effects could become contaminated due to households living in close proximity with other study participants (Malawi SCTP Evaluation Team, 2013). The design is also more administratively and ethically feasible because the program did not have the financial resources to reach all households immediately.

The follow-up occurred at the end of 2014 and concluded in February 2015. Overall attrition was low, 95 percent of the baseline sample was retained and detailed attrition analysis finds no evidence of selective attrition. Beneficiary households had received five or six cash payments at the time of follow-up data collection. Each payment accounted for two months so results can be interpreted as one-year impacts of the program (Malawi SCTP Evaluation Team, 2015).

An important note about the follow-up is that this survey was conducted in Malawi's lean season while baseline was conducted after the harvest. There was a significant decline in consumption of around 25 percent for both study arms at follow-up, on par with regional consumption fluctuations between the same time periods in Malawi's 2010 Integrated Household Survey. However, the SCTP appears to be protective for beneficiary households during these seasonal changes as evidenced by greater average consumption across a number of food and nonfood categories (Malawi SCTP Evaluation Team, 2015).

Data

For our purposes in this paper, the sample includes households who responded to subjective well-being questions in both waves. There was one respondent per household, typically the main caregiver in the household but not necessarily the household head. The full household panel includes 3,365 households (1,605 treatment and 1,760 control) consisting of all households that responded to subjective well-being questions in both waves. The individual panel of 2,919 (1,520 treatment and 1,399 control)

consists of the same respondent in both waves and is a smaller subset of these households.

Measures

To measure subjective well-being this study includes constructs of quality of life, relative well-being, and future expectations. Quality of life measures are constructed from a series of questions gauging individual's perceptions of life satisfaction (Douthitt, MacDonald, & Mullis, 1992). Life satisfaction refers to a person's global assessment of their life such as whether they find life pleasant or fulfilling. This is considered a cognitive, judgmental process, where a person's judgments are dependent upon a comparison of one's present circumstances with a standard which each individual sets for him or herself (Diener, Emmons, Larsen, & Griffin, 1985). Therefore, we did not externally impose any reference for comparison so that subjective well-being measures center on a person's own judgments.

To measure the quality of life, respondents were asked how much they agree with the following statements from strongly agree (5) to strongly disagree (1):

1. In most ways my life is close to ideal.
2. The conditions in my life are excellent.
3. I am satisfied with my life.
4. So far I have gotten the important things I want in life.
5. If I could live my life over, I would change almost nothing.
6. I feel positive about my future.
7. I generally feel happy.
8. I am satisfied with my health.

These questions are drawn from the Satisfaction with Life Scale (SWLS) (Diener et al., 1985) and the WHO Quality of Life Scale (WHOQOLS)(WHO, 1998). The first five questions comprise the SWLS, which is narrowly focused on an individual's overall life satisfaction. The SWLS has shown good internal consistency and construct validity (Kobau, Sniezek, Zack, Lucas, & Burns, 2010). The last three questions come from the WHOQOLS and covers positive affect as well as overall quality of life. Quality

of Life (QoL) is a continuous measure generated by summing the responses from each item of the scale. The resulting scale ranges from 8 to 40 with higher scores reflecting greater quality of life.

The study also collects caregiver perceptions of their relative well-being with respect to their societal economic status. Literature has confirmed that income evaluated relative to others has a significant effect on individuals' perception of well-being at least among developed societies (Clark et al., 2008). Evidence from developing societies is more inconsistent. For example, Ravallion and Lokshin (2010) find that among the poor in Malawi, subjective well-being is not correlated with mean income in one's neighborhood. However, Fafchamps and Shilpi (2009) find that relative consumption is an important predictor of subjective well-being among the poor even in isolated villages in Nepal.

We measure relative well-being using a visual stepladder with six choices from poor (1) to rich (6). Respondents are asked to place themselves on one of these steps in addition to their neighbors and friends. We generated two binary variables, one that measures relative well-being in comparison to friends and the other in comparison to neighbors. The variables measure if individuals perceive themselves to be either the same or better off compared to worse off than their friends and neighbors.

The last construct, future outlooks, is measured by asking respondents for their perception of how they feel their life will go (better, same, or worse) in one, two, and three years from now. Binary indicators measure whether individuals feel their life will be better off in the future compared to the same or worse off. As compared to life satisfaction, which is an assessment of one's current circumstances, these questions on future well-being have respondents gauge the unknown future and tap into concepts of expectation and optimism. Psychological theory proposes that optimism as a personality trait would affect subjective well-being through expectations about the future (Scheier & Carver 1985). Some literature has found that dispositional optimism correlates well with other measures of subjective well-being such as life satisfaction and positive affect (Lucas Diener, & Suh, 1996). Optimism may also be a latent sentiment too. Experimental evidence from an intervention targeting gratitude show that participants exposed to a self-guided reflection of their blessings targeting could cultivate optimism about the near future (Emmons

& McCullough, 2003).

The independent variable is treatment status, a binary measure for households randomly chosen to receive the cash transfer. Individual correlates of subjective well-being controlled for include age, age-squared, gender, marital status, education, and chronic health issues (Dolan et al., 2008; Wiemann et al., 2015). Baseline values of household correlates are also controlled for including household size and total members in age groups (0-5, 6-11, 12-17, 18-65, and 65+). Baseline values of these measures are used because household composition could be endogenous to the income shock.

If a positive income shock increases happiness, shocks that would reduce income such as death of an income earner should analogously have a negative impact on happiness. By testing the relationship between negative shocks and subjective well-being, we can ensure that our measures are sensitive to negative shocks and respond appropriately. Respondents were asked about negative shocks that occurred within the previous 12 months such as floods and droughts, high food prices, death and serious illness of household members, and conflict or violence. We test a couple of measures, total number of shocks and an indicator for the death of an income earner. In addition, respondents were asked to assess the likelihood of experiencing negative shocks in the next year, a food shortage and needing financial assistance. Indicators for each shock measure whether the respondent believes there a likely or very likely chance the event will occur in the next year.

Methods

The determinants of subjective well-being (SWB) are typically modeled empirically as an additive function of the social, economic, and environmental factors (Xs) involved where the error term (ε_i) captures individual differences in reporting (Dolan et al., 2008). :

$$SWB_{it} = \alpha + \beta_1 X_{1_{it}} + \beta_2 X_{2_{it}} + \cdots + \varepsilon_{it}$$

We start with this basic specification and use three different models to test the effect of treatment on SWB. First is an OLS linear regression model on the wave 2, cross-section data.

$$(1) \quad Y_i = \alpha + \beta_1 T_i + \beta_2 X_i + e_i$$

Y_i is the individual measure of subjective well-being, T_i is an indicator variable for being in a treatment household, and X_i is a vector of individual control variables.

The second model is a Differences-in-Differences (DD) regression model, which uses panel data to account for baseline values of SWB and group level differences across the two study arms. Equation 2 shows the basic empirical specification where Y_{it} is an individual, time specific measure of subjective well-being, T_i*P_t is an indicator for cash transfer receipt in the second wave and represents the DD estimate of the treatment effect since it is the product of treatment status (T_i) and second time period (P_t).

$$(2)\ Y_{it} = \alpha + \beta_1 T_i * P_t + \beta_2 T_i + \beta_3 P_t + \beta_4 X_{it} + e_{it}$$

The final specification is a fixed effects model to control for individual reporting differences and unobserved characteristics such as personality that might bias the treatment effects. These show up in the unobserved error term, V_i, and are assumed fixed over time. Individual fixed effects will also wipe out any time indifferent control variables such as gender and treatment status.

$$(3)\ Y_{it} = \alpha_i + \beta_1 T_i * P_t + \beta_2 P_{it} + \beta_3 X_{it} + e_{it} + v_i$$

Regressions include household probability weights and standard errors are clustered at the village cluster level, the level of random assignment to treatment.

Results

Randomization and Summary Statistics

The data for this study comes from a carefully designed, randomized experiment and thus in theory, second round results should be enough to find a treatment effect if randomization was successful at balancing T and C groups. Nonetheless, in a field experiment that is part of a larger governmental intervention, successful randomization is more difficult to achieve than experiments designed and implemented by the same research team. For example, we might find bureaucrats affecting randomization (intentionally or not), resulting in imperfect implementation. Randomization may also be imperfect and where randomization results in unevenness between groups, it is important to control for those baseline characteristics. Bruhn & McKenzie (2009) even recommend controlling for baseline variables that are

thought to influence future outcomes, whether or not their means are statistically different, because including variables that are good predictors of the outcome soak up residual variance, increasing power. Additionally, examining balance in this particular evaluation is important because the randomization of the program was done at the cluster level, while the outcomes of interest are at the individual level.

Table 2.2. Success of randomization: key indicators at baseline by treatment status

	Baseline characteristics	
	Treatment	**Control**
Observations	*1,608*	*1,761*
Key Program Indicators		
Poverty and Food Security		
Poverty rate, individuals (%)	90.3	92.8
Eat only one meal per day (%)	21.3	19.1
Economic Activity & Productive Assets (households)		
Operate an enterprise (%)	24.1	22.6
Cultivate land (%)	95.6	96.0
Selling any crops (%)	21.6	23.9
Adult Health (age 50+)		
Morbidity (%)	55.9	49.9
Any disability (%)	13.9	14.9
Adolescent Schooling & Labor		
Ganyu work for pay (age 10-17)	41.1	38.9
School enrollment (14–17)	64.3	71.3
Safe Transitions to Adulthood		
Ever had sex (age 13-19)	34.8	31.6
Depressive symptoms (age 13-19)	44.9	50.6
Young Child Health & Nutrition		
Underweight (age 0-5)	19.3	16.9
Consumed Vit A rich foods previous day (6-59 months)	67.4	60.9
Demographic and Household Characteristics		
Per Capita Consumption (mean annual MWK)	43,891	41,357
Age (mean)	58.7	56.8
Female (%)	83.2	84.8
Chronic illness (%)	47.2	40.5
Ever attended school (%)	27.8	30.4
Married (%)	29.8	29.2
Household size (mean)	4.5	4.5
Number of shocks in past 12 months (mean)	2.5	2.5
Death in past 12 months (%)	3.8	3.2
Believes will have future financial or food shock in next 12 months (%)	53.5	53.3

Notes: No significant differences between baseline T and C groups at (p-value<0.1)

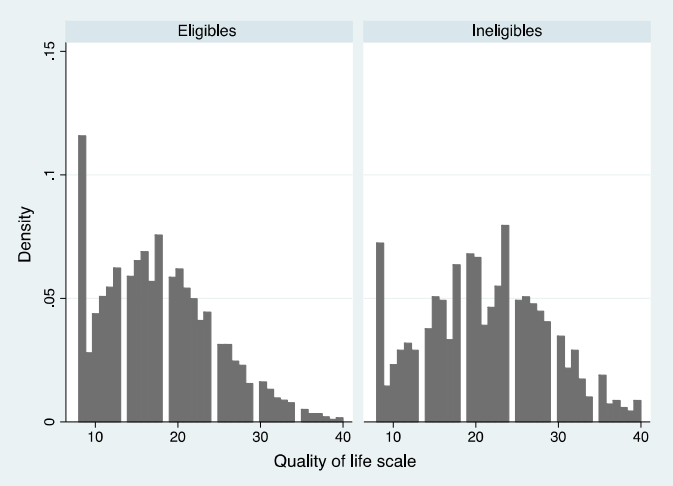
The baseline summary statistics presented in at the bottom panel of Table 2.2 show that the vast majority of caregiver respondents are female (over 80 percent) with an average age just below 60. Approximately a third of the sample has attended school at some point in their life and another third is

currently married.

The study's main evaluation focuses on six key areas and primary outcomes in these areas were tested for statistical differences between the two groups at baseline using OLS regression and accounting for the survey design to adjust standard errors. The top panel of Table 2.2 shows that randomization was successful for the panel sample used here in all key program areas. Mean characteristics between the treatment and comparison groups are balanced across these domains and there are no significant differences (p-value<0.1). In addition, all outcome and control variables used in this paper are balanced at baseline as shown in the bottom panel of Table 2.2.

At baseline, we also interviewed 821 ineligible households that were randomly selected from the same village clusters. We use this ineligible group to place our sample's responses in context and give evidence that subjective measures correspond to expected objective characteristics. Given that eligible households are the poorest households in the community, ineligible households have a number of different characteristics. Ineligible households are wealthier, have fewer household members, and household heads are younger and more likely to be married.

Figure 2.1. Histogram of QoL scale scores at baseline for eligible and ineligible households



Quality of Life:

The internal consistency of the Quality of Life (QoL) scale is respectably high with a Cronbach Alpha score of 0.83 (using both waves). Factor analysis reveals a single construct consistent with the

literature on life satisfaction scales (Frey & Stutzer, 2002). Figure 2.1 graphically shows the distribution of scores at baseline for the full eligible sample and ineligibles.

At baseline, the mean value for eligible respondents is 18 compared to 21 for Ineligibles. About 10 percent of eligible respondents report the lowest value (8) on the QoL scale, while only 0.1 percent report the highest value (40) and 95 percent of respondents have a value lower than 30. In comparison, scores for ineligibles have a more normal distribution and only 6 percent report the lowest score while 12 percent have a score over 30.

Table 2.3. Baseline values of subjective well-being for T, C and Ineligibles

	Treatment Mean (SD)	**Control** Mean (SD)	**Ineligible** Mean (SD)
QOL scale score[1]	17.5 (6.6)	18.2 (6.9)	21.2 (7.5)
Scale items			
In most ways my life is close to ideal	2.0 (1.1)	2.0 (1.2)	2.4 (1.2)
The conditions in my life are excellent	2.1 (1.2)	2.2 (1.3)	2.5 (1.3)
I am satisfied with my life	2.4 (1.3)	2.5 (1.4)	2.9 (1.3)
So far I have gotten the important things I want in life	1.8 (1.1)	1.8 (1.0)	2.1 (1.2)
If I could live my life over, I would change almost nothing	2.3 (1.3)	2.3 (1.4)	2.5 (1.3)
I feel positive about my future	2.2 (1.2)	2.3 (1.2)	2.8 (1.3)
I generally feel happy	2.3 (1.2)	2.4 (1.2)	2.8 (1.3)
I am satisfied with my health	2.5 (1.3)	2.6 (1.4)	3.2 (1.4)
Future well-being			
Better in a year	0.53	0.53	0.67
Better in 2 years	0.45	0.47	0.61
Better in 3 years	0.42	0.46	0.59
Relative well-being			
Same or better off than neighbors	0.48	0.52	0.64
Same or better off than friends	0.43	0.49	0.63
Self	1.2 (0.5)	1.2 (0.5)	1.6 (0.7)
Neighbors	1.9 (0.8)	1.9 (0.9)	1.9 (0.9)
Friends	1.9 (1.0)	1.9 (1.0)	2.0 (1.0)
Observations	*1,678*	*1,853*	*821*

[1] Range of 8-40 from the sum of scale item questions (scored 1-5)

Table 2.3 reports subjective baseline statistics for eligible T and C groups separately and

ineligibles. The mean value is around 18 for both T and C groups. Additionally, both T and C eligible respondents report middle values for life and health satisfaction (around a 2.5 out of 5), but report slightly lower values for all other items. Placing these values in context, we find higher values for ineligibles respondents living in the same communities. Their overall QoL scale score (21), both life and health satisfaction scores (2.9 and 3.2 respectively), and all other scale items are larger for ineligibles possibly reflecting the role economic hardship plays in subjective well-being for our sample. For QoL scores and all other measures in Table 2.3, we tested for balance by treatment status and find no significant differences at the 10 % level.

Future well-being:

Baseline statistics for future well-being measures in Table 2.3 show that majority of eligible households (53%) think that their life will be better in one year. However, the proportion believing life will be better decreases slightly when respondents think about their life in 2 years and 3 years in the future. Ineligible results are considerably higher but follow the same pattern of decreasing in the more distant future.

Relative well-being*:*

For relative well-being, Table 2.3 shows both respondents' placements on the economic wealth stepladder and indicators generated from these responses on whether they believe they are the same or better off than their friends and neighbors. At baseline, both T and C respondents consider themselves to be at the bottom. On a 1 (poor) to 6 (rich) scale, respondents have mean score of 1.2 or 'poor'. In comparison, respondents placed their friends and neighbors slightly higher on the scale with averages at 1.9, almost a step above themselves. Ineligible respondents perceived themselves to be slightly higher up the ladder (1.6), but had the same perception of their friends and neighbors, which might shed some light on how much relative wealth might be a shared community concept.

Empirical Analysis

This paper focuses analysis on three subjective well-being measures that represent each area discussed above. The Quality of Life (QoL) scale is a continuous measure used to measure life satisfaction while binary indicators are used for future well-being (life will be better in 2 years) and relative well-being (relative wealth is the same or above neighbors). We limit our analysis to these three measures as they are representative of overall data patterns as we found similar results using the other indicators.

Eighty-five percent of households have the same respondents at baseline and follow-up, but some households have different main respondents in the two waves. We use both the household and individual panels albeit for some different purposes. We use the household panel to measure the impact of determinants on subjective well-being and to test for sensitivity of our specifications. We also report results of the income shock using the household panel, but the individual panel is used to control for personality and individual reporting differences that could affect subjective well-being responses. Using both samples we will be able to show whether there is any apparent bias within the results using household panel when we do control for these individual, personality differences.

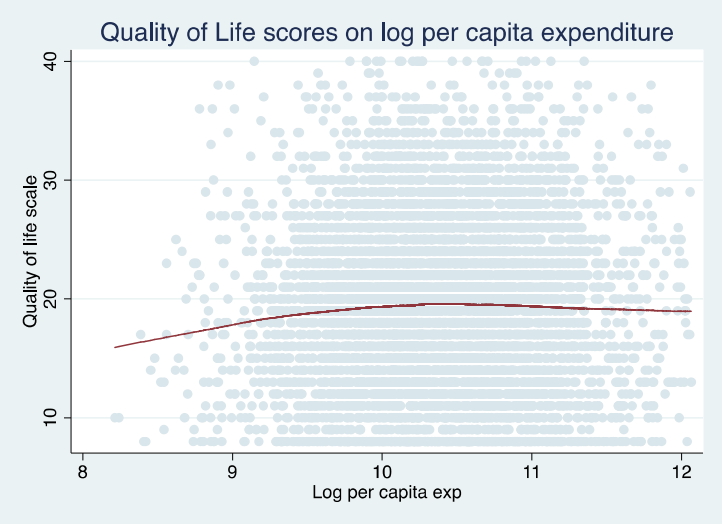
Determinants:

In the first step of analysis, we look at the impact of individual and household determinants on our subjective well-being outcomes. According the literature on correlates of subjective well-being, demographic variables such as income, sex, and age are related to individual subjective well-being but effects are relatively small. In general, positive correlates to subjective well-being include income, self-perceived good health, and marital status (being married) while female gender and age are more likely to be negative correlates (Diener et al., 2009).

Since the expectation is that a positive income shock can increase happiness, it is important to understand how consumption impacts subjective well-being. Figure 2.2 graphically represents the relationship between consumption (in logarithms) and QoL scores (range of 8-40) using a local linear

regression (Lowess) model. There is a slight rise in scores as per capita (pc) expenditure increases at lower levels of consumption, but relationship flattens at higher levels of consumption.

Figure 2.2. Lowess graph of QoL scores on household consumption at Wave 1



Although the Lowess graph in Figure 1 does not display a strong relationship, Table 2.4 shows that log pc consumption expenditure is a strongly significant determinant of QoL at baseline. In addition to consumption, there are many other determinants of subjective well-being so each of the three outcomes were tested on the full baseline sample using linear regression and controlling for individual and household covariates. According to qualitative evidence from baseline, poor health is also a significant cause of stress and anxiety for caregivers and therefore could be an important contributing factor to low subjective well-being. Table 2.4 shows that chronic illness (proxy for poor health) is an important determinant of QoL, lowering scores by 1.6 points for suffers of chronic illnesses. Additionally, being married is a strong, positive determinant of QoL increasing scores by 1.2 points over non-married caregivers. Other strong determinants of QoL at baseline include a caregiver's age (negatively associated) and household composition variables (both positive and negative).

Table 2.4. Baseline determinants of subjective well-being among caregivers (OLS)

	Life will be better in 2 years	Quality of life scale	Relative well-being: same or better off than neighbors
Treatment	-0.03	-0.87	-0.06
	(0.06)	(0.92)	(0.06)
Female	-0.04	-0.15	-0.05
	(0.03)	(0.45)	(0.02)*
Age	-0.00	-0.09	0.00
	(0.00)*	(0.03)**	(0.00)
Age squared	0.00	0.00	-0.00
	(0.00)	(0.00)*	(0.00)
Ever attended school	0.05	-0.18	0.03
	(0.03)*	(0.31)	(0.02)
Chronic illness	-0.05	-1.59	-0.02
	(0.03)*	(0.59)**	(0.03)
Married	0.05	1.16	0.06
	(0.02)**	(0.31)***	(0.02)**
Log pc expenditure	0.06	1.22	0.03
	(0.03)**	(0.40)***	(0.02)
Household size	0.01	0.33	0.01
	(0.01)	(0.18)*	(0.02)
Household Members:			
0-5 years	-0.01	-0.29	-0.03
	(0.02)	(0.24)	(0.02)
6-11 years	-0.00	-0.43	-0.01
	(0.02)	(0.19)**	(0.02)
12-17 years	0.02	-0.08	-0.01
	(0.02)	(0.17)	(0.02)
65 and over	-0.04	-0.46	-0.01
	(0.02)**	(0.21)**	(0.02)
Constant	0.12	8.52	0.16
	(0.31)	(4.47)*	(0.24)
R^2	0.06	0.06	0.02
N	3,369	3,369	3,369

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** p<0.05 ***p<0.01.

The other subjective well-being outcomes, future and relative well-being, show some similar relationships with individual and household determinants but have fewer significant ones. Log per capita expenditure is a strong, positive predictor of future well-being (p-value<0.05) but it is not predictive of relative well-being. Chronic illness is also a significant, negative predictor of future well-being. Notably, gender is only predictive of relative well-being. The heavy saturation of female caregivers in the sample,

however, means there is not much gender variation to test. The only significant determinant across all outcomes is being married, which has a positive association with subjective well-being.

In addition to the baseline sample, we use the panel of control group respondents to measure determinants—these are households that never receive the cash transfer during the study period. Table 2.5 shows the impacts of determinants using a fixed effects model to control for any unobserved differences fixed overtime. We use the household panel to pull out some impacts for variables that could change between members of households but that are fixed within individuals like gender and whether they ever attended school.

Table 2.5. Determinants of subjective well-being among control group using household fixed effects

	Life will be better in 2 years	Quality of life scale	Relative wealth: same or better off than neighbors
Time	0.05	1.62	-0.05
	(0.03)	(0.59)**	(0.05)
Female	0.07	0.84	-0.10
	(0.07)	(0.82)	(0.06)
Age	0.00	-0.16	0.01
	(0.01)	(0.08)*	(0.01)
Age squared	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
Ever attended school	0.12	2.32	-0.09
	(0.06)*	(1.12)*	(0.08)
Chronic illness	-0.01	-1.06	0.03
	(0.04)	(0.45)**	(0.05)
Married	0.10	2.52	0.06
	(0.06)	(0.70)***	(0.06)
Log pc expenditure	0.08	0.56	0.04
	(0.04)*	(0.70)	(0.04)
Constant	-0.38	15.78	0.09
	(0.50)	(7.82)*	(0.38)
R^2	0.03	0.07	0.01
N	3,197	3,444	3,438

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** *p*<0.05 ***p<0.01.

Compared to the baseline sample, the impact of log pc expenditure is much smaller and less significant for future well-being (p-value<0.1) and no longer predictive of QoL. There are still a number of other significant predictors of QoL though, including positive ones such as ever attending school and being married. In contrast to the baseline sample, school attendance has a positive effect (p-value<0.1) on

QoL and future well-being for this panel of control households. Gender, however, is no longer a significant a determinant of relative well-being.

Taken together, determinant analysis for these two groups reveals that our measure of life satisfaction, QoL scale, is more strongly predicted by individual and household variables than future outlooks or relative well-being. Consumption and poor health have stronger relationships to subjective well-being at baseline than amongst the control group panel. Additionally, being married is the only determinant of all of the subjective well-being variables at baseline. In general, determinants appear to have the expected relationships with subjective well-being measures according to the literature.

Effect of treatment on subjective well-being:

Next we estimate the impact of the treatment (cash transfer) on subjective well-being. We first show the effect of log per capita expenditure on QoL scores again but with Wave 2 data to determine if the relationship between expenditure and happiness differs discernibly after receiving transfers. As mentioned earlier, per capita consumption expenditure is much lower at follow-up due to data collection occurring during the lean season. Therefore, the control group is key to our estimation strategy as it accounts for this seasonality.

Figure 2.3. Lowess graph of QoL scores on household consumption for T and C at Wave 2

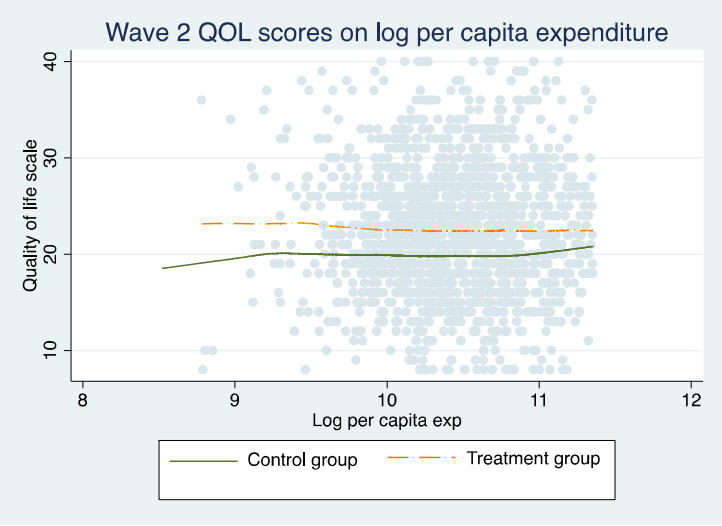


Figure 2.3 shows the relationships between QoL and consumption in Wave 2 separately for T and C groups. At Wave 2, the relationship between consumption and QoL scores has not changed much since baseline. While both treatment and control lines show little relationship between QoL scores and consumption, the treatment group clearly has higher QoL scores across all levels of consumption. This divide is largest at lower levels of consumption and weakens at the highest levels of consumption.

As described in the Methods sections, we estimate three specifications to test the impact of treatment on our subjective well-being outcomes. Results are shown in Tables 6-8. For each outcome, we start with an unadjusted model using the full household panel and then sequentially add individual and household controls. The last model includes all controls and keeps only households in the individual panel (same respondent in both rounds).

The results of treatment on subjective well-being using the OLS specification are shown in Table 2.6. The cash transfer has a positive and significant impact on caregivers' subjective well-being for QoL and future well-being. The largest effect sizes for each outcome are seen in the last models, which includes all controls and the individual panel. Caregivers in treatment households score 2.57 points greater on the QoL scale, which represents 18 percent of the mean and has a magnitude of 0.35 of a standard deviation (SD). This is similar to the Give Directly study results showing an increase of 0.45 SD in the overall index of psychological well-being for the treatment group, which is higher than the effects on happiness (a 0.19 SD) and life satisfaction (0.14 SD) individually. Additionally, caregivers receiving the cash are 18 percentage points more likely to believe in a better future. The impact of the cash transfer is strongly robust across all measures; point estimates are only slightly larger for QoL with additional controls. Furthermore, the treatment impact for QoL and future well-being maintains strong significance (p-value<0.01) across all models.

The second specification we test in Table 2.7 is a DD model with panel data to control for baseline scores and time trends. Results in Table 2.7 show that using panel data to control for baseline scores is important and makes a difference for both the magnitude and significance of treatment outcomes. In

comparison to the OLS results, QoL estimates are larger and more significant across all models (p-value<0.01). The magnitude of point estimates has increased by almost one point from 2.57 to 3.42 (or 0.5 SD) for the individual panel. Also, treatment effects on future well-being are slightly larger and strongly significant at the 1% level. The last model using the individual panel shows that caregivers in treatment are 22 percentage points more likely to believe in a better future. While relative well-being point estimates are also larger, treatment respondents are twice as likely (a 6 percentage point increase) to believe they are the same or better off than their neighbors22, results are insignificant.

Table 2.6. OLS analysis of cash transfer on measures of subjective well-being in Wave 2

	Life satisfaction (Quality of Life Scale)				Future well-being (Life will be better in 2 years)				Relative well-being (Same or better off than neighbors)			
Treatment	2.26	2.41	2.40	2.57	0.17	0.18	0.17	0.18	0.05	0.05	0.05	0.06
	(0.61)***	(0.56)***	(0.56)***	(0.53)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)	(0.04)	(0.04)	(0.04)
Demographics		X	X	X		X	X	X		X	X	X
Household Characteristics			X	X			X	X			X	X
Individual panel				X				X				X
Constant	19.80	20.36	15.61	13.57	0.52	0.55	0.28	0.34	0.44	0.41	0.32	0.33
	(0.25)***	(1.35)***	(2.95)***	(3.19)***	(0.02)***	(0.10)***	(0.23)	(0.25)	(0.03)***	(0.10)***	(0.26)	(0.28)
R^2	0.03	0.07	0.08	0.07	0.03	0.10	0.11	0.11	0.00	0.01	0.02	0.02
N	3,365	3,364	3,364	2,919	2,839	2,838	2,838	2,455	3,353	3,352	3,352	2,907

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** *p*<0.05 ***p<0.01. Controls include Demographics (Female, age, age squared, ever attended school, chronic illness, married;) Household characteristics (Baseline values of log per capita expenditure, household size, total age group categories,(0-5, 6-11, 12-17, 65+))

Table 2.7. Difference-in-differences (DD) analysis of cash transfer on measures of subjective well-being

	Life satisfaction (Quality of Life Scale)				Future well-being (Life will be better in 2 years)				Relative well-being (Same or better off than neighbors)			
Treatment*Time	3.31	3.28	3.18	3.42	0.20	0.20	0.20	0.22	0.11	0.11	0.12	0.12
	(0.88)***	(0.89)***	(0.89)***	(0.94)***	(0.07)***	(0.07)***	(0.07)***	(0.07)***	(0.07)	(0.07)	(0.07)	(0.08)
Time	1.54	1.53	1.56	1.42	0.05	0.04	0.04	0.03	-0.05	-0.05	-0.05	-0.05
	(0.59)**	(0.58)**	(0.59)**	(0.61)**	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
Treatment	-1.05	-0.89	-0.84	-0.90	-0.04	-0.02	-0.03	-0.04	-0.06	-0.06	-0.06	-0.06
	(0.94)	(0.93)	(0.91)	(0.94)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Demographics		X	X	X		X	X	X		X	X	X
Household Characteristics			X	X			X	X			X	X
Individual panel				X				X				X
Constant	18.26	19.99	11.37	10.46	0.47	0.63	0.17	0.23	0.49	0.43	0.26	0.24
	(0.68)***	(0.83)***	(2.80)***	(2.99)***	(0.03)***	(0.08)***	(0.18)	(0.20)	(0.04)***	(0.06)***	(0.19)	(0.21)
R^2	0.07	0.11	0.11	0.10	0.03	0.09	0.10	0.09	0.00	0.01	0.01	0.01
N	6,896	6,895	6,733	5,838	6,370	6,369	6,207	5,374	6,884	6,883	6,721	5,826

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** *p*<0.05 ***p<0.01. Controls include Demographics (Female, age, age squared, ever attended school, chronic illness, married;) Household characteristics (Baseline values of log per capita expenditure, household size, total age group categories,(0-5, 6-11, 12-17, 65+))

Table 2.8. Fixed effects analysis of cash transfer on measures of subjective well-being

	Life satisfaction (Quality of Life Scale)			Future well-being (Life will be better in 2 years)			Relative well-being (Same or better off than neighbors)		
Treatment*Time	3.20	3.23	3.45	0.19	0.19	0.21	0.12	0.12	0.13
	(0.88)***	(0.88)***	(0.92)***	(0.07)**	(0.07)**	(0.07)***	(0.07)	(0.07)	(0.08)
Time	1.56	1.53	1.48	0.05	0.04	0.03	-0.05	-0.05	-0.04
	(0.60)**	(0.60)**	(0.64)**	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.06)
Demographics		X	X		X	X		X	X
Individual panel			X			X			X
Constant	17.76	21.95	32.17	0.45	0.58	0.67	0.46	0.61	0.73
	(0.21)***	(1.28)***	(5.37)***	(0.02)***	(0.15)***	(0.46)	(0.02)***	(0.15)***	(0.34)**
R^2	0.13	0.15	0.15	0.06	0.08	0.06	0.01	0.01	0.01
N	6,896	6,895	5,838	6,370	6,369	5,374	6,884	6,883	5,826

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** *p*<0.05 ***p<0.01. Controls include Demographics (Female, age, age squared, ever attended school, chronic illness, married;) Household characteristics are defined at the baseline and drop out of fixed effects models.

Interestingly, time also has a significant effect on QoL scores, an impact of about 1.5 points. Despite this time trend, the impact of the cash transfer is still larger compared to the OLS model in Table 6. Thus, controlling for baseline differences and time trends is important; it leads to slightly larger treatment effects and increases internal validity.

In the final specification, a fixed effect model, we add to the last model by introducing an individual-level fixed effect to control for any unobserved, individual heterogeneity in responses such as personality and different reporting scales. The results in Table 2.8 show that there is no change in the treatment effect with addition of individual fixed effects suggesting that unobserved heterogeneity is not a concern for this sample. Point estimates are robust for each outcome and are still significant at the 1% level for QoL and future well-being in the individual panel. The

addition of fixed effects also slightly increases the treatment impact on QoL scores amongst the individual panel to 3.45 points (0.5 SD), the largest point estimate of all models.

Additional analysis:

The results from these three specifications give strong evidence that cash transfer receipt is leading to a greater quality of life and belief in a better future, however, the income increase does not appear to impact relative well-being. Happiness literature though suggests that relative well-being could actually work as a determinant of happiness instead of a measure of well-being on its own (Weinmann et al., 2015). Therefore, in Table 2.9 we add baseline values of relative well-being (same or better off than neighbors) as an additional control to test whether perceptions of relative standing directly impacts the two other outcomes. We only compare OLS and DD specifications because fixed effect models drop these time invariant baseline covariates. Compared to Table 2.6 and 2.7 estimates, the treatment effect in Table 2.9 is unchanged (both significance and magnitude) after controlling for relative well- being at baseline. The direct effect of relative well-being is also insignificant and thus relative well-being is not a determinant of subjective well-being of our sample.

Table 2.9. Effect of cash transfer on QoL scale and future well-being controlling for baseline SWB (individual panel)

	Life satisfaction (Quality of Life Scale)		Future well-being (Life will be better in 2 years)	
	OLS	DD	OLS	DD
Treatment*Time		3.42		0.22
		(0.94)***		(0.07)***
Treatment	2.57	-0.94	0.18	-0.04
	(0.52)***	(0.92)	(0.04)***	(0.06)
Time		1.42		0.03
		(0.61)**		(0.04)
Baseline relative well-being	-0.15	-0.53	-0.01	-0.01
	(0.20)	(0.34)	(0.02)	(0.02)
Constant	13.57	10.49	0.34	0.23
	(3.20)**	(3.00)***	(0.25)	(0.20)
R^2	0.07	0.11	0.11	0.09
N	2,919	5,838	2,455	5,374

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** p<0.05 ***p<0.01. Controls include Demographics (Female, age, age squared, ever attended school, chronic illness, married;) Household characteristics (Baseline values of log per capita expenditure, household size, total age group categories,(0-5, 6-11, 12-17, 65+))

Sensitivity Analysis:

Thus far in our analysis, the QoL scale has shown high internal validity since it is consistent and robust across specifications. Internal validity, however, is also dependent on the ability of the measure to correctly represent the concept it defines; for QoL this concept is life satisfaction. As a sensitivity analysis to test the construct validity of the QoL scale, we examine whether the scale predicts negative shocks in the expected opposite direction as treatment to confirm that it incorporates appropriate emotional affect in response to one's experiences.

Using the individual panel, we test a fixed effects specification on three measures of shocks: the number of shocks in the previous 12 months, household death in the previous 12 months, and anticipation of a future shock (either financial or food) in the next 12 months. Additionally, we include treatment as a control in a second model to further see whether the cash transfer is protective of life satisfaction above these negative shocks. Since shocks could arguably be endogenous to treatment and we depart from causal analysis to validate this construct, in Table 2.2 we do show that these shocks are balanced at baseline. At follow-up, the total number of shocks in the previous year decreased from a mean of 2.5 to fewer than 2 for both groups, but the percent of the sample that experienced a death remained constant around 3 percent. Additionally, both groups were less likely to believe in future shocks at follow-up (T, 34 % and C, 44 %), declining from 53 percent at baseline.

The results in Table 2.10 show that each of these shocks has a negative relationship with QoL, serving to defend its construct validity. Each additional shock a household experienced in the previous 12 months decreases QoL scores by almost one point, significant at the 1% level. Likewise, the shock of a household member's death significantly decreases scores by 1.4 points. Belief of future shocks decreases scores by 2.3 points, also significant at the 1% level. With the addition of the treatment variable (treatment*time), both total shocks and future negative shocks still have a significant impact on QoL scores and point estimates are on the same order of magnitude. Moreover, the treatment effects in the second models are similar in size and significance as the effects found in Tables 2.8 and 2.9, validating

the robustness of the cash transfer impact on QoL for beneficiary households. Negative shocks and the positive income shock, therefore, appear to be orthogonal to each other and life satisfaction is an experience that can respond to multiple external events at the same time.

Table 2.10. Effect of negative shocks and anticipated future shocks on QoL scale using fixed effects (individual panel)

Type of Shock	Number of shocks in last 12 months		Death in household in last 12 months		Believes will have future shocks	
	(1)	(2)	(1)	(2)	(1)	(2)
Effect of shock	-0.86	-0.86	-1.41**	-1.11	-2.33	-2.13
	(0.18)***	(0.19)***	(0.67)	(0.73)	(0.47)***	(0.41)***
Treatment*Time		3.46		3.43		3.20
		(0.82)***		(0.93)***		(0.92)***
Time	2.55	0.83	3.18	1.47	2.86	1.30
	(0.60)***	(0.58)	(0.61)***	(0.64)**	(0.58)***	(0.64)*
Age	-0.47	-0.47	-0.47	-0.47	-0.42	-0.42
	(0.18)**	(0.16)***	(0.19)**	(0.17)***	(0.18)**	(0.16)**
Age squared	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)**	(0.00)***	(0.00)**	(0.00)**	(0.00)**	(0.00)**
Chronic illness	-0.84	-0.70	-0.88	-0.75	-0.95	-0.81
	(0.45)*	(0.42)	(0.45)*	(0.43)*	(0.42)**	(0.41)*
Married	1.66	1.79	1.75	1.90	1.60	1.74
	(0.65)**	(0.63)***	(0.66)**	(0.64)***	(0.67)**	(0.65)**
Constant	34.95	34.80	32.57	32.37	32.15	32.03
	(5.95)***	(5.25)***	(6.04)***	(5.36)***	(5.80)***	(5.21)***
R^2	0.14	0.17	0.12	0.15	0.14	0.17
N	5,838	5,838	5,838	5,838	5,838	5,838

Notes: Standard errors in parenthesis clustered at the VC level, *p<0.1; ** *p*<0.05 ***p<0.01. Household characteristics are defined at the baseline and drop out of fixed effects models.

Discussion

This study reveals that in just about a year's time, Malawi's cash transfer can have a profound effect on the subjective well-being of caregivers in beneficiary households. We find a strong, positive impact of the income shock on individuals' life satisfaction and perception of future well-being but do not find any impact on their perception of relative well-being. This finding lines up with evidence of positive impacts on objective measures of well-being at the household and individual-level. Appendix Table A1 illustrates the variety of impacts found during the follow-up midline evaluation including strong impacts on food consumption, economic productivity, school enrollment, and morbidity (Malawi SCTP

Evaluation Team, 2015). As the program aims to reduce hunger, the cash importantly helps to increase food expenditures and the number of meals eaten compared to the control group. This shows that the program was particularly protective for households during the lean season when the survey was conducted. Additionally, households used the money to increase agricultural productivity, purchasing livestock and agricultural assets, and increasing crop production. Furthermore, another main use of the cash is to help meet the costs of sending children to school; there were strong impacts on child schooling including increased enrollments and decreased dropouts (Malawi SCTP Evaluation Team, 2015).

While these positive impacts would in most respects appear to be good news, there is a concern amongst some that such programs could result in "leapfrogging". In the context of cash transfer programs, leapfrogging refers to a situation when program beneficiaries quickly move to a higher standard of living that leaves behind other community members who were nearly as poor but did not receive the program (Ellis, 2012). In this situation, feelings of unfairness and bitterness could arise and lead to lowered social cohesion within the community. This could help explain the negative subjective well-being consequences found in the Give Directly study as transfers make up a large percentage of pre-program consumption, but given that the Malawi SCTP distributes smaller transfers and only to a small percentage of the community, leapfrogging is likely less of a concern. The relative well-being results also suggest this is true since beneficiary caregivers still do not rate themselves as better off than their neighbors or friends.

This quantitative evidence from Malawi is also substantiated by qualitative evidence from in-depth caregiver interviews collected at follow-up. Caregivers in beneficiary households describe how the cash has been crucial for them to afford to eat regular meals, make home improvements, buy livestock, and send their children to school. Many of their stresses are alleviated, making them happier. Asked about personal changes since her baseline interview, one caregiver says,

> There has been an improvement in my heath and also my heart condition. I used to be very worried and stressed in the past because I had too much responsibility yet there wasn't enough money to take care of all those responsibilities. But since we started receiving money from the cash transfer program I have been able to take care of some responsibilities that I couldn't then. As a result I worry less and am usually happy which also has contributed to the improvements in my health and heart condition.

This statement highlights the importance of income to improve livelihoods for the very poor populations this program targets as well as the connection between health and happiness. Additionally, caregivers admit that they are hopeful for the future. General feelings are that they believe their lives will continue to get better and their children's future will be more promising as they are able to continue with their education. For example, another caregiver explains that she is happier and less worried now about the future because of the transfer,

> As I have said am a happy person now, I no longer have stress and am not worried because I know that when the time comes to receive the money, I will be able to buy things the household lacks now.

Moreover, she is also grateful to the government throughout the interview suggesting that gratitude and future outlooks may go hand in hand,

> Am just thankful because my household was very poor, in a rain season like this, sleep could not come because the house was leaking. We were really very poor, today my children have sleeping mats, are able to wash and bath using soap, and there is food in the household, so I say, thank you.

In addition to the substantiation from the objective measures and qualitative evidence, we find that the results of the cash transfer on subjective well-being are very robust. Both QoL and future well-being are strongly significant across all specifications and models. The cross-section OLS specification is predictably the least precise because it does not control for the time trend or baseline scores. In the other two specifications that use panel data, effects of the cash transfer are larger and change little with the addition of the controls. Even introducing treatment into regressions of negative shocks on subjective well-being does not reduce the strong, positive impact of the cash transfer. Moreover, results from Table 2.10 show that negative and positive shocks together can have strong, independent impacts on life satisfaction, possibly reflecting how positive and negative psychological states can exist simultaneously (Diener and Emmons, 1984; Watson, 1988). Literature has even found that in times of severe stress such as the death of a family member, co-occurance of aversive psychological states is common and part of the coping process (Folkman, 1997).

The positive time trend, however, is an anomaly. It is unclear why control households reported higher life satisfaction and future outlooks at the second wave. There was no concurrent rise in external economic circumstances, and in fact follow-up data collection occurred during the lean season when consumption was much lower for all households, a decline of around 25 percent from baseline (Malawi SCTP Evaluation Team, 2015). While it was the lean season, it was also the rainy season during follow-up data collection, and a possible connection could exist between the rains and subjective well-being if the rains signal that the growing season is under way and bounty is to come. However, some recent literature has rejected the use of intrapersonal comparisons (Wiemann et al., 2015). According to Rayo and Becker (2007), people develop internal references in response to life circumstances as an evolutionary response in order to sustain a minimum level of satisfaction. Therefore, individuals' criteria for a satisfied life can change overtime depending on context. It is impossible to say for sure that individuals interpret questions the same between time periods. Differences in references points at the time of survey could change the interpretation of subjective well-being questions such that an individual's 20 on the QoL scale in 2013 does not correspond the same level of happiness that a 20 does in 2015. While this could create noise in our estimates, the large sample size and experimental design help validate our results—the noise would randomly be assigned. Even withstanding this interference, we are not making conclusions about the values reported but instead are concerned about trends in the data overtime as an effect of an exogenous income shock.

Interestingly, while results are strongly positive for measures of quality of life and future well-being, we find no impacts on relative well-being. According to the literature, people's happiness is judged relative to an internal reference point, which is determined by their past experiences and environments. Therefore, the perception of low relative economic standing in a community reflects lower happiness because compared to others, there is potential to be happier. As reported in the Data section, transfer size as a share of pre-program household consumption is lower than the generally accepted 20 percent threshold for most households. It might be that this modest increase in income is not enough for

households to consume as much as their friends and neighbors and so relative to their community, they are still worse off. Therefore, the absolute income effect is likely driving the positive results we see for life satisfaction and future well-being. The null effect, however, seems to align with prior work in Malawi that found no impact of income on relative well-being among the poorest communities (Ravallion & Lokshin, 2010).

Limitations

As discussed throughout this paper, the limitations of this study mainly concern the reliability of subjective well-being measures. For one, they might suffer from measurement error because of personality bias or affect at the time of survey. Additionally, behavioral economic literature has pointed to issues that could confound results like biases of "reference points" and "habituation" (Kahneman, Diener, & Schwarz, 1999) even amongst individuals overtime (Rayo & Becker, 2007). While the time trend observed amongst control group in this study may suggest changing perceptions of subjective questions between baseline and follow-up, we do not put emphasis on the actual value of measures (the main concern expressed in the literature about reporting subjective well-being results) but instead focus on changes in trends between treatment arms. Since our results are strong and robust, and as the study uses a randomized design with a large sample size, this reduces concern that the reliability of measures is an issue.

Individual heterogeneities could also present a problem when making interpersonal comparisons of welfare as we do with the household panel. This study is strengthened by its use of experimental, panel data and methods that control of individual heterogeneities. We use fixed effects among the individual panel to wipe away personality biases and differences in interpretations. However, in accordance with recent evidence from Beegle et al. (2012) that finds biases have only a minor impact, we also find trivial differences between the household and individual panels so personality biases are not a concern in this sample.

Finally, there is concern that subjective well-being measures are not a good marker for understanding how poor people in particular are doing. People habituate and adapt to their situations and so the chronically poor may have lower thresholds for defining their well-being. The poor in India, for instance, are quick to say that they have high life satisfaction even though this does not line up with objective measures of health and productivity (Clark, 2012). Thus, their responses to subjective well-being questions could be impractical as a means of understanding how poverty affects overall welfare because their responses inadequately reflect their deprivation in areas such as health, material essentials, and education (Sen, 1990). While this would confound estimation of the relationships between poverty and subjective-wellbeing, making it harder to understand how cash transfers actually impact subjective well-being, the purpose of using subjective well-being data in this study is to compare welfare impacts of a program given to a homogenous group of poor households. We focus on data trends and do not interpret the meaning of reported values. Moreover, we do not suggest solely relying on subjective well-being to assess overall well-being and the capability of someone to rise out of poverty. We are suggesting that it could be an additional component and illustrate well-being on a more holistic level since it can incorporate other elements important to human flourishing.

Conclusion

This study shows that a positive income shock from a large-scale cash transfer program in Malawi has a strong positive impact on beneficiary caregivers subjective well-being both in terms of life satisfaction and future outlooks. The randomized, longitudinal study design combined with strong, robust impacts allows us to defend a causal relationship between income and subjective well-being. Objective and qualitative evidence from the Malawi SCTP evaluation further substantiate this evidence. Even small income increases are immensely valuable to the very poor. Caregivers use the money to improve their families' livelihoods, ensuring provision of their basics needs including food, shelter, and clothing. The reduction of these daily stresses makes caregivers happy about their current situations and gives them hope that the future will continue to get better.

The use of self-reported well-being may help capture a more inclusive picture of well-being than would reliance only on objective measures. The subjective approach is a broader concept and can include other important dimensions of a person's well-being such as social connectedness, pleasurable experiences, and life meaning (Rojas, 2015). It also is an end goal for many of the other things people seek like income—it is not desired for itself but because it can help people to achieve happiness. Nevertheless, self-reports of well-being are limited when it comes to public policy, especially given that the poor's reported happiness may minimize their true deprivation. Governments could potentially justify a lack of progress towards greater social equality by asserting that the poor are nevertheless happy. Ultimately, governments should not rely exclusively on either objective or subjective measures to judge welfare but used together they can more accurately reflect well-being.

Future research will be needed to understand if the absolute income effect will continue to have an impact on subjective well-being or if happiness will flatten out as people habituate to their new circumstances. Haushofer, Reisinger, and Shapiro (2015) find some evidence for hedonic adaptation after revisiting Kenyan households in the Give Directly cash transfer study. They find that effects for both treatment and control groups dissipated over time once the transfers stopped. However, the important distinction again between this program and Malawi's is that the Give Directly scheme provides one-time transfers compared to the more consistent, long-term transfers from the SCTP and other similar government programs.

It will also be important to investigate how greater life satisfaction can influence spending decisions and future outcomes. Cash transfer and other poverty alleviation program evaluations should continue to include subjective well-being metrics to add to this evidence base. With the growth of cash transfer programs across Africa, it will be important to find out whether there is an association between growth in these metrics and successful transition out of poverty cycle. This critical knowledge can be used to enhance the effectiveness of social protection policy for the poor across Africa.

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