Ethiopian Journal of Economics

Special Issue on Dynamics of Poverty and Wellbeing in Ethiopia

Volume XXV Number 2 October 2016

Table of Contents

A Publication of
THE ETHIOPIAN ECONOMICS ASSOCIATION
(EEA)

VOLUME XXV NUMBER 2 October 2016

Published in May 2017

Dynamics of Poverty and Wellbeing in Ethiopia
An Introduction to a Special Issue of the Ethiopian Journal of Economics[1]

Dean Jolliffe[2], Alemayehu Ambel[1], Tadele Ferede[3] and Ilana Seff[4]

Abstract

Understanding change is critical to policy formulation. Who benefits, who loses from change, and what causes change are core policy questions. Panel data are central to understanding change, and this special issue of the journal is devoted to five papers examining change in wellbeing as measured by two waves of data from the Ethiopia Socioeconomic Survey (ESS). The papers cover changes in consumption poverty, multi-dimensional poverty, food security, malnutrition in the form of wasting and underweight status, and smoothing patterns of nonfarm enterprise activities. The ESS data is freely available for download and immediate use. While the papers in this issue draw from the first two waves of data (2011-12 and 2013-14), the third wave of the ESS (2015-16) is now also publicly available. The ESS is a collaborative effort of the Central Statistical Agency of Ethiopia and the World Bank's Living Standards Measurement Study – Integrated Surveys of Agriculture program.

Keywords: Ethiopia, LSMS-ISA, panel data, poverty, multi-dimensional poverty, food security, malnutrition, nonfarm enterprise
JEL Codes: I32, I15, O12, Q12

---

[1] *Acknowledgements*: We are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding assistance. We also thank Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw and Alemayehu Seyoum Taffesse for their generous insight and feedback and Demirew Getachew and Tadele Ferede for their support in dissemination of this paper. Finally, we deeply appreciate all the comments on this paper received from participants in the Workshop on Dynamics of Wellbeing and the Ethiopian Economic Association's annual conference.
[2] World Bank, Washington, DC, USA
[3] Addis Ababa University, Addis Ababa, Ethiopia
[4] Department of Population and Family Health, Columbia University Mailman School of Public Health, New York, NY, USA

1. Introduction

Designing policy is often about how best to induce beneficial change. Policy aimed at reducing poverty and improving wellbeing needs to be informed with the knowledge of what factors are related to changes in individual or household outcomes. Repeated samples of cross-sectional data are highly informative about levels and profiles of poverty and various dimensions of wellbeing, and can provide measures of change at the national or regional level. But, cross-sectional data is largely uninformative about change in outcomes for individuals or households. In contrast, panel data such as the recently released Ethiopia Socio-economic Survey (ESS), monitor households over time with repeat visits and provide detailed information on the changing status of the sample households over time.

Simply in terms of descriptive statistics, panel data offers important information that cannot be unpacked from cross-sectional data. As one example, using cross sectional data, World Bank (2015, Table 1) reports that poverty in Ethiopia declined by 9 percentage points between 2005 and 2011.[5] A naïve interpretation of this might be that 9 percent of the population went from being poor in 2005 to not poor in 2011, but of course this fails to account for households that may have become poor in this period. All we know from the cross-sectional estimates is that (9 percentage points) more people moved out of poverty than became poor. The cross sectional estimates cannot tell us how many people were poor for some part of the two time periods.

Panel data also offers significant value in reducing potential bias from confounding factors in the regression model context. The empiricist may observe that a household has increased income over time, while also observing that the household has changed farming practices. Despite the observed correlation between the two, the estimated effect of the new

[5] This estimate is based on data from the Household Income and Consumption Expenditure survey, which is nationally representative cross-sectional household data. The estimated poverty rate in 2005, based on the national poverty line was 38.7 percent and this dropped to 29.6 percent by 2011.

farming practice may be affected by other confounding factors biasing the estimated parameters. For example, if unobserved ability affects both the likelihood of adopting the new practice and the return to the new practice, then failing to control for ability will result in omitted-variable bias in the estimated return to adopting the new practice. Because a first-difference estimator can essentially sweep away all time-invariant unobservable attributes of the household (or whatever the unit of analysis), panel data significantly reduces the potential for unobservable omitted variables to bias regression inference.

For these reasons, panel data can play a large role in helping the researcher, analyst and policy makers in understanding drivers of change. This special issue presents five papers using the ESS panel data to examine changes in poverty and other dimensions of wellbeing in Ethiopia between 2011/12 (ESS wave 1, ESS1) and 2013-14 (ESS wave 2, ESS2).

2. Overview of papers

The ESS began in 2011 (ESS1), with 3,969 rural and small town households. In 2013, a second wave (ESS2) was administered, revisiting the ESS1 households and an additional 1,500 urban households; the panel sample includes rural and small town households only. Four of the five papers in this issue use these first two waves, while a fifth paper explores change within the year, leveraging the timing of multiple household visits and recall data within the ESS1.

The first two papers in this special issue examine cross-sectional trends and panel dynamics of wellbeing using three different poverty measures. The first paper examines changes in consumption and consumption-based poverty, and compares these to changes in an index of nonmonetary aspects of wellbeing. Poverty can be viewed as taking many different forms, ranging widely over a set of monetary (consumption or income) and nonmonetary dimensions (health and education). While the body of literature on poverty dynamics is extensive, the majority of studies draw conclusions about the dynamics of income- or consumption-based poverty only; there is a growing,

but still relatively young, literature base on the dynamics of the multi-dimensional nonmonetary aspects of poverty.

The authors find that, despite defining both measures of poverty to capture the bottom 30 percent of their underlying distributions (consumption per adult equivalent and a weighted deprivation index), only a fourth of individuals who are poor in either dimension, are poor in both dimensions. In other words, if someone is identified as poor as measured by consumption deprivation, there is only a 25 percent chance that this person will also be identified as poor as measured by deprivation in the nonmonetary index. Similarly, there is little overlap between quintiles of annual consumption per adult equivalent and the deprivation index in both years; again only 25 percent of the rural and small town population fall in the same quintile of both distributions. This illustrates that the choice to use a monetary or non-monetary measure of poverty has a meaningful impact on *who* will be identified as poor at a given point in time.

When comparing the dynamics of the two poverty indicators, separately, similar levels of movement in and out of poverty are observed. However, even though the dynamics of multidimensional and relative consumption-based poverty seem to tell similar stories, the authors find evidence suggesting that changes in the two underlying values of deprivation and consumption are independent of each other; that is, knowing what happens to an individual's deprivation index between waves is not informative of what happens to that individual's consumption over the same period, and vice versa. Approximately 59 percent of individuals whose deprivation index worsened between waves also experienced a decline in consumption; the other 41 percent saw an improvement in their consumption. Similarly, nearly 53 percent of individuals who improved in their multidimensional wellbeing actually experienced a worsening in consumption. Testing the hypothesis of independence with a Pearson's chi-squared statistic, results in failure to reject the null hypothesis that the two distributions are independent ($p=0.267$).

The second paper similarly examines the dynamics of poverty by analyzing changes in poverty status based on annual consumption per adult equivalent and household asset ownership. The authors first assess changes in consumption expenditures; in the aggregate, total and food expenditures decreased between 2012 and 2014, while nonfood expenditures increased. Additionally, the composition of expenditure shifted slightly; on average, households shifted their relative share of consumption to nonfood items. Further, as Bennett's law of food demand predicts, forward movers (that is, those whose expenditures increased over the waves) spent smaller shares on starchy staples, but larger shares on nutritious foods like animal-source foods, vegetables and fruits; conversely, backward movers increased the proportion spent on staples and decreased the relative share spent on more nutritious foods.[6] These results show that movement in and out of poverty is also accompanied by shifts in wellbeing as measured through quality of food consumption.

The authors also compared dynamics of consumption-based measures of poverty to asset-based ones. An interesting distinction with this approach is that both of these measures are typically viewed as capturing a monetary measure of wellbeing, though consumption is viewed as short-run daily wellbeing, while asset indices are often interpreted as long-run proxies for wealth. Approximately equal proportions of the population escape and fall into consumption-based poverty between waves (15 and 16 percent, respectively); while for asset-based poverty measures, 14 percent escaped from poverty while 9 percent of individuals fell into poverty. This suggests that they asset-based measure of poverty is slightly more stable (perhaps due both to greater stability in longer-run measures and to there being less noise in these measures). In contrast to the first paper, when testing for independence in change of these two measures, this paper rejects the hypothesis of independence. That is to say observing that someone has improved in the dimension of asset-based measure of wellbeing does inform us that this person is also more likely to have improved in the dimension of consumption. There appears to be overlap in the signal from observing

[6] For a discussion of Bennett's law, and comparison with Engel's related law, see Timmer, Falcon and Pearson (1983).

change in these two monetary measures of wellbeing despite their conceptual dissimilarity.

Two key findings emerge from the first two papers. First, assessing changes in wellbeing through cross-sectional trends fails to capture the extensive amount of movement in and out of wellbeing at the individual level; and, second, changes in one indicator of wellbeing over time do not necessarily imply changes in another measure. The third paper explores these two themes using yet another measure of wellbeing: food security. The authors of this paper examine four measures of food security – two consumption-based (calories and dietary diversity) and two-experience based (whether food insecurity was experienced in any month, and whether any actions were taken in response). Food insecurity is a critical issue in Ethiopia; considering all four measures in both 2012 and 2014, the share of the food insecure population never fell below 25 percent. Consequently, understanding the complexities of chronic and transitory food insecurity, as well as how consumption- and experience-based measures interact, is important for policy design.

Similar to papers one and two, the authors of this paper find that while insecurity appears to remain stagnant when examining cross-sectional trends, there is actually significant movement in and out of food insecure states. For example, although approximately 30 percent of rural and small-town individuals had inadequate dietary diversity in both 2012 and 2014, the panel data show that 46 percent had inadequately diverse diets at some point over this period. Further, while many individuals demonstrated improvement in several food security indicators over time, a substantial share of the population saw their food security status worsen from 2012 to 2014; 23 percent of the population transitioned from adequate to inadequate calorie consumption and 18 percent of individuals reported facing zero months of food insecurity in wave 1 but at least one month of food insecurity in wave 2.

Comparing the four measures of food insecurity in the cross-section reveals similar patterns of food insecurity in levels and trends; but, analysis of the panel data shows there is very little co-movement of the measures. For most

combinations, observing improvement in a consumption-based measure of food security for an individual tells an observer very little about whether that same individual has also improved in an experiential-based measure.

The fourth paper in this special issue examines the dynamics of under nutrition among children living in rural and small-town Ethiopia. The paper looks specifically at changes in wasting and underweight; wasting, defined by a weight-for height z-score below -2, is a measure of acute and severe malnutrition, while underweight, defined by a weight-for-age z-score below -2, is a broader measure of malnutrition in children 6-59 months. Both forms are associated with negative health, development, and long-term outcomes. While many studies have looked at correlates of underweight and wasting in Ethiopia using cross-sectional analysis, this paper exploits the panel setup of the ESS to estimate fixed-effects models for changes in each outcome. The fixed-effects model improves upon the cross-sectional analysis by controlling for all time-invariant characteristics that may influence the explanatory variables in addition to wasting and underweight.

The ESS data show that underweight prevalence declined slightly from 27 percent in 2012 to 25 percent in 2014, while wasting prevalence stalled at 11 percent. Male children, those with illiterate mothers, male household heads, and older household heads, and those experiencing illness in the last two months were significantly more likely to have negative nutrition outcomes (lower z-scores or higher likelihood of wasting/underweight). Furthermore, having a solid roof, improved toilet, female cow, and laying hen were repeatedly significantly associated with positive outcomes.

While more children recovered from being underweight (16 percent) than became underweight (11 percent), 12 percent of children were underweight in both years, emphasizing the need to better understand what drives *changes* out of undernourishment. After controlling for individual fixed effects, the authors find that illness in the last two months remained significantly associated with changes in both z-scores and underweight status, increasing negative outcomes for each. Additionally, community-level access to main road access, which was not significant in the cross-sectional models, was

associated with positive changes in weight-for-height z-scores. When also controlling for baseline status, they observed that factors driving changes to or from undernourished states vary, and children wasted at baseline were generally more responsive to household level changes than non-wasted children. For example, children wasted at baseline saw improvements in weight-for-height z-scores when they gained an improved toilet or water source; non-wasted children were not statistically significantly affected by such changes.

The final paper included in this special issue uses only the first wave of the ESS data but adds to the literature on wellbeing dynamics in Ethiopia through its findings on seasonal wellbeing and income generation. Specifically, this paper explores the role non-farm enterprises (NFEs) play in seasonal income generation, consumption smoothing, and risk mitigation. Many studies from sub-Saharan Africa show that NFE operation is positively correlated with household welfare and that NFEs present an opportunity for households to smooth their income in the agricultural off-season. Gaining a better understanding of these mechanisms in Ethiopia, where more than 20 percent of rural and small town households operate an NFE, is helpful for developing effective and sustainable policies targeting vulnerable agricultural households. Nearly 54 percent of NFE-operating households report their NFEs operate seasonally. However, the authors do not find evidence suggesting this seasonality complements agricultural activity; the most active months for NFE activity line up with the harvest and crop sale seasons, peaking immediately after the harvest and almost simultaneously with the sale of crops. Furthermore, very few enterprises report high NFE activity during planting season. Rather than using NFEs to supplement periods of low agricultural income, households generate a disproportionately high influx of income from the months of October to January.

Additionally, NFE households do not report lower rates of food insecurity than their non-NFE counterparts. The authors use a negative binomial regression model to estimate the effect of NFE income on food insecurity spells, as measured by the number of months a household reported facing food insecurity in the past year. One might reasonably expect two

households at the same *level* of consumption -- where one is engaged in farming and the other is engaged in farming and has an NFE -- to exhibit different *patterns* of consumption throughout the year. Consequently, if NFEs were helping households to buffer against food insecurity, one would expect each additional 1,000 Birr of NFE income to have a negative impact on months of food insecurity. However, this paper shows that an additional 1,000 Birr of NFE income has no statistically significant differential bearing on months of food insecurity. Further, the authors find no correlation between operating an NFE and facing fewer spells of food insecurity.

3. Facilitating Data Use

In releasing these articles in a special issue of this journal, our aim is both to contribute to the literature on dynamics of wellbeing in Ethiopia and also to highlight the potential scope of the ESS data for research covering a wide array of topics. The ESS consists of five questionnaires. A household questionnaire administered to all households in the sample that collects demographic and socioeconomic details on individuals in the household. A community questionnaire, administered to a selected group of community members, collecting information on the socio-economic indicators of the enumeration areas where the sample households reside.[7]And, there are three agriculture questionnaires -- post-planting, post-harvest, and livestock questionnaires -- administered to all household members who are agriculture holders, that is those engaged in agriculture activities.[8]

The community questionnaire obtains information on community organizations; resource management; changes in the community; key events;

[7]The community data is not necessarily representative of all communities in Ethiopia, but is the community-level data associated with the sample of households with are representative of the population of Ethiopia. The community data represent information that is common to the households.

[8] More specifically, a holder is a person who exercises management control over the operations of the agricultural holdings and makes the major decisions regarding the utilization of the available resources. S/he has technical and economic responsibility for the holding. S/he may operate the holding directly as an owner or as a manager. Hence it is possible to have more than one holder in single sampled households. As a result, the ESS may include more than one agriculture questionnaire in a single sampled household if the household has more than one holder.

community needs, actions and achievements; access to infrastructure; and local retail price information. The post-planting and post-harvest agriculture questionnaires focus on crop farming activities and solicit information on land ownership and use; farm labor; inputs use; GPS land area measurement and coordinates of household fields; agriculture capital; irrigation; and crop harvest and utilization. The livestock questionnaire collects information on animal holdings and costs; and production, cost and sales of livestock by products. In most cases the instruments are largely the same across waves of the ESS – One exception to this is the livestock module which was revised significantly in wave 3 of the ESS.

The household questionnaire provides information on basic demographics; education; health (including anthropometric measurement for children); labor and time use; saving; food and non-food expenditure; household nonfarm income-generating activities; food security and shocks; safety nets; housing conditions; assets; credit; and other sources of household income. Household location is geo-referenced in order to be able to later link the ESS data to other available geographic data sets.

To enhance the value of the ESS data, a set of geospatial variables are included with the ESS release and re linked to the data with the geo-referenced household locations. These variables include measures of distance, climatology, soil and terrain, and other environmental factors. As a specific example, there are geospatial variables measuring distance between field and household, slope and elevation of field, and potential wetness index for field locations. Time-series on rainfall and vegetation that identify the ESS agricultural season relative to normal conditions, are also part of the processed variables. All of these data are intended to provide an understanding of how geophysical characteristics vary at the landscape level.

The Ethiopian Socioeconomic Survey is a collaborative project between the Central Statistics Agency of Ethiopia and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture (LSMS-ISA) program. The data, questionnaires, manuals, basic information documents, and data launch reports are all freely available for download at: http://go.worldbank.org/HWKE6FXHJ0

References

Timmer, C. P., Falcon, W.P., Pearson, S.R. (1983). *Food Policy Analysis*. Published for the World Bank [by] The Johns Hopkins University Press, Baltimore.

World Bank Group. (2015). *Ethiopia Poverty Assessment*. Washington, DC: World Bank. Retrieved on April 1, 2017 from: http://hdl.handle.net/10986/21323.

Multidimensional Poverty Dynamics in Ethiopia: How do they differ from Consumption-based Poverty Dynamics?[1]

Ilana Seff[2] and Dean Jolliffe[3]

Abstract

Poverty can take many different forms, ranging widely over dimensions both monetary, such as consumption or income, and nonmonetary, such as health and education. One large class of nonmonetary measures of poverty is the multidimensional poverty index (MPI); recent studies document that people identified as poor in one dimension are often different from those who found to be poor in another dimension. This paper extends the literature by examining whether MDP dynamics are similar to the dynamics of a related consumption-based measure of poverty. Using two waves of Ethiopian panel data (2011-12 and 2013-14) we estimate poverty based on a monetary value of real consumption and a nonmonetary weighted deprivation index (our underlying measure of MDP). Similar to studies for other countries, we find that the two estimates of poverty identify significantly different groups of Ethiopians as poor. A key contribution of this paper is the finding that changes in consumption are largely independent of changes in multidimensional wellbeing: Awareness that an individual's wellbeing improved over time as measured by improvements in the weighted deprivation index provides no information about whether his or her wellbeing has improved where consumption is concerned.

Keywords: Ethiopia, child malnutrition, wasting, underweight, panel data analysis
JEL Classification: C33, I10, I31

---

[1] ***Acknowledgements*:** We are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding assistance. We also thank Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw and Alemayehu Seyoum Taffesse for their generous insight and feedback and Demirew Getachew and Tadele Ferede for their support in dissemination of this paper. Finally, we deeply appreciate all the comments on this paper received from participants in the Workshop on Dynamics of Wellbeing and the Ethiopian Economic Association's annual conference.
[2] Department of Global Health, George Washington University, Washington, DC, USA
[3] World Bank, Washington, DC, USA

1. Introduction

Poverty is typically measured by estimating whether an individual has enough income, or consumes enough, to surpass some social definition of basic needs. This approach allows for a measure that can reflect many dimensions of wellbeing, such as consumption of food, shelter, transportation, and many other elements; it also can rely on market-determined prices to provide socially determined weights for each element. The appeal is in the simplicity of relying on economic interactions to provide assessments of the relative value of many different dimensions of wellbeing. One concern with this approach, however, is that there are nonmonetary dimensions of wellbeing that are excluded from the measures because there are no prices for them, possibly resulting in badly informed poverty policy discussions.

Alkire and Santos (2014) and Morrell (2011) both suggest that poverty is often a product of factors extending beyond income or consumption and that measuring it requires consideration of numerous elements and understanding how they interact over time. Hulme and Shepherd (2003) note that measures of poverty that focus on nonmonetary dimensions of wellbeing can serve as an important complement to monetary-based measures to paint a more complete picture of longer-term poverty and the experience of poverty.

Recognizing the shortcomings of monetary approaches to measuring poverty, and the complexity of multidimensionality, Alkire and Foster (2011) developed the now widely used Oxford Poverty and Human Development Initiative (OPHI) Multidimensional Poverty Index (MPI), along with the corresponding weighted deprivation index (*k)* and headcount indicator of multidimensional poverty (MDP).*K* takes into account three dimensions of wellbeing—health, education, and living standards—with each dimension contributing an equal share to the index. Selection of these dimensions and the corresponding indicators of deprivation is primarily driven by the quality of the data available, the context of the population of interest, and the research question (Alkire and Santos, 2010).

Alkire *et al*. (2014) also noted that consumption- and income-based poverty data are usually available only at intervals of three to ten years, limiting the ability to regularly track progress and make time-sensitive policy recommendations. In contrast, using MDP allows for flexibility in deciding which dimensions and indicators to include, how to establish thresholds for these indicators, and how relatively to weigh each factor of input. This leeway is particularly beneficial given the data constraints in developing countries. While absolute estimates of monetary poverty typically require expansive and detailed income or consumption datasets that meet specific international standards, MDP can be constructed using a variety of sources of data, including Demographic and Health Surveys (DHS) and Living Standards Measurement Surveys (LSMS).

In addition to divergences in the construction of consumption- or income-based poverty and of MDP, comparative studies reveal that the two measures may not necessarily be correlated. Bourguignon et al. (2010) and Alkire *et al.* (2014) concluded that positive income trends do not always represent improvements in non income deprivations. Comparing economic growth (GDP) in India and Bangladesh between 1990 and 2011, Dreze and Sen (2013) found that India's dominating GDP growth was dwarfed by Bangladesh's progress in improving under-5mortality rates, maternal mortality, immunization coverage, and female literacy. Examining cross-country data for 1990 to 2008, Bourguignon *et al.* (2008, 2010) found no significant correlation between non income MDGs and economic growth. Further, few studies have estimated MDP and consumption-based poverty from the same data. Klasen (2000) did so using a nationally representative dataset for South Africa and identified minimal overlap (2.9 percent) between the severely income-poor and the severely multiply-deprived; more recently, estimates of both measures of poverty were released by the Government of Bhutan using Bhutan's Living Standard Survey 2012 (Royal Government of Bhutan, 2014). For developed countries, Nolan and Whelan (2011) in their study of 26 European countries did not find any in which more than 50 percent of individuals experienced poverty in income *and* material deprivation indicators. Finally, in an analysis of 22 developing countries, Alkire and Roche (2013) found that only two countries

exhibited statistically similar trends over time for both income-based and multidimensional poverty reduction.

Progress in reducing poverty is typically assessed by comparing cross-sectional trends over time. This method provides valuable information about changes in poverty among the population as a whole and helps us understand the risk factors for poverty at a given point in time, but it does not provide insight into the dynamics of poverty, such as identifying what characteristics determine whether a household transitions from poor to nonpoor and vice versa. However, panel data, which follow the same individuals or households over time, make it possible to capture more refined changes in poverty and thus assess poverty dynamics. Panels make it possible to look at the likelihood of moving in and out of poverty and to identify determinants of chronic vs. transient poverty. The latter is a crucial distinction; while chronic poverty may be more responsive to asset allocation and an increase in physical capital infrastructure, transient poverty typically requires safety nets or cash transfer programs (Baulch and Hoddinott, 2000; World Bank, 2001).

The literature on poverty dynamics is extensive, but the majority of the studies draw conclusions only about the dynamics of income- or consumption-based poverty (see Bane and Ellwood, 1986; Barrett, 2005; and Woolard and Klasen, 2005 for a few examples). However, there is a growing, though still relatively young, literature on the dynamics of MDP (Apablaza and Yalonetzky, 2013).These studies suggest that changes in MDP take place much more slowly than in monetary-based poverty. Since being considered multidimensionally nonpoor necessitates accumulation of assets and increased investment in health and education, households are not likely to move in and out of MDP rapidly or repeatedly. For this reason, it is widely agreed that MDP is more indicative of long-term poverty. A household's consumption- or income-based poverty status, on the other hand, can change rapidly (Alkire and Roche, 2013) with a sudden increase in income (moving the household out of a poor state) or an idiosyncratic shock (moving the household into a poor state). Finally, while some studies (as noted above) compare *trends* in consumption-based poverty and MDP, very

few have looked at the extent to which these two indicators co-move at the household level.

The Ethiopia Socioeconomic Survey (ESS)[4] dataset used in this analysis is unique in two ways: (1) It ambitiously follows a panel sample of Ethiopian households that is representative of all rural and small-town households, allowing for analysis of MDP trends and dynamics over time. (2) In addition to collecting data on well being that can be used as inputs for MDP, the ESS has detailed consumption and income modules which enable us to compare trends and dynamics of poverty using both traditional and multidimensional measures. Our findings suggest there have been mild declines in MDP among rural and small-town Ethiopians. Of nine deprivations studied, lack of access to an improved water source saw the largest decline, falling about11.1 percent between 2012 and 2014.Panel data analysis reveals that nearly 82percent of households were poor in both waves (were chronically multidimensionally poor), 4 percent fell into poverty between the waves, 8 percent escaped poverty, and 6 percent stayed nonpoor.

We also find that the bottom 30 percent of the distributions of k and consumption per adult equivalent contain minimal overlap; among those in the bottom 30 percent of the distribution in either dimension, only 35 percent fall in the bottom of the other dimension. We then contribute to the literature on the dynamics of wellbeing by finding considerably different patterns of mobility for individuals when k is compared with consumption; an individual's change in k thus provides no insight into his or her change in consumption, and vice versa. We also find evidence suggesting that adverse shocks are picked up by nonmonetary but not monetary measures of poverty, which further supports the notion that policymakers tracking changes in wellbeing would be wisest to apply both monetary and nonmonetary measures.

[4] The ESS is a collaborative project of the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture (LSMS-ISA) project that collects multitopic panel data at the household level.

In what follows, section 2 describes the data and construction of the multidimensional estimates of poverty. Section 3 presents cross-sectional trends and panel dynamics for MDP. Section 4 explores differences between MDP and consumption-based poverty, as well as between the underlying indicators, in both the cross-section and dynamically. Section 5 discusses the findings, and section 6 concludes.

2. Study Setting and Data

2.1 Study Setting

MDP in Ethiopia is quite high, especially compared to other countries in the region (Alkire and Roche, 2013). In 2011, according to OPHI estimates derived from DHS data, 87.3 percent of Ethiopians were multidimensionally poor[5], making it the second poorest country in the world in this dimension (OPHI, 2013). Between 2005 and 2011, MDP declined only 2.2 percentage points (pp); in the same period, income poverty declined more than twice as fast (Alkire and Roche, 2013). Yet using the national monetary poverty line, in 2011 only 29.6 percent of the Ethiopian population was considered poor (World Bank, 2015).

Dercon and Krishnan (2000) looked at the dynamics of consumption-based poverty in rural Ethiopia using data from three points in time, each six months apart, and found that 30 percent of rural Ethiopian households were 'sometimes poor' and 24.8 percent were 'always poor'. In comparing a consumption-centric poverty measure to MDP, Brück and Kebede (2013) hypothesized that in rural Ethiopia short-term shocks impact consumption poverty and simultaneous long-term shocks affect MDP. Theyfound that drought plays a role only in consumption poverty. Furthermore, they found that a large segement of households are either exclusively MDP or consumption-poor and thatsome MDP households are among those in the top quintile of consumption.

[5] OPHI defines MDP at $k >= 0.33$.

2.2 Data

We analyzed data from two waves of the ESS, which began as the Ethiopia Rural Socioeconomic Survey (ERSS) in 2011 (ESS1). The first wave of data collection covered only rural and small-town areas. In 2013, when a second wave of the survey was administered, the sample was expanded to urban areas (ESS2). Our analysis was restricted to the panel sample, which is nationally representative of all rural and small-town areas in Ethiopia. For the panel sample, the survey was conducted in a series of three visits: the post-planting questionnaire was administered between September and October of 2011 (ESS1) and 2013 (ESS2); the livestock questionnaire in November of 2011 (ESS1) and 2013 (ESS3); and the household, community, and post-harvest questionnaires between January and April of 2012 (ESS1) and 2014 (ESS2).

The ESS used a stratified, two-stage sampling scheme[6]. The regions of Ethiopia served as the strata, from which enumeration areas (EAs) were selected proportionally based on the regional population[7]. A total of 290 EAs were selected from rural areas and 43 from small towns; 12 households were then chosen from each EA. The first wave had an extremely low nonresponse rate of 0.7%; the final interviewed sample was 3,969 households. Tracking between ESS1 and ESS2 was done at the household level and at 4.9 percent the attrition rate was also very low, producing a sample of 3,776 households which were surveyed in both waves. To maintain the same balanced panel sample for all analyses, we further restricted the final analytical sample by excluding households for which information was missing on any of the nine deprivations or on real consumption per adult equivalent. Restricting households with such item nonresponses resulted in a loss of 15 percent of the sample, for a final

[6] For detailed information on the sampling design, see the Basic Information Document at http://go.worldbank.org/ZK2ZDZYDD0.

[7] Due to sample size constraints, the data are only regionally representative for the most populous regions: Amhara, Oromiya, SNNP, and Tigray.

balanced sample of 3,197 households[8].

2.3 Weighted Deprivation Index and MDP

We used the OPHI methodology as a guide in creating our weighted deprivation index; because the ESS is an extensive survey, we were able to include in it nearly all OPHI-defined deprivations. However, a few modifications were needed because we were using only one data source (of course, the gain is that we were able to use panel data to analyze the dynamics of MDP).Figure 1illustrates where our list of deprivations diverges from those in the OPHI index[9].In line with the OPHI methodology, we incorporate three dimensions of wellbeing— education, health, and living standards—with each dimension weighted to represent one-third of the index. Individual indicators are weighted equally within a given dimension (Figure 1).

Deprivations from OPHI's methodology incorporated into our index were[10]: **1a.** At least one child aged 7-15 years in the household is not attending school. **1b.** No one in the household has at least six years of education. **2b.** Household does not have access to an improved water source. **2c.** Household does not have access to improved sanitation. **3a.** Household does not have access to electricity. **3b.** Household does not have a finished floor. **3c.** Household does not use solid cooking fuel. **3d.** Household does not have a

[8] A household is in our final balanced sample only if it is in both waves and not missing any variables of interest. However, this does not guarantee the composition of the households is the same in both waves. A panel household may, for example, have four members in wave 1 and five in wave 2.

[9]Dimensions and indicators are often selected based on data constraints as well as alignment with researcher aspirations. While Alkire and Santos (2010) used child mortality and nutrition as health indicators, due to data availability constraints Brück and Kebede (2013) used child mortality and adult morbidity, which suggests indicating the flexibility of MDP measures. Brück and Kebede also added access to water as their study's living standard indicator in line with the Millennium Development Goals. Alkire and Santos also used nested weights in which dimensions and the indicators within them are weighed equally. By calculating significance probabilities, Brück and Kebede found indicators within dimensions to be highly dependent on one another, which suggested their appropriate categorization.

[10] Indicator numbers correspond to those in Figure 1.

radio, television, or phone, or the household lacks a transportation asset as well as land, livestock, or a refrigerator. In contrast to OPHI's *k*, our index does not include an indicator of recent cases of mortality within the household because this information was only collected in wave 2 of the ESS and thus cannot be assessed in the panel dimension.

The other primary difference between the two indices is found in deprivation 2a: in the OPHI methodology, this indicator takes into account both child and adult malnutrition, whereas our indicator provides information only about child malnutrition. Thus, deprivation 2a in our index is defined as the household having at least one stunted child aged 6-59 months.[11]

[11]Households ineligible for a certain deprivation are automatically considered 'not deprived'. For example, for deprivation 2a, households with no children aged 6-59 months are not deprived.

Figure 1: Constructing *k*, divergences from OPHI

	OPHI index		Our index	Criteria for deprivation
1. Education (1/3)	Years of schooling (1/6)		Years of schooling (1/6)	1a. At least one child aged 7-15 years is not attending school
	School attendance (1/6)		School attendance (1/6)	1b. No one in the household has at least 6 years of education
2. Health (1/3)	Child mortality (1/6)		Nutrition (1/9)	2a. At least one 6-59-month-old child in the household is stunted
	Nutrition (1/6)		Water (1/9)	2b. Household does not have access to an improved water source
			Sanitation (1/9)	2c. Household does not have access to an improved sanitation facility
3. Living Standards (1/3)	Electricity (1/18)		Electricity (1/12)	3a. Household does not have access to electricity
	Sanitation (1/18)			
	Water (1/18)		Floor (1/12)	3b. Household does not have a finished floor
	Floor (1/18)			
	Cooking fuel (1/18)		Cooking fuel 1/12)	3c. Household does not use solid cooking fuel (uses wood, charcoal, leaves, or manure)
	Assets (1/18)			

To classify a household as poor or nonpoor, a minimum number of weighted dimensions are established and only those who are deprived in dimensions exceeding this value are considered poor (Alkire and Foster, 2011). OPHI traditionally uses a cutoff of k>=0.33 to define the poverty threshold. We analyze results separately, using two different cutoff points:(1) We use the standard cutoff of k>=0.33 to make results comparable with external estimates of MDP. (2)We identify the value of k in each wave such that the proportion of individuals experiencing MDP matches the proportion facing relative consumption-based poverty (approximately 30 percent in rural and small-town areas).[12] By allowing k to change each year, this estimate (hereafter referred to as multidimensional-equivalent poverty [MDEP])can similarly be thought of as a relative nonmonetary estimate of poverty.

3 Results

3.1 Trends in MDP

The ESS data suggest that between 2012 and 2014MDPdeclined in rural and small-town areas of Ethiopia from 90 to 86 percent. Table 1 highlights trends for each deprivation, elucidating which dimensions are likely to have been responsible for the4pp decrease in MDP. Deprivation 2b, having no access to an improved source of drinking water[13], saw the largest decline, from 47.7 percent to 36.5 percent. This improvement is in line with the progress observed from 2000 to 2011, when the proportion of those without access to improved water fell from 82 to 59 percent (Ambel *et al.*, 2015)[14]. Mild improvements are also observed for deprivations 1b and 3d, suggesting that, on average, households are becoming more educated and are acquiring more communication, transportation, and other assets. In both years the prevalence

[12] This is derived from the official rural prevalence of poverty in 2010/11 reported by Ethiopia's Ministry of Finance and Economic Development.

[13] Improved water sources as defined by WHO (2006) consist of water piped into a dwelling, water piped into a yard or plot, a public tap or standpipe, a tubewell or borehole, a protected dug well, a protected spring, bottled water, or rainwater.

[14] Note that the 2000-2011 estimates are derived from a different data source, the Welfare Monitoring Survey (WMS), a nationally representative survey carried out in 2000, 2005, and 2011. Nonetheless, both our results and those of Ambel, Mehta, and Yigezu (2015) highlight similar patterns of change in access to improved water.

of deprivations in household use of solid cooking fuel and ownership of a finished floor hovered near 97 percent. Finally, we do not observe statistically significant worsening in any single deprivation.

Table 1: Trends in deprivations underlying *k*

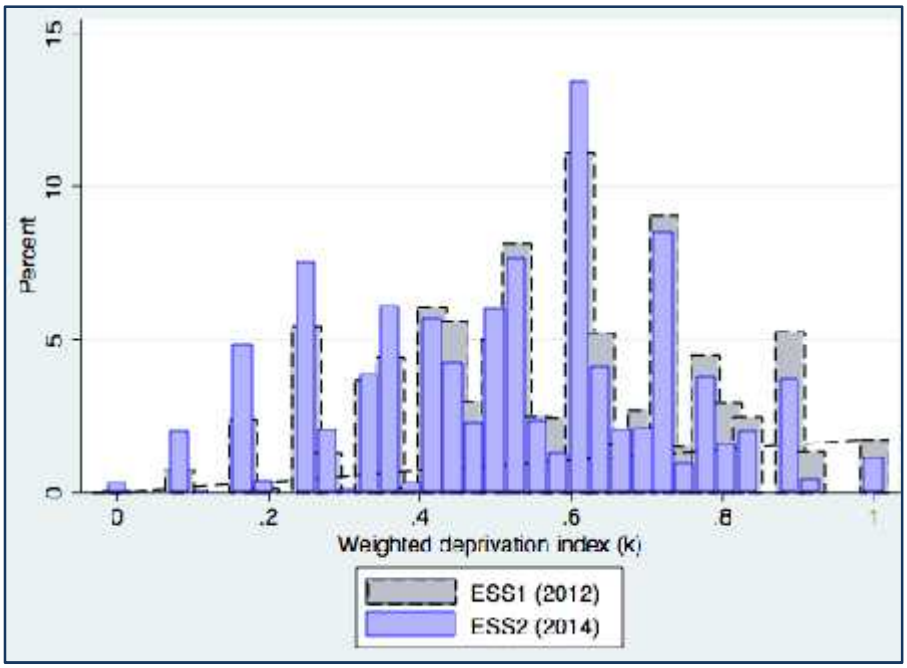
	2012 (SEs)	2014 (SEs)	2014-2012
1a. At least 1 child aged 7-15 not in school	0.272	0.277	0.005
	(0.016)	(0.014)	
1b. No one in household has at > 6 years of education	0.663	0.601	-0.062***
	(0.017)	(0.018)	
2a. A child aged 6-59 months is stunted	0.244	0.213	-0.031**
	(0.013)	(0.012)	
2b. No access to improved drinking water	0.476	0.365	-0.111***
	(0.031)	(0.028)	
2c. No access to improved sanitation	0.394	0.407	0.013
	(0.025)	(0.024)	
3a. No access to electricity	0.873	0.855	-0.018**
	(0.016)	(0.017)	
3b. Household does not use solid cooking fuel	0.972	0.984	0.012
	(0.013)	(0.005)	
3c. Household does not have a finished floor	0.961	0.958	-0.003
	(0.006)	(0.006)	
3d. Household missing community or mobility/livelihood asset	0.612	0.546	-0.066***
	(0.019)	(0.018)	

Note: Difference is significant at *p<0.1; **p<0.05; ***p<0.01. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample size was 3,197 households in each wave. Standard errors are adjusted for stratification and clustering.

After constructing the weighted sum of all nine deprivations, *k*, we compare shifts in its distribution between waves 1 and 2. We observe mild improvements in the distribution; with mass shifting to the left in 2014 (see

Figure 2). Furthermore, we observe at least some improvement across the entire distribution; the proportion of individuals with extremely high *k* values also decreases slightly between 2012 and 2014, signaling some progress among those suffering from extreme MDP. However, the improvements observed on the left side of the distribution (where individuals exhibit fewer deprivations) are greater in magnitude than those observed among the extremely poor.

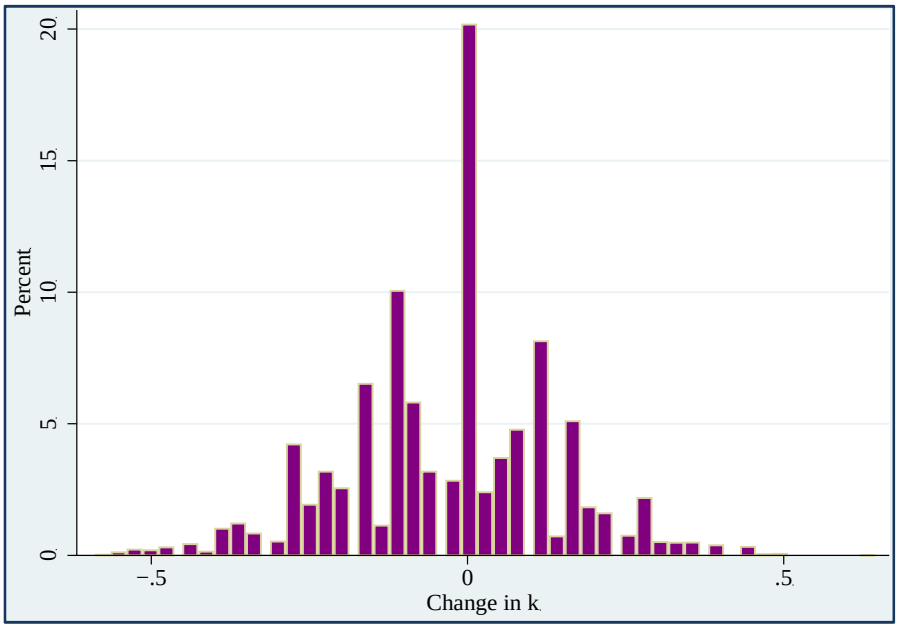
Figure 2: Distribution of deprivation (*k*), 2012 and 2014



While Figure 2 tells us about the overall changes in *k* at the national level, it provides no insight into the average magnitude of change experienced at the individual level. However, using a panel dataset, we can assess the average size of the changes individuals experienced in multidimensional wellbeing between waves 1 and 2.Figure 3 presents the distribution of change in *k*. As expected given the modest shifts to the left, over the same period we find that more individuals enjoyed a decline in deprivations (47 percent) than accumulated more deprivations (33 percent). Nonetheless, we still see a considerable mass centered around zero. In wave 2 nearly 38 percent of the

population deviated less than 0.1 from their wave 1 *k* value, and 20 percent experienced no change in their deprivation index.

Figure 3: Distribution of change in deprivation (*k*), 2012-2014



3.2 MDP Dynamics

Table 2 portrays the dynamics of MDP in rural and small-town Ethiopia between 2012 and 2014. Some 82 percent of households are chronically poor, meaning that in both waves their deprivation index was at least *k*=0.33.Movement in and out of MDP was minimal—only 11 percent of households experienced a transition; however, nearly twice as many households exited than entered poverty (7.54 vs. 3.69 percent).Perhaps not surprisingly, these dynamics vary significantly by rural and small-town area and between regions. While 86 percent of households in rural areas are chronically multidimensionally poor, this is a persistent burden for only 38 percent of small-town households. Furthermore, the share of small-town households exiting poverty between 2012 and 2014 is more than double the proportion doing so in rural areas (16.71 vs. 6.88 percent).

Amhara exhibits the highest burden of chronic poverty: more than88 percent of its households were poor in both waves. SNNP, with only 78 percent of households in chronic poverty, also has the highest relative share, 9.67 percent, of households that were nonpoor in both waves. The largest relative decline in poverty between waves 1 and 2 is observed in the 'other regions' category, where 10 percent of households improved their multidimensional wellbeing and exited poverty. In Amhara only 6 percent of households exited poverty.

Table 2: MDP dynamics, *k*=0.33

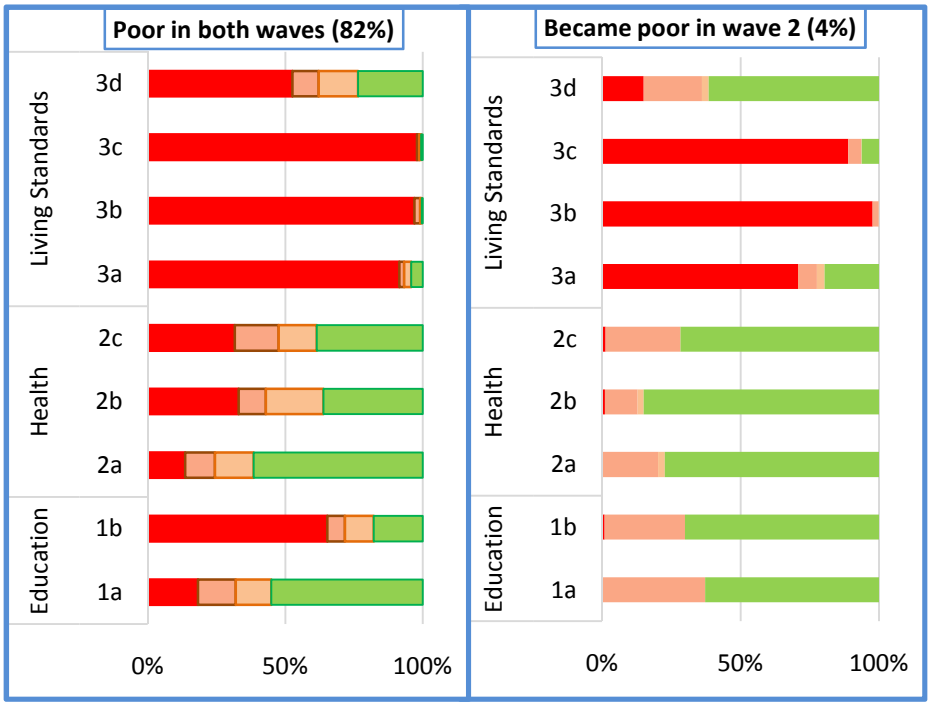
	Poor in both waves	Become poor in wave 2	No longer poor in wave 2	Not poor in either wave	Sample size (households)
Total	82.47	3.69	7.54	6.30	3,197
Rural	85.65	3.38	6.88	4.09	2,799
Small town	38.44	7.99	16.71	36.86	398
Amhara	88.47	2.12	5.63	5.78	715
Oromiya	82.67	4.62	8.10	4.61	636
SNNP	78.30	3.99	8.05	9.67	848
Tigray	81.32	4.24	8.30	6.13	337
All other regions	80.77	2.45	9.52	7.25	661

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample size consists of 3,197 households.

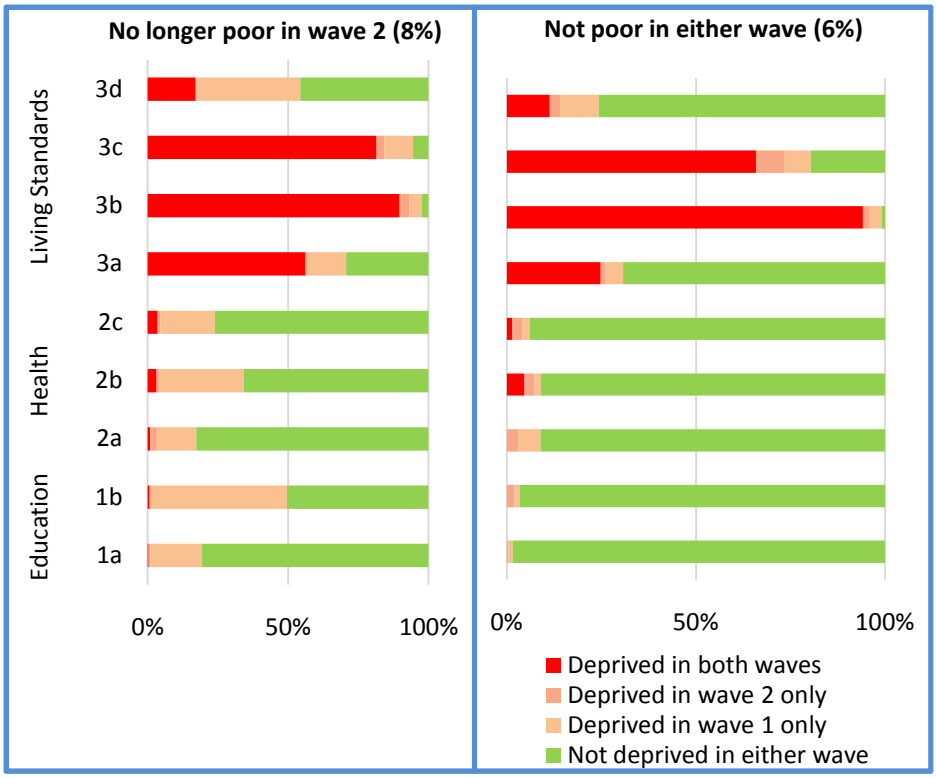
Next, we analyze the dynamics of each individual deprivation separately, according to the category of a household's poverty dynamic. This helps us assess the extent to which households within a given category look similar in terms of specific deprivations. This analysis can be particularly insightful for the two transitioning groups of households. For example, do nearly all households moving out of an MDP state between waves see an improvement in a particular deprivation? Similarly, what new deprivation may be causing a household that was previously nonpoor to enter a poor state?

Regarding the latter question, we find that households moving into poverty in wave 2 are significantly more likely than any other group to become deprived in indicators 1a, 1b, and 3d, meaning they are most likely falling into MDP due to a decline in their education levels, participation, or living standard assets. Conversely, households that exit poverty are most likely to experience an improvement in indicators 1b and 3d, as well as in 2b. Thus, a household's escape from poverty is most likely driven by asset acquisition, increased investment in duration of education, and new access to an improved water source. We also find that housing-related deprivations (3a, 3b, and 3c) represent the most prevalent chronic deficits for all four poverty dynamic groups and are virtually universal among the chronically poor; for example, in both waves 97.9 percent of chronically poor households do not use solid cooking fuel.[15]

Figure 4: Dynamics of deprivations, by poverty dynamics category



[15] Ballon and Apablaza (2012) note similarly high levels of housing-related deprivations among those chronically suffering MDP in Indonesia.



4 MDP and Consumption-Based Poverty

4.1 Contrasting MDP and Consumption-based Poverty in the Cross-section

In the previous section, we used an MDP cutoff of k>=0.33to mimic the standard cutoff approach. To better assess the overlap between multidimensional and consumption-based poverty, which is significantly lower than MDP defined using a k>=0.33 cutoff, we look at a new estimate of MDP that uses a more severe threshold. We identify the k cutoff such that MDP equals consumption-based poverty in wave 1 (30 percent among rural and small-town households), and relative consumption-based poverty in wave 2 (also the bottom 30 percent among rural and small-town households). The corresponding weighted deprivation values are k>=0.72 in wave 1 and k>=0.67 in wave 2; households with a k value above or equal to

0.72 in wave 1 (or above or equal to 0.67 in wave 2) are considered to be MDEP[16]. In this section, we explore the extent to which these two estimates of poverty identify the same individuals as poor, as well as compare overlap in the two underlying indicators, consumption and *k*.

Tables 3a and 3b depict the overlap and mismatch between MDEP and consumption-based poverty estimates in 2012 and 2014.Dual poverty, defined as falling in the bottom 30 percent of the distributions of both real annual consumption per adult equivalent and *k*, was 12 percent among rural and small-town households in both years. Oromiya has the lowest prevalence of dual poverty at 8 percent in both 2012 and 2014.Nationally, more than half of individuals considered poor in one dimension are *not* considered poor in the other. This dissonance can have important implications for policy development targeted towards the 'poor'.

Furthermore, those that are MDEP but not monetarily poor as compared to the reverse are not consistent across regions. For example, in both years, in SNNP the relative burden of consumption-based-only poverty is greater than that of MDE-only poverty. In Oromiya, the opposite is true; the prevalence of MDEP-only is nearly double that of consumption-based-only poverty. The minimal overlap observed between the two estimates of poverty parallels findings from similar studies in other countries.[17]

[16] See Appendix Table A for the MDEP dynamics (similar to Table 3).

[17] See presentations from the OPHI workshop, "Dynamic Comparison between Multidimensional Poverty and Monetary Poverty" at http://www.ophi.org.uk/workshop-on-monetary-and-multidimensional-poverty-measures/.

Table 3a: Overlap of consumption-based poverty and MDEP, 2012

MDEP	**Poor**	**Poor**	**Nonpoor**	**Nonpoor**	**Overlap**
Consumption-based	**Poor**	**Nonpoor**	**Poor**	**Nonpoor**	
National (rural and small town)	0.12	0.16	0.18	0.54	0.66
Rural	0.13	0.17	0.18	0.53	0.66
Small town	0.03	0.01	0.17	0.78	0.81
Domains of analysis					
Amhara	0.18	0.18	0.25	0.39	0.57
Oromiya	0.08	0.17	0.11	0.64	0.72
SNNP	0.12	0.11	0.21	0.55	0.67
Tigray	0.11	0.17	0.15	0.57	0.68
All other regions	0.12	0.20	0.16	0.52	0.64

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample consists of 3,197 households.

Table 3b: Overlap of consumption-based poverty and MDEP, 2014

MDEP	**Poor**	**Poor**	**Nonpoor**	**Nonpoor**	**Overlap**
Consumption-based	**Poor**	**Nonpoor**	**Poor**	**Nonpoor**	
National	0.12	0.16	0.18	0.53	0.65
Rural	0.13	0.17	0.18	0.52	0.65
Small town	0.02	0.04	0.16	0.78	0.80
Domains of analysis					
Amhara	0.16	0.18	0.24	0.42	0.58
Oromiya	0.08	0.17	0.13	0.61	0.69
SNNP	0.16	0.10	0.22	0.53	0.69
Tigray	0.09	0.16	0.14	0.61	0.70
All other regions	0.12	0.20	0.21	0.47	0.59

Note: Observations are weighted to make results representative of all rural and small town individuals in Ethiopia. Balanced panel sample consists of 3,197 households.

Tables 4a and 4b demonstrate where individuals fall on the intersection of the distributions of annual consumption per adult equivalent and *k*. In 2012, only about 27 percent of rural and small-town Ethiopians fell into the same quintile of both distributions; 34 percent of individuals were one quintile apart when the two indicators were compared; and 39 percent were two or more quintiles apart. The pattern in 2014 was similar. This supports our assertion that whether we use a monetary or nonmonetary measure of poverty makes a difference in who will be identified as poor. In fact, 73 percent of individuals would be placed in a different quintile depending on whether or not wellbeing was being defined by consumption or by deprivations in nonmonetary dimensions.

Table 4a: Cross-tabulation of consumption and k quintiles, 2012

Consumption quintiles	Quintiles of k (weighted deprivation index)				
	Poorest	2nd	3rd	4th	Wealthiest
Poorest	5.98	4.34	3.38	3.29	2.99
2nd	5.06	4.57	2.74	3.76	3.74
3rd	3.63	2.86	3.95	4.92	4.26
4th	2.96	3.82	3.12	4.47	5.93
Wealthiest	1.76	2.35	3.18	5.3	7.63

Table 4b: Cross-tabulation of consumption and k quintiles, 2014

Consumption quintiles	Quintiles of k (weighted deprivation index)				
	Poorest	2nd	3rd	4th	Wealthiest
Poorest	5.46	3.87	5.48	3.5	2.48
2nd	5.09	3.17	4.37	3.65	3.86
3rd	3.08	3.41	5.01	4.77	4.5
4th	2.02	3.04	4.66	3.8	5.78
Wealthiest	1.14	2.17	4.33	3.78	7.57

Note: Green cells represent individuals who fall in the same quintile whether the underlying variable is *k* or consumption; yellow individuals classified as one quintile apart; and red individuals who are two or more quintiles apart depending on the underlying variable.

4.2 MDEP and Consumption-based Poverty Dynamics Compared

In the previous subsection, we discovered significant differences in the distributions and corresponding poverty estimates between measures of MDEP and a relative measure of monetary wellbeing (for both measures, we define as poor an individual who falls in the bottom 30 percent of the distribution). This finding underscores the fact that numerous factors must be considered when deciding which measure to use for calculating poverty or identifying particularly vulnerable groups. In this subsection, we compare the dynamics of multidimensional and monetary wellbeing between the two waves and find significant differences in panel dynamics between the two measures, as well as evidence suggesting there is little to signal changes in *k* and changes in consumption.

Figure 5 contrasts the dynamics of MDEP and relative consumption-based poverty. Depictions of chronicity differ depending on the underlying measure. In contrast to the 17 percent of rural and small-town Ethiopians who face chronic MDEP, using traditional consumption-based estimates only 14 percent are identified as chronically poor. We also find that consumption-based poverty shifts more substantially, with nearly 31 percent moving in or out of poverty between 2012 and 2014; only 26 percent of households transitioned between multidimensionally poor and nonpoor states.

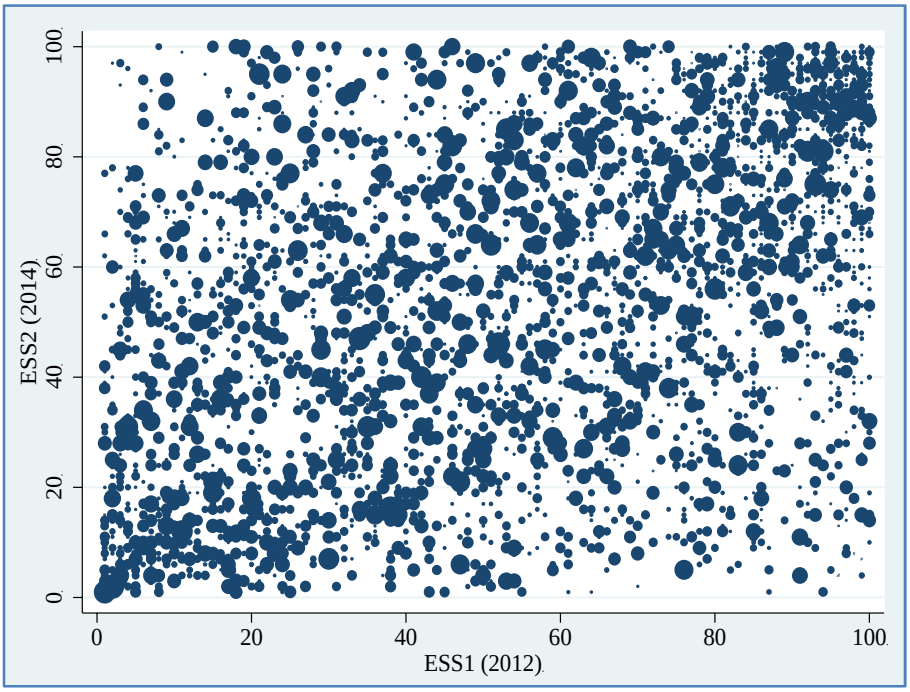
Figure 5: Dynamics of MDEP and relative consumption-based poverty, Percent

		MDEP		Consumption-based poverty	
		Wave 2		Wave 2	
		Poor	Nonpoor	Poor	Nonpoor
Wave 1	Poor	16.6	12.4	14.4	14.4
	Not poor	11.6	59.4	16.2	55.0

Note: Dark red cells represent chronically poor individuals, light red those who fell into poverty between waves 1 and 2, light green those who have exited poverty, and dark green those were not poor in either wave.

The marked difference in movement over time between *k* and annual consumption per adult equivalent is demonstrated in Figures 6 and 7. The scatter plot of annual consumption per adult equivalent (expressed in percentiles) between 2012 and 2014 is widely dispersed. Though households are more densely concentrated along the 45-degree line of equality, there is still significant variation. This suggests that it is relatively easy for a household to move substantially up or down the consumption gradient over a short period; a sizable proportion of households in the top quintile of consumption in 2012 fall into the bottom quintile in 2014, and vice versa. In comparison, the scatter plot of *k* is significantly more concentrated at the line of equality. There are effectively no households with $k<0.20$ in 2012 but $k>0.80$ in 2014, or vice versa.

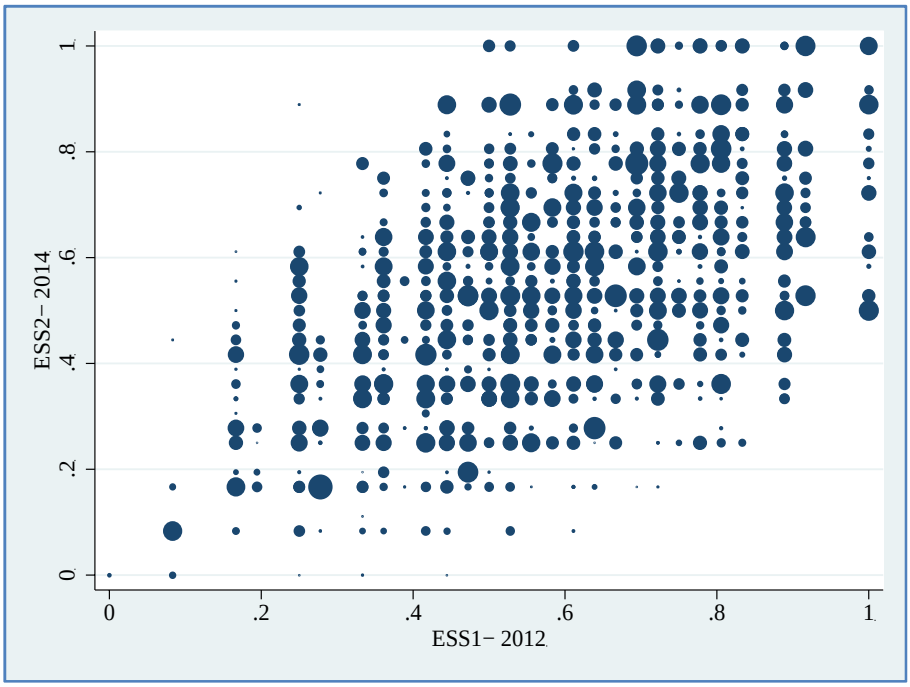
Figure 6: Annual consumption per adult equivalent, 2012 and 2014, percent



These findings suggest that real annual consumption per adult equivalent, the underlying variable for consumption-based poverty, is significantly more

volatile than*k*, the input variable for MDEP, and that the *k* value in wave 1 is more predictive of the *k* value in wave 2. In fact, while the *k* values of the two waves have a statistically significant correlation coefficient of 0.662, consumption in wave 2 is correlated only 18 percent with wave 1 consumption. Put another way, having information about an individual's *k* value in wave 1 helps predict the *k* value in wave 2, but knowing an individual's consumption in period 1 does not help to accurately predict consumption in wave 2.

Figure 7: Weighted deprivations index (*k*), 2012 and 2014



Furthermore, knowing what happens to an individual's *k* between waves does not provide any useful information about what happens to that individual's consumption, and vice versa. Approximately 59 percent of individuals whose *k* worsened between waves also experienced a decline in consumption; the other 41 percent saw their consumption improve (see Table 5a).Similarly, for nearly 53 percent of individuals who improved in *k* their consumption actually worsened. In fact, using the Pearson's chi-

squared test of independence, we fail to reject the null hypothesis that the two distributions are independent (p=0.267).

Table 5a: Contrasting changes in *k* and changes in consumption

Real consumption per adult equivalent	*K*			*Total*
	Worsened	Stayed the same	Improved	
Worsened	0.191	0.112	0.297	*0.552*
Improved	0.139	0.091	0.218	*0.448*
Total	*0.330*	*0.203*	*0.475*	*1.000*

Note: A Pearson's chi-squared test of independence fails at p=0.267 to reject the null hypothesis that the two variables are independent of each other. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The balanced panel sample covers 3,197 households.

However, if we aggregate information on *k* and consumption so that we are looking at changes over certain thresholds rather than just increases or decreases, we do observe some signaling between the two categorical distributions. Panel A in Table 5b demonstrates the contingency table for consumption-based poverty and MDP (defined as *k*>=0.33). Given the considerable mass centered in the middle (60.6 percent of individuals do not move past the threshold in either dimension), we find that there is some dependence between the two distributions. Using Pearson's chi-squared test of independence, we reject the null hypothesis that the two distributions are independent at p=0.003. An individual's movement in or out of MDP does provide some information content on that individual's movement in or out of consumption-based poverty. However, we find that this signal declines substantially if the *k* threshold is increased to match that for MDEP. Here (see Panel B in Table 5b), we reject the null hypothesis with only minimal confidence.

Table 5b: Contrasting changes in relative consumption-based poverty, MDP, and MDEP

Relative consumption-based poverty	Panel A -- MDP			*Total*
	Worsened	**Stayed the same**	**Improved**	
Worsened	0.002	0.153	0.007	*0.162*
Stayed the same	0.032	0.606	0.056	*0.694*
Improved	0.002	0.131	0.011	*0.144*
Total	*0.037*	*0.890*	*0.069*	*1.000*
	Panel B --MDEP			
Worsened	0.028	0.112	0.023	*0.162*
Stayed the same	0.073	0.536	0.085	*0.694*
Improved	0.016	0.113	0.016	*0.144*
Total	*0.116*	*0.760*	*0.124*	*1.000*

Note: A Pearson's chi-squared test of independence for Panel A fails, at p=0.003, to reject the null hypothesis that the two variables are independent of each other. For Panel B, at p=0.069 the test also fails to reject the null. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The balanced panel sample covers 3,197 households.

The findings presented in Tables 5a and 5b pose a dilemma for policymakers because consumption and *k* are two measures that should both be measuring wellbeing but they are not moving together. How should policymakers evaluate the content of these two measures, both of which are presumed to be measuring wellbeing? We explore this issue by examining how each of the measures is correlated with adverse shocks that should presumably be adversely affecting both measures. We find that shocks are driving movement as expected with MDEP but not with relative consumption-based poverty.

Table 6 presents mean values for having experienced various shocks between waves 1 and 2, according to an individual's poverty dynamic group as measured through monetary and nonmonetary dimensions. We also compare estimates between groups with the same baseline poverty status; for

instance, among those who were nonpoor in 2012, we examine whether there are observed differences in experiencing a shock between waves for those that remained nonpoor vs. those who fell into poverty.

Table 6: Exposure to shocks across poverty dynamic categories, MDEP and consumption-based poverty

	Poor in both waves	Become poor in W2	No longer poor in W2	Not poor in either wave	Diff. for moving out of poverty	Diff. for moving into poverty
	(i)	(ii)	(iii)	(iv)	(i)-(iii)	(ii)-(iv)
MDEP						
Any shock in last 12 mos	0.46	0.46	0.40	0.32	0.063	0.148**
Food price shock	0.15	0.22	0.15	0.09	-0.001	0.130***
Natural disaster	0.20	0.13	0.14	0.10	0.055	0.027
Price of agric. input shock	0.09	0.18	0.11	0.08	-0.022	0.094**
Loss of livestock	0.06	0.05	0.06	0.03	0.003	0.023
Death/illness in household	0.13	0.10	0.12	0.11	0.012	-0.006
Relative consumption-based poverty						
Any shock in last 12 mos	0.37	0.39	0.34	0.37	0.030	0.022
Food price shock	0.16	0.17	0.10	0.11	0.060	0.064**
Natural disaster	0.17	0.12	0.14	0.11	0.027	0.009
Price of agric. input shock	0.07	0.10	0.07	0.11	-0.003	-0.010
Loss of livestock	0.02	0.07	0.04	0.04	-0.015	0.038
Death/illness in household	0.12	0.10	0.07	0.13	0.049	-0.023

Note: The values are mean values of the row labels within each poverty dynamic category. For example, the top left cell can be translated as '46 percent of chronically MDEP households have experienced a shock between waves 1 and 2'. MDEP is defined as having k>=0.72 in wave 1 and k>=0.67 in wave2. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Differences and F-tests are significant at *p<0.1; **p<0.05; ***p<0.01. The balanced panel sample covers 3,197 households in each wave.

Among households that were not MDE poor in 2012, those that fell into poverty were 15pp more likely to have experienced a shock between the two

waves. This pattern is not observed when looking at movement across consumption-based poverty dynamics categories. Furthermore, MDEP appears to shift depending on whether the shocks were to food prices or agricultural input prices. Thus, from a policy standpoint MDEP has the desirable quality that it is correlated with something that can be expected to have adverse effects on wellbeing.[18]

Whether or not this finding is generalizable, we consider it a useful insight for Ethiopia.

5 Discussion

The evidence suggesting that shocks can drive changes in nonmonetary measures of poverty implies that *k* can be a useful indicator for monitoring reactions to adverse shocks. One possible explanation for why the consumption poverty measure does not seem to identify these same shocks as clearly is that consumption may contain more measurement error (as suggested by the evidence on the sensitivity of measured consumption to questionnaire design) than is found in *k*.

The susceptibility of income and consumption data to measurement error is widely recognized (see, e.g., Bound and Krueger, 1991; Pischke, 1995). Due to the time and financial burdens associated with diaries, ESS consumption data are collected using recall questionnaires. Sarkar (2012) suggests respondent recall error can contribute to mismeasurement in actual consumption. Furthermore, the length of the period recalled can affect a respondent's recall: Longer periods make it harder for the respondent to correctly remember consumption behaviors, but shorter periods may lead to magnification of recall bias, since reported consumption will have to be scaled up more to calculate annual consumption. The latter is particularly

[18] The Alkire-Foster method (2011) allows for significant flexibility in selecting components. The process of choosing deprivations for inclusion in the underlying index is arbitrary and largely dependent on data availability. Given the components selected for measuring MDP here, it is perhaps not surprising that changes in MDEP are correlated with exposure to certain shocks.

problematic for food consumption data which, typically and in the case of the ESS, are collected for the 7 days preceding the survey. In fact, Lanjouw and Lanjouw (1997) suggest that there can be considerable mismeasurement of food consumption and expenditure in household surveys.(For further evidence of the sensitivity of measured consumption to questionnaire design, see Jolliffe, 2001; Winter, 2003; Pradhan, 2009; Beegle *et al.* 2012; Browning *et al.* 2014; and Jolliffe *et al.*, 2014.)

Furthermore, consumption-based poverty estimates require numerous inputs in addition to household survey reports of consumption. These factors, among them spatial and temporal price indices, prices for nonpurchased goods, and equivalence scales, are vulnerable to their own measurement errors (Deaton, 2003).Selecting components of expenditure to include in the consumption aggregate can also be difficult; decisions on whether to include poorly estimated items reported in nonstandard units can have profound impacts on the consumption aggregate and the corresponding choice of poverty line.

In contrast, there are fewer factors that might cause measurement error in the weighted deprivation index. First, inputs for the weighted deprivation index do not rely on respondent recall; respondents report on their *current* asset ownership, housing status, and educational attainment. Unlike with consumption and consumption-based poverty, calculating *k* and MDP does not require integrating inputs that may vary by region, such as prices of goods; criteria for deprivations are standard across regions. The primary sources of error in *k* may derive from the data entry process or anthropometric collection of data on children under5.

In looking at cross-sectional trends, measurement error that is mean zero and independent of estimated consumption does not induce bias in the estimated poverty rate; in the aggregate, the error terms cancel each other out (Lanjouw and Lanjouw, 1997). However, measurement error is a more pertinent issue when using panel data to assess the dynamics of household consumption, income, or poverty. Generally speaking, because random measurement error in the consumption aggregate will exaggerate the

magnitude of change over time for a given individual, the result will be an overestimate of the amount of movement in and out of poverty (Glewwe and Gibson, 2005). In the context of the ESS, between 2012 and 2014 this exaggeration could explain the differences observed between the magnitude of changes in *k* and MDP compared to that of changes in consumption and consumption-based poverty.

This raises the question, how much of the observed mobility in consumption can be attributed to measurement error? Glewwe (2005) performed a similar exercise using panel data from Vietnam and found that measurement error accounts for over 33 percent of measured movement in per capita expenditure and 13 percent of measured inequality. Aguero *et al.* (2007) used two waves of panel data t from South Africa to determine the proportion of observed income mobility that can be attributed to measurement error. Using health measures to instrument for wave 1 income, they found that 14 to 60 percent of movement between waves could be explained by measurement error in the income aggregate.

Regardless of the magnitude of measurement error underlying consumption mobility, it is unlikely that this error explains all the discrepancies observed between MDEP and consumption-based poverty dynamics. Consumption is arguably the easiest and quickest living standard to change; because *k* is inherently 'stickier', it may take households longer to accumulate enough savings to invest in multidimensional facets of wellbeing. Most likely, disparities in observed mobility between *k* and consumption can be attributed to a mix of many different factors.

5. Conclusion

MDP, as defined using the standard cut-off of k>=0.33, is a widespread burden in Ethiopia, in terms of both cross-sectional prevalence and chronic poverty over time. MDP fell only 4 pp between 2012 and 2014, from 90 to 86 percent, and at both points 82 percent of households were poor. Transitions into and out of MDP are primarily driven by changes in four deprivations (1a. At least one child aged 7-15 years in the household is not

attending school.1b. No one in the household has at least six years of education. 2b. Household does not have access to an improved water source. 3d. Household does not have a radio, television, or phone, or, lacks a transportation asset, land, livestock, or refrigerator); this suggests that certain facets of wellbeing are more susceptible to change over a two-year period.

We also compare relative consumption-based poverty and MDEP, which capture the bottom 30 percent of the distributions of consumption and *k*, to assess how these two indicators interact in the cross-section and over time. Our cross-sectional analyses show that these two measures identify two very different groups as poor. In 2012, among those who were poor in either dimension, only one-third were poor in both; the same applies for 2014. This discordance needs to be considered when designing policies and programs targeting the poor – the poverty indicator selected to identify the target population can have a profound impact on who receives program benefits.

However, the minimal overlap between consumption-based poverty and MDEP in the cross-section is not entirely surprising; similar results have been found in other countries. Perhaps more interesting from a policy perspective is the lack of agreement observed between the dynamics of these two dimensions. Among individuals who experienced an improvement in their weighted deprivation index between 2012 and 2014, over half experienced a decline in their consumption. In fact, the distributions of directional changes in *k* and consumption are effectively independent; we fail to reject the null hypothesis using Pearson's chi-squared test of independence. This lack of correlation suggests that having information about an individual's change in consumption over time does not make it possible to predict change in his or her *k*, and vice versa. This finding has implications for how we assess progress in improving the wellbeing of individuals over time. Until more is learned about precisely what each of these measures is picking up, a policymaker could be missing important changes in wellbeing by focusing only on either monetary or nonmonetary measures of wellbeing or poverty. Until further evidence provides more understanding of what each indicator is capturing, both should be tracked.

References

Aguero, J., Carter, M., and May, J. (2007). "Poverty and inequality in the first decade of South Africa's democracy: What can be learnt from panel data from KwaZulu-Natal?", *Journal of African Economies*, 16(5):782-812.

Alkire, S., and Santos, M. (2010). "Acute multidimensional poverty: A new index for developing countries". OPHI Working Paper no. 38, Oxford Poverty and Human Development Initiative, Oxford, UK.

Alkire, S., and Foster, J. (2011). "Counting and multidimensional poverty measurement", *Journal of Public Economics*, 95(7-8): 476.

Alkire, S., Foster, J., Seth, S., Santos, M., Roche, J., and Ballon, P. (2014). *Multidimensional Poverty Measurement and Analysis: Chapter 1 - Introduction*. Oxford, United Kingdom: Oxford Poverty and Human Development Initiative.

Alkire, S., and Roche, J. (2013). *How Multidimensional Poverty Went Down: Dynamics and Comparisons.* Oxford, United Kingdom: Oxford Poverty and Human Development Initiative.

Alkire, S., and Santos, M. (2014). "Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index", *World Development*, 59: 251.

Ambel, A., Mehta, P., and Yigezu, B. (2015). "Multidimensional poverty in Ethiopia: Changes in overlapping deprivations "*Policy Research Working Paper*, no. 7417, World Bank. Retrieved on March 2, 2017 from: http://documents.worldbank.org/curated/en/692441467999110169/ Multidimensional-poverty-in-Ethiopia-changes-in-overlapping-deprivations.

Apablaza, M., and Yalonetzky, G. (2013). *Decomposing Multidimensional Poverty Dynamics*. Oxford, United Kingdom: Oxford Poverty and Human Development Initiative.

Ballon, B., and Apablaza, M. (2012). *Multidimensional Poverty Dynamics in Indonesia: Research in-Progress. Dynamic Comparison between Multidimensional Poverty and Monetary Poverty*, Oxford, UK: Oxford Poverty and Human Development Initiative.

Bane, M., and Ellwood, T. (1986). "Slipping into and out of poverty: The dynamics of spells. *Journal of Human Resources"*, 21(1): 1–23. doi: 10.2307/145955

Barrett, C. B. (2005). "Rural poverty dynamics: Development policy implications". *Agricultural Economics*, 32: 45–60. doi:10.1111/j.0169-5150.2004.00013.x.

Baulch, B., and Hoddinott, J. (2000). "Economic mobility and poverty dynamics in developing countries", *Journal of Development Studies*, 36(6): 1.

Beegle, K., De Weerdt, J., Friedman, J., and J. Gibson. (2012). "Methods of household consumption measurement through surveys: Experimental results from Tanzania", *Journal of Development Economics*, 98(1): 3–18.

Bound, J., and Krueger, A. B. (1991). "The extent of measurement error in longitudinal earnings data: Do two wrongs make a right?" *Journal of Labor Economics*, 9(1):1-24.

Bourguignon, F., Benassy-Quere, A., Dercon, S., Estache, A., Gunning, J., Kanbur, R., Klasen, S., Maxwell, S., Platteau, J., Spadaro, A. (2008). *Millennium Development Goals at Midpoint: Where Do We Stand*? Brussels: European Commission. Retrieved on April 1, 2017 from: https://ec.europa.eu/europeaid/sites/devco/files/study-millenium-development-goals-200810_en.pdf

Bourguignon, F., Benassy-Quere, A., Dercon, S., Estache, A., Gunning, J., Kanbur, R., Klasen, S., Maxwell, S., Platteau, J., Spadaro, A. (2010). "Chapter 2: The Millennium Development Goals, an assessment", In R. Kabur and M. Spence (eds.), *Equity and Growth in a Globalizing World*, World Bank: Washington, DC. doi: 10.1596/978-0-8213-8180-9.

Browning, M., Crossley, T., and J. Winter. (2014). "The measurement of household consumption expenditures". *Annual Review of Economics* 6 (1): 475-501. doi: 10.1146/annurev-economics-080213-041247.

Bruck, T., and Kebede, S. (2013). *Dynamics and Drivers of Consumption and Multidimensional Poverty*, Berlin: German Institute of Economic Research.

Deaton, A. (2003). "Household surveys, consumption, and the measurement of poverty", *Economic Systems Research*, 15(2): 135-59. *doi:10.1080/0953531032000091144*.

Dercon, S., and Krishnan, A. (2000). "Vulnerability, seasonality, and poverty in Ethiopia", *Journal of Development Studies*, 36(6): 25.

Drèze, J., and Sen, A. K. (2013). *An Uncertain Glory: India and its Contradictions*. Princeton, New Jersey: Princeton University Press.

Glewwe, P. (2005). "How much of observed economic mobility is measurement error? A method to remove measurement error, with an application to Vietnam", *World Bank Economic Review*, 26(2): 236-264. doi: 10.1093/wber/lhr040

Glewwe, P., and Gibson, J. (2005). "Chapter VIII. Analysis of poverty dynamics', in *Handbook on Poverty Statistics: Concepts, Methods and Policy Use*, Geneva: United Nations.

Hulme, D., and Shepherd, A. (2003). "Conceptualizing chronic poverty", *World Development*, 31(3): 403.

Jolliffe, D. (2001). "Measuring absolute and relative poverty: The sensitivity of estimated household consumption to survey design", *Journal of Economic and Social Measurement*, 27 (1-2): 1–23.

Jolliffe, D., Lanjouw, P., Chen, S., Kraay, A., Meyer, C., Negre, M., Prydz, E., Vakis, R., and K. Wethli. (2014). *A Measured Approach to Ending Poverty and Boosting Shared Prosperity: Concepts, Data, and the Twin Goals*. Washington, DC: World Bank. http://elibrary.worldbank.org/doi/book/10.1596/978-1-4648-0361-1.

Klasen, S. (2000). "Measuring poverty and deprivation in south Africa", *Review of Income and Wealth*, 46(1): 33.

Lanjouw, P., and Lanjouw, J. (1997). "Poverty comparisons with non-compatible data". Policy Research Working Paper Series, no. 1709, World Bank, Washington DC.

Ministry of Finance and Economic Development. (2012). *Ethiopia's Progress Towards Eradicating Poverty: An Interim Report on Poverty Analysis Study (2010/11)*, Addis Ababa: Ministry

Morrell, D. (2011), "Who is poor?" *Harvard Magazine*, 2011 (Jan-Feb). 9-10. Retrieved on April 1, 2017 from: http://harvardmag.com/pdf/2011/01-pdfs/0111-9.pdf

Nolan, B., and Whelan, C. (2011). *Poverty and Deprivation in Europe*. London: Oxford University Press.

Oxford Poverty and Human Development Initiative. (2013). *Ethiopia Country Briefing*. Oxford, United Kingdom: OPHI. Retrieved on April 1, 2017 from: http://www.ophi.org.uk/wp-content/uploads/Ethiopia-2013.pdf

Pischke, J. S. (1995). "Measurement error and earnings dynamics: Some estimates from the PSID validation study," *Journal of Business & Economic Statistics*, 13(3): 305-314.

Pradhan, M. (2009). "Welfare analysis with a proxy consumption measure: Evidence from a repeated experiment in Indonesia," *Fiscal Studies*, 30 (3-4): 391–417.

Royal Government of Bhutan. (2014). *Bhutan Multidimensional Poverty Index 2012*, Thimphu: National Statistics Bureau. Retrieved on April 1, 2017 from: http://www.nsb.gov.bt/publication/files/pub0ll1571bt.pdf

Sarkar, S. (2012). *Multidimensional Poverty in India: Insights from NSSO Data. Dynamic Comparison between Multidimensional Poverty and Monetary Poverty Workshop*, Oxford, UK: Oxford Poverty and Human Development Initiative. Retrieved on April 1, 2017 from http://www.ophi.org.uk/wp-content/uploads/Sandip-Sarkar-Multidimensional-Poverty-in-India.pdf

WHO and UNICEF. (2006). *Core Questions on Drinking-water and Sanitation for Household Survey*, Geneva: World Health Organization.

Winter, Joachim. (2003). "Response bias in survey-based measures of household consumption", *Economics Bulletin* 3(9):1-12.

Woolard, I., and Klasen, S. (2005). "Determinants of income mobility and household poverty dynamics in South Africa", *Journal of Development Studies*, 41(5)" 865–897, https://doi.org/10.1080/00220380500145313.

World Bank. (2001). *Risk Management in South Asia: A Poverty-focused Approach Report*. (No. 23509-SAS). Washington, DC: World Bank.

World Bank Group. (2015). *Ethiopia Poverty Assessment*. Washington, DC: World Bank. Retrieved on April 1, 2017 from: http://hdl.handle.net/10986/21323.

Appendix Table A: Dynamics of multidimensional equivalent poverty estimate, *k*=0.72

	Poor in Both Waves	Become Poor in Wave 2	No Longer Poor in Wave 2	Not Poor in Either Wave	Sample Size (*Households*)
Total	16.43	11.66	12.25	59.65	N=3,197
Rural	17.50	12.16	12.93	57.41	N=2,799
Small town	1.61	4.70	2.90	90.79	N=398
Amhara	22.14	11.54	15.14	51.17	N=715
Oromiya	14.17	11.63	11.28	62.92	N=636
SNNP	12.98	12.68	9.99	64.36	N=848
Tigray	16.46	8.98	11.30	63.26	N=337
All other regions	20.83	10.98	16.43	51.76	N=661

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The *k* cutoff used to establish a multidimensional equivalent poverty estimate was determined based on the *k* value that would generate the same prevalence of poverty identified in wave 1 using annual consumption per adult equivalent.

Once Poor always Poor? Exploring Consumption- and Asset-based Poverty Dynamics in Ethiopia[1]

Kashi Kafle[2], Kevin McGee[3*], Alemayehu Ambel[3], Ilana Seff[4]

Abstract

This paper examines the dynamics of wellbeing in Ethiopia by assessing changes in poverty status based on consumption and asset ownership. Using panel data from the first two waves of the Ethiopia Socioeconomic Survey (ESS), we discover that although the cross-sectional poverty remains relatively unchanged (approximately 30% in both 2012 and 2014), the proportion of the population experiencing consumption poverty at some point during this period is 47%. An asset-based measure of poverty exhibits fewer transitions in and out of poverty. Examination of the direction and magnitude of change in consumption both at aggregate and sub-group levels indicates that despite a stagnant poverty rate, consumption patterns have changed significantly. The forward movers and non-poor households have increased their share of spending on nutrient-dense foods, while the chronic poor and backward movers have increased spending shares on staples (reduced on nutrient-dense foods). Our findings indicate that availability of longitudinal data at the household level provides additional insights on the dynamics of wellbeing that would be impossible to understand using cross sectional data only.

Keywords: Wellbeing dynamics, Ethiopia, LSMS-ISA, consumption-based poverty, asset-based poverty
JEL Codes: I32, E21, O12

---

[1] *Acknowledgements*: The authors are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding assistance. The authors would also like to thank Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw, Alemayehu Seyoum Taffesse, Dean Jolliffe and two anonymous reviewers for their generous insight and feedback and Demirew Getachew and Tadele Ferede for their support in the dissemination of this paper. Finally, we are appreciative of all comments received on the presentation of this paper from participants in the Workshop on Dynamics of Wellbeing.
[2] Kashi Kafle is with the Research and Impact Assessment Division (RIA) of the International Fund for Agricultural Development (IFAD), Rome, Italy.
[3] Kevin McGee and Alemayehu Ambel are with the Development Economics Data Group of the World Bank, Washington DC, USA
*Corresponding author (kmcgee@worldbank.org)
[4] Ilana Seff is with the Development Economics Research Group of the World Bank, Washington DC, USA

1. Introduction

In recent years Ethiopia has experienced remarkable economic growth with a per capita growth rate of approximately 8% per year (World Bank, 2015). In 2000, 44% of the population lived below the national poverty line but the number dropped to less than 30% in 2011 (Abro, Alemu, & Hanjra, 2014; World Bank, 2015). The substantial reduction in national poverty coincided with rapid economic growth driven largely by growth in the agricultural sector (Abro *et al.*, 2014; Martins, 2014; World Bank, 2015, 2016). As more than 85% of Ethiopians are engaged in agriculture (FAO, 2011; Mengistu, 2003; World Bank, 2015), and agriculture constitutes 43% of national GDP and 90% of exports (FAO, 2011), policies that affect the agricultural sector can have large ramifications on wellbeing dynamics. Despite promising growth in the economy led by agriculture, it is worrisome to policymakers that the benefits of growth and development may not be equally distributed among all residents. The disproportionate distribution of economic growth is evident in the existing literature (Barrett *et al*., 2006; Bezemer & Headey, 2008; Lipton, 1977) and empirical evidence exists in the case of Ethiopia as well (Abro *et al.*, 2014; Bogale, Hagedorn, & Korf, 2005).

Abro *et al.* (2014) assess the impact of agricultural productivity growth on household poverty dynamics and find that poor people in rural Ethiopia benefitted the least from growth in the agriculture sector; they either had limited access to assets or owned fewer productive farm assets/factors of production. One explanation is that people at the bottom of the economic ladder may be least affected by economic growth because returns to assets depend on initial wealth status (Barrett *et al.*, 2006). However, people in the neighborhood of the poverty line may see their wellbeing status change as the economy grows. This raises an obvious but rather pinpointing policy question: why have some of the poor benefited very little from economic growth, while others have benefited more? Are the same households poor at each point in time or is there movement in wellbeing status? Understanding these questions is critical for designing suitable policy instruments, but these questions are difficult to answer without examining the dynamics of wellbeing and exploring the characteristics of the transitory and chronic

poor. Answering these questions helps not only in identifying the portion of the poor population left out by cross-sectional analysis but also in designing policy instruments to best serve them.

A large body of existing literature has examined the dynamics of wellbeing in various countries, but many of these analyses ignore the multidimensional nature of poverty dynamics as they use poverty classifications based on income(Barrett, 2005; Baulch & Hoddinott, 2000; Duncan *et al.*, 1993; Woolard & Klasen, 2005), or consumption expenditures only (Dercon & Krishnan, 2000). A large body of empirical evidence suggests that poverty measures based on income or expenditures are subject to measurement error and often fail to distinguish between structural and transient poverty (Carter & Barrett, 2006a; Carter & May, 2001). There is a strong current of development literature that considers household assets as an alternative measure of wealth status and uses both consumption and asset-based measures to assess wellbeing dynamics. However, this approach is not free of criticism; while wellbeing dynamics based on asset holdings may perform better than other measures, it is not immediately clear as to how we combine multidimensional assets to form a single wealth measure. One set of studies converts all assets to monetary values and calculates an aggregated wealth measure (Liverpool-Tasie & Winter-Nelson, 2011), but others combine assets to form a weighted index using principal component analysis (Booysen, van der Berg, Burger, Maltitz, & Rand, 2008; Filmer & Scott, 2008; Moser & Felton, 2007; Sahn & Stifel, 2000). No matter how they use assets, many of these studies still miss the 'true' poverty dynamics as they lack nationally representative longitudinal data at the household level and are forced to rely on cross-sectional or pooled cross-sectional data instead (Dang & Lanjouw, 2013). The Ethiopia Socioeconomic Survey (ESS)[5] provides us a unique opportunity to further examine this issue as it comprises a wide breadth of information by integrating household and agricultural survey questions. The ESS dataset enables us to explore both

[5] The Ethiopia socioeconomic survey is a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank's Living Standards Measurement Study-Integrated Survey of Agriculture (LSMS-ISA) initiative

consumption and asset-based wellbeing dynamics simultaneously in a way that would be impossible to do with pooled cross-section data.

This paper examines the dynamics of wellbeing in Ethiopia by assessing poverty status based on both consumption expenditures and asset ownership. The paper is divided into two main parts. The first part investigates how consumption-based wellbeing and poverty status are changing over time. Availability of longitudinal data at the household level allows us to track direct changes in the wellbeing of households rather than only examining the change in average wellbeing between two cross sections. Using the first two waves of the ESS, we assess the dynamics of consumption-based poverty in rural Ethiopia and examine the extent to which this poverty is transient or chronic. As the relative shares of these two types of poverty can have important implications for poverty reduction policies, we focus on households transitioning into or out of poverty between 2012 and 2014 and examine how the level and composition of consumption has changed.

Our analysis is guided by the notion that even though the poverty prevalence is approximately the same in 2012 and 2014, at 30%, there may be significant changes in household consumption patterns. Taking advantage of the longitudinal data at the household level, we break down the consumption aggregate into food and non-food groups, and further into various food and non-food subgroups, to assess the direction and magnitude of changes in consumption. We believe that breaking down the total consumption to various food and non-food categories offers insights on how people change their dietary patterns and other expenses when they move in and out of poverty. These types of analyses could not be explored with the consumption aggregate only. We then explore characteristics of chronic vs. transitory poor households by assessing the extent of poverty dynamics by gender and education level of the household heads. Profiling demographic characteristics by poverty status helps us understand the underlying mechanism of consumption-based poverty dynamics.

In the second part of the paper, we examine wellbeing dynamics based on the socioeconomic status of the households. The socioeconomic status is

measured with a weighted index calculated using the principal component analysis (PCA) on 52 different assets. Assets are loosely defined and include all household durables, housing characteristics, livestock, and agricultural tools and equipment. Since agriculture is a key economic activity for the majority of households in rural and small town areas (Martins, 2014), including livestock and agricultural assets as a wealth measure may reveal the wellbeing dynamics not captured in the aggregate consumption. We define an asset-based poverty line such that the proportion of those that are asset-poor is equal to the proportion of those who are consumption poor in 2012. Then, holding this line fixed for 2014, we examine the dynamics of asset-based wellbeing between 2012 and 2014. Finally, to understand how consumption-based poverty fares against asset-based poverty, we compare and contrast wellbeing dynamics based on asset and consumption poverty lines.

2. Data

The data used in this study comes from the Ethiopia Socioeconomic Survey (ESS), a collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank's Living Standards Measurement Study - Integrated Surveys of Agriculture (LSMS-ISA) that collects multi-topic panel data at the household level. The first wave of the survey includes only rural and small town areas and the second wave of the survey expands to also include urban areas. As our analysis is based on panel households only, the urban sample is automatically excluded. All our results are representative at the national level for rural and small town areas only. Each survey was administered over a series of three visits. In the first wave the post-planting questionnaire was administered between September and October of 2011 followed by the livestock questionnaire in November of 2011 and the household, community, and post-harvest questionnaires in January and April of 2012. A similar method was used for the second wave of data collections, which took place from September of 2013 to April of 2014.

The ESS used a stratified, two-stage sampling scheme. The regions of Ethiopia served as the strata and enumeration areas (EAs) were

proportionately selected based on regional population size. In the first wave, a total of 290 and 43 EAs were selected from rural and small town areas, respectively and a total of 12 households were chosen from each enumeration area. The non-response rate was extremely low at 0.7 percent, and the final interviewed sample included 3,969 households from rural and small town areas. In the second wave, 100 EAs were added from urban areas giving a total of 433 EAs and 5,262 households. However, because urban households were not surveyed in wave 1, they are excluded from the analysis.

Table 1 presents a detailed breakdown of exclusion criteria and corresponding sample loss. The attrition rate between waves was less than 5 percent yielding a surveyed panel sample of 3,776 rural and small town households. However, the final sample used in this analysis is 3,481 because we imposed further restrictions on our sample as follows. We drop 65 households from wave 1 and 128 households from wave 2due to missing information in the consumption aggregate construction.[6]We then exclude all households with zero total consumption (46 in wave 1 and 22 in wave 2) followed by households that subsequently do not match between waves as a result of previous exclusion criteria. Finally, we exclude 45 households whose absolute change in consumption between waves is larger than 25,000 Birr/year per adult equivalent. The threshold is identified at 25,000 Birr/year because we assume that a change in consumption larger than 25,000 Birr is purely noise in the data as it is equivalent to a presumably implausible transition from below the 1st percentile to above the 99th percentile or vice versa.

[6] Missing information refers to households reporting purchase price but no purchase records or with purchased items but no valid conversion factor to convert food items to monetary values

Table 1: Sample size and exclusion criteria

Exclude households if:	Wave 1		Wave 2	
	Total	**Excluded**	**Total**	**Excluded**
1. Lost to attrition	3969	193	3776	-
2. Missing information for consumption aggregates*	3776	65	3776	128
3. Zero total consumption	3711	46	3648	22
4. Unmatched in two waves	3665	139	3626	100
5. Absolute change in consumption >25k Birr/year	3526	45	3526	45
Sample size	3481	488	3481	295

Notes. *Missing information refers to the situation when households reported a purchase price but there is no purchase record or there are no conversion factors ('prices') for certain items the households consumed.

2.1 Characteristics of sample households

Table 2 presents demographic characteristics of sample households at baseline (2011/12) and follow-up (2013/14). The average adult equivalent household size of rural and small town Ethiopia is4.8 adults in wave 1. The adult equivalent size is calculated by multiplying household size with an adult equivalent factor which varies by age group and gender. The rest of the analysis uses adult equivalent size in lieu of household size because the latter fails to account for differences in age and gender of household members.[7] Among other variables, the dependency ratio of 1.4 indicates that, on average, each household has 40% more economically inactive members (children less than 15 and adults older than 65 years of age) than working age members. While all working age people may not have a valid source of income and therefore the real dependency ratio may be even higher, the ratio indicates that

[7] We also analyze consumption- and asset-based wellbeing dynamics using household size instead of adult equivalent size. The main results for the consumption-based wellbeing dynamics are presented in the Appendix but are not discussed in the main text because, even though the size of point estimates for per-capita consumption and other variables differ, the underlying story of wellbeing dynamics is qualitatively identical.

the majority of the Ethiopian population is economically inactive. As implied by the high dependency ratio, the number of children in Ethiopian households is quite large. In fact, households have approximately 4 children on average with 1 child below age 6 and approximately 3 children ages 6 to 18. All household characteristics remain more or less constant over time.

Table 2: Demographic characteristics for households in rural and small town areas

Characteristics	2011/12		2013/14	
	Mean	Std error	Mean	Std error
Household				
Adult Equivalent Size	4.8	0.05	4.9	0.05
Dependency ratio†	1.4	0.03	1.6	0.04
Number of kids below 6	1.1	0.03	1.1	0.04
Number of Kids 6-18	2.5	0.05	2.6	0.05
Rural	0.94	0.01	0.94	0.01
Household head				
Religion (1=Christian)	0.67	0.03	0.67	0.03
Religion (1=Muslim)	0.30	0.03	0.30	0.03
Religion (1=Other)	0.03	0.01	0.02	0.01
Sex (1=Female, 0=Male)	0.15	0.01	0.16	0.01
Married (1=yes, 0=No)	0.88	0.01	0.86	0.01
Age (years)	44.2	0.34	45.7	0.35
Can read and write (1=yes, 0=No)	0.47	0.02	0.46	0.02
Education (1=Never school,0=else)	0.60	0.02	0.59	0.02
Education (1=Primary, 0=else)	0.35	0.02	0.35	0.02
Education (1=Secondary, 0=else)	0.05	0.01	0.05	0.01
Observations	*3481*		*3481*	

Notes. Point estimates are population weighted means. Standard errors are adjusted for stratification and clustering.

†Dependency ratio is missing for 126 households because they have no working age members at all.

In addition to household demographics, household head characteristics such as age, gender, and education are also pivotal in understanding household's wellbeing status. Although a vast majority (87%) of household heads are

married, only 15% of households are headed by a female. On average, household heads are 44 years old in 2012 and 46 years old in 2014. Approximately 47% of household heads are literate. The low literacy rate follows from the observation that 60% of household heads have never attended school, 35% have attended primary school only (up to 8th grade), and 5% have attended secondary school or higher (above 9th grade). As shown in Table 1, approximately 14% of full sample households were excluded from the final analytical sample. If the excluded households are substantially different from the included households, this could introduce some selection bias into the results. In Table 3, we compare basic characteristics for the included and excluded samples at baseline (2011/12). The far right column of Table 3 also contains the results of an adjusted Wald test for the difference between the included and excluded sample means. The excluded sample does not significantly differ from the included sample on most demographic characteristics and both the excluded and included samples are identically distributed across regions. However, the samples are different on two characteristics: religion and education of the head of the household. Fewer excluded household heads were Muslim and fewer had completed primary school. Although the two samples are similar in most respects, these few differences could potentially introduce some bias and therefore the results must be interpreted with some caution.

3. Methods

This paper takes a unique approach to assess the dynamics of wellbeing in Ethiopia. First we compute a consumption-based poverty line utilizing a panel of households from the first two waves of the ESS and categorize households as chronically poor, forward movers, backward movers, and non-poor. This analysis is followed by an asset-based approach that employs identical methods to establish an asset-based poverty line and classify households into the four different poverty groups. The analysis then draws on both consumption- and asset-based approaches and compares and contrasts wellbeing dynamics based on the two dimensions.

Table 3: Demographics for included and excluded households

	Included	Excluded	Difference
Household			
Adult Equivalent Size	4.8	4.5	
Dependency ratio	1.4	1.3	
Number of kids below 6	1.1	1.0	
Number of Kids 6-18	2.5	2.3	
Rural	0.94	0.95	
Region			
Tigray	0.06	0.07	
Amhara	0.25	0.28	
Oromia	0.42	0.38	
SNNP	0.22	0.19	
Others	0.06	0.08	
Household head			
Religion (1=Christian)	0.67	0.75	
Religion (1=Muslim)	0.30	0.20	**
Religion(1=Other)	0.03	0.06	
Sex (1=Female, 0=else	0.15	0.13	
Married (1=Yes, 0=No)	0.88	0.88	
Age	44.2	43.4	
Can read and write (1=Yes, 0=No)	0.47	0.40	
Education(1=Never school, 0=else)	0.60	0.67	*
Education(1=Primary,0=else)	0.35	0.26	**
Education(1=Secondary,0=else)	0.05	0.07	
Observations	3481	488‡	

Notes: Point estimates are population weighted means. Standard errors are adjusted for stratification and clustering. Significance level: *** <0.01, ** <0.05, * <0.1

‡The number of observations for the excluded sample varies for several variables depending on data availability.

3.1 Consumption poverty line

The consumption poverty line is based on the official poverty headcount ratio of 30% in 2012 (World Bank, 2015). To adjust for inflation at the national level and make the values comparable across waves, we inflate the value of wave 1 consumption to wave 2 levels by a factor of 1.21as reported in the 2015 annual report of the Central Statistical Agency (CSA, 2015). We then set the poverty line to a value that corresponds to the 30thpercentile of total consumption in wave 1.Based on this poverty line (3246 Birr/year per adult equivalent in 2014 terms) we identify households that are descending into poverty (Backward movers), moving out of poverty (Forward movers), poor in both waves (Chronic poor), and non-poor in both waves (Always non-poor).

3.2 Asset poverty line

The asset poverty line is also determined according to the asset based poverty headcount in the wave 1 data. We use 52 total assets that include 34 household durables, 8 livestock species, and 10 variables for dwelling characteristics. Asset variables that are not in both survey waves are excluded from the analysis. Our approach in this paper is to have a more comprehensive definition of household "assets" as any store of wealth. Therefore, we elected to include some assets which could be classified as a means of production (i.e. agricultural assets and livestock). One justification for their inclusion is that the sample consists mainly of rural households with the majority involved in agricultural activities and therefore we argue that these assets are often a critical component of household welfare of these households[8].

We use principal component analysis, with the first principal component serving as scoring factors for computing a weighted index. This index is

[8]One potential criticism of this approach is that households do not derive their wellbeing directly from these productive assets, but rather they are a means to enable purchase of other assets that contribute to wellbeing.

commonly referred to as an asset index, wealth index, or socioeconomic index. In this paper, we call it an asset index. Economics status based on the asset index is sometimes referred to as wealth status or socioeconomic status. The first principal component captures the maximum variance (i.e. inequalities) in the data and therefore serves as a valid measure of wealth or socioeconomic status (Filmer & Scott, 2008; Vyas & Kumaranayake, 2006; McKenzie, 2005; Filmer & Pritchett, 2001). To make the asset index comparable across waves and equivalent to the approach we used to calculate the consumption poverty line, we pooled assets across two waves, obtained scoring factors, means, and standard deviations for the pooled data, and use the estimates to calculate period specific asset indices. If prices are viewed as weights, using pooled scoring factors for the asset index is equivalent to using the inflated prices in calculating the consumption poverty line. Our use of pooled data to obtain the scoring factors and other mean estimates is strongly supported in the literature (Booysen *et al.*, 2008; Harttgen, Klasen, & Vollmer, 2013; Sahn & Stifel, 2000, 2003).

Table 4 provides summary statistics and scoring factors for all 52 asset variables used in the analysis. The asset poverty line is established with the same method used to generate the consumption poverty line. First, we identify the asset poverty line that corresponds to the 30th percentile of the wave 1 asset index. This same poverty line (asset index value of -0.963) is set in wave 2. This allows us to identify households that are falling into poverty (Backward movers), moving out of poverty (Forward movers), poor in both waves (Chronic poor), and non-poor in both waves (Always non-poor). Since asset variables are either binary (ownership) or count (number owned), the variable weights are easy to interpret. In case of binary asset variables, acquisition of a particular type of asset (one or many) changes the value of the asset index according to that asset's weight. For example, owning a car increases the asset index by 2.98 but using firewood or dung as cooking fuel decreases the asset index by 0.29. For count variables such as number of cattle, acquiring an additional unit of asset changes the value of the asset index by that asset's weight. For example, owning one more cattle decreases the asset index by 0.003 and having one more room in the house increases the asset index by 0.09.

Table 4: Summary statistics and scoring factors for asset variables

Assets ownership	Scoring factors	Mean	SD	Scoring factors/SD
Household durables†(=1 if own, 0 else)				
Kerosene stove	0.14	0.031	0.173	0.81
Butane stove	0.17	0.006	0.080	2.15
Electric stove	0.20	0.011	0.103	1.90
Blanket	0.04	0.896	0.305	0.13
Mattress, bed	0.08	0.684	0.465	0.16
Watch/clock	0.09	0.284	0.451	0.19
Telephone	0.21	0.025	0.157	1.36
Cellphone	0.13	0.356	0.479	0.27
Radio, tape	0.10	0.353	0.478	0.21
TV	0.27	0.044	0.204	1.33
CD/VCD/DVD	0.27	0.029	0.167	1.62
Dish antenna	0.27	0.023	0.151	1.80
Sofa	0.25	0.013	0.113	2.25
Bicycle	0.17	0.020	0.141	1.18
Motorbike	0.19	0.010	0.101	1.86
Cart (hand)	0.17	0.011	0.107	1.60
Animal cart	0.11	0.029	0.167	0.68
Sewing machine	0.15	0.015	0.120	1.25
Weaving equipment	0.12	0.014	0.116	1.06
Mitad-electric	0.25	0.009	0.096	2.61
Mitad-modern	0.13	0.058	0.233	0.56
Refrigerator	0.24	0.011	0.104	2.34
Car	0.22	0.005	0.073	2.98
Gold/silver	0.10	0.245	0.430	0.24
Wardrobe	0.16	0.034	0.180	0.90
Storage shelf	0.14	0.116	0.320	0.43
Biogas stove	0.18	0.006	0.080	2.27
Water storage pit	0.10	0.030	0.170	0.62
Sickle	-0.04	0.837	0.370	-0.12
Axe	0.02	0.440	0.496	0.04
Pick Axe	0.01	0.511	0.500	0.03

Plough	-0.05	0.702	0.457	-0.10
Plough (modern)	0.09	0.027	0.161	0.54
Water pump	0.20	0.025	0.157	1.30
Livestock (number)				
Cattle	-0.01	4.080	4.551	-0.003
Sheep	-0.02	1.866	4.047	-0.005
Goat	-0.02	1.835	5.341	-0.004
Horse	-0.003	0.134	0.513	-0.005
Donkey	-0.01	0.523	0.877	-0.012
Mule	-0.001	0.038	0.226	-0.004
Camel	-0.01	0.132	1.556	-0.005
Chicken	-0.02	3.441	5.340	-0.004
Housing characteristics				
Floor (1= Cement, 0 else)	0.13	0.030	0.171	0.76
Wall (1= Cement, bricks, 0 else)	0.07	0.006	0.076	0.87
Kitchen (1= Improved, 0 else)	0.06	0.644	0.479	0.13
Roof (1= CGI, tiles, 0 else)	0.08	0.491	0.500	0.16
Light source (1= Electricity, 0 else)	0.09	0.337	0.473	0.18
Toilet (1= Flush, pit, 0 else)	0.06	0.614	0.487	0.13
Number of rooms	0.10	1.879	1.020	0.09
Drinking water (1= Protected, 0 else)	0.05	0.564	0.496	0.11
Cooking fuel (1= Firewood, 0 else)	-0.05	0.972	0.166	-0.29
Own home (1=Yes, 0 No)	-0.04	0.940	0.237	-0.18

Notes: All point estimates, scoring factors, means, and standard deviation, are population weighted estimates and based on pooled data across two waves. Asset variables are sorted by their weights.

†All household durables take a value of 1 if household owns them and 0 if the household does not own.

4. Wellbeing dynamics

In this section we present the dynamics of wellbeing using consumption-and asset-based poverty lines. We present a detailed analysis of wellbeing dynamics based on consumption expenditures followed by an assessment of asset-based dynamics and a comparison between the two approaches.

4.1 Consumption expenditures

Table 5 presents consumption expenditures for the full panel sample in 2012 and 2014. The first three rows present total, food, and non-food consumption expenditures and the next two rows reflect the shares of food and non-food expenditures. Food expenditures include expenses for 25 different food items from 5 different food groups; staples, pulses, animal source foods (ASF), vegetables and fruits (veg/fruit), and other miscellaneous food items.[9] Non-food expenditures cover all other expenses not related to food. Health expenses are excluded due to data unavailability.

Table 5: Consumption expenditures of households in rural and small town areas

Expenditures	Full Sample		
	Wave 1 (2011/12)	**Wave 2 (2013/14)**	**Diff**
Total	5378	4973	-405**
	(163.0)	(141.1)	
Food	4398	3911	-487***
	(142.1)	(122.6)	
Nonfood	980	1062	81**
	(46.7)	(44.9)	
Food and nonfood shares			
Food	0.82	0.78	-0.04***
	(0.01)	(0.01)	
Nonfood	0.18	0.22	0.04***
	(0.01)	(0.01)	
Observations	3481	3481	

Notes. Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1.

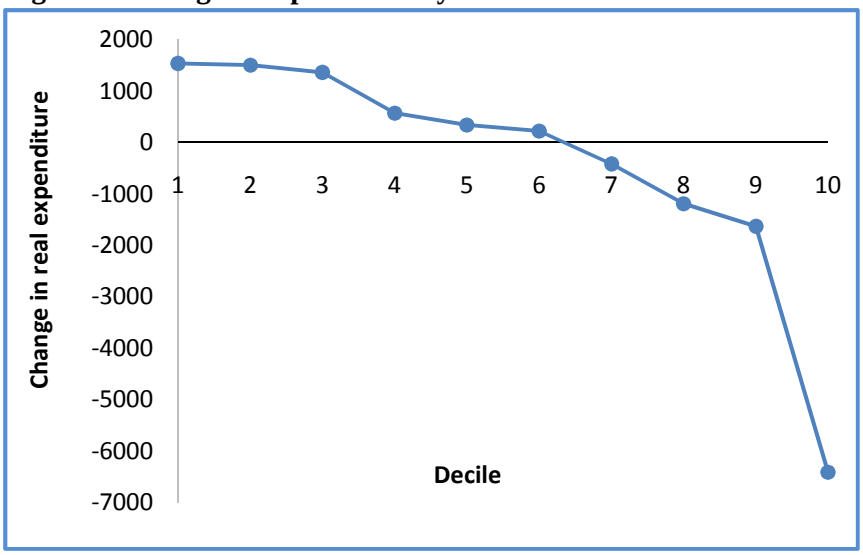
[9] Staples include teff, wheat, barley, maize, sorghum, and millet. Pulses include horse beans, chick pea, field pea, lentils, niger seed, and linseed and 'veg/fruit' includes onion, banana, potato, kocho, and bula. Similarly, ASF includes meat, milk, cheese, and eggs and 'other food' includes sugar, salt, coffee, and chat/khat.

All expenditures are expressed in 2014 levels and reflect real annual Birr per adult equivalent. Results based on per-capita expenditure are in Table A1 in Appendix. Point estimates differ but the pattern for wellbeing dynamics is qualitatively the same.

In the aggregate, total and food expenditures decreased between 2012 and 2014; nonfood expenditures increased over this same period. On average, compared to the budget shares in 2012, Ethiopian households decreased the food budget share by 4% in 2014 but increased the non-food budget share by 4%. Because total consumption has also decreased over time, improvements in the wellbeing status of rural and small town Ethiopians may be not as substantial as it has been reported previously (World Bank, 2015, 2016; Martins, 2014). One potential reason for this difference is that our results are based on rural and small town samples only and do not reflect dynamics in urban areas. It suggests that this growth has not consistently translated into improved wellbeing among households in rural and small towns in Ethiopia.

Does this drop in mean consumption translate to an increase in poverty? Despite a statistically significant drop in mean consumption from 5378 Birr/person in 2012 to 4973 Birr/person in 2014 (Table 5), we find that the change in the poverty rate was not statistically significant. Therefore, it appears that poverty has largely remained the same across the two waves. Further exploration of the data reveals that the drop in mean consumption is potentially a result of measurement error in wave 1, particularly on the upper end of the distribution. Figure 1 presents the average change in consumption for each expenditure decile in wave 1. The average change consistently and gradually decreases as one moves along the wave 1 distribution until reaching the highest wave 1 decile. At the 10th decile, the change in consumption drops substantially. This drop either implies (1) that the richest households saw a large decrease in expenditures between waves or (2) that there was measurement error in wave 1 that was not present in wave 2 and registered as a large decrease for mismeasured households. Measurement error seems the more likely explanation since we wouldn't expect such wide swings in light of the fact that food consumption makes up a large portion of consumption throughout the distribution. When we exclude the 10th decile, the average change in expenditure is positive (and weakly significant). The decrease in mean consumption therefore does not appear to be a robust result.

Figure 1: Change in expenditure by wave 1 decile



Even though the poverty rate did not significantly change between waves, there is still potential for significant movement into and out of poverty. Table 6 presents the poverty transition matrix between waves 1 and 2. Approximately one-third of Ethiopian households lived in poverty in each wave (30% in wave 1 and 32% in wave 2). However, nearly 47% of households were poor at some point during this period; approximately 16% of households lived below the poverty line in both waves, 15% were poor in wave 1 but moved out of poverty in wave 2, and another 16% fell back to poverty in wave 2. Similar patterns hold for both rural and small town areas although the poverty rate in small towns is much lower. In small towns,9% of individuals were chronically poor, 10% were forward movers, and 11% were backward movers, meaning that30%of small town households were poor at some point between 2012 and 2014. Although repeated cross-sectional surveys can capture the share of households that are currently poor, they cannot capture the share of households that have experienced poverty over time. Our findings indicate that even over a relatively short period (2 years), the share experiencing poverty is much larger than indicated by current poverty rates in Ethiopia.

Table 6: Proportion of poor and non-poor households based on consumption

Wave 1 (2011/12)	Wave 2 (2013/14)		Total
	Non-poor	Poor	
Full sample			
Non-poor	53.3	16.4	*69.7*
	(2.17)	(1.18)	(*1.89*)
Poor	14.6	15.7	*30.3*
	(1.25)	(1.47)	(*1.89*)
Total	*67.9*	*32.1*	*100*
	(*2.01*)	(*2.01*)	
Rural			
Non-poor	52.1	16.8	*68.9*
	(2.29)	(1.26)	(*1.99*)
Poor	14.9	16.2	*31.1*
	(1.33)	(1.55)	(*1.99*)
Total	*67.1*	*32.9*	*100*
	(*2.12*)	(*2.12*)	
Small Town			
Non-poor	70.0	11.3	*81.3*
	(3.29)	(2.09)	(*2.74*)
Poor	9.8	8.9	*18.7*
	(2.11)	(2.12)	(*2.74*)
Total	*79.9*	*20.1*	*100*
	(*3.03*)	(*3.03*)	

Notes: Point estimates are population weighted proportions. Standard errors adjusted for stratification and clustering are in parentheses.
Rural sample includes 3063 households and small town sample includes 418 households. Results based on per-capita expenditure are in Table A2 in Appendix. The proportion of non-poor remains the same but the proportion of chronic poor increases and the proportion of transitory poor decreases by a small percentage.

Table 7 presents consumption expenditures for households that were poor in

wave 1 and either remained poor (chronic poor) or moved out of poverty (forward movers) in wave 2. Chronically poor households exhibit no change in the amount of overall consumption and a small change in food-only consumption over time, but we find that the share of food consumption has decreased by 3%. Interestingly, the chronic poor increased both the amount and share of non-food consumption expenditures suggesting some movement in consumption pattern even though they are trapped in chronic poverty. In contrast, the forward movers increase the amount of consumption expenditure on all food and non-food items, but do not see an increase in the share of food or non-food consumption.[10]

Table 7: Consumption expenditures of households poor in baseline (2012/13)

Expenditures	Chronic poor			Forward movers		
	Wave 1	**Wave 2**	**Diff**	**Wave 1**	**Wave 2**	**Diff**
Total	2212	2187	-26	2510	5563	3053***
	(54.0)	(43.9)		(49.2)	(217.4)	
Food	1805	1699	-106*	1992	4553	2561***
	(52.1)	(40.4)		(46.7)	(224.5)	
Nonfood	407	487	80***	517	1010	493***
	(19.9)	(24.9)		(24.2)	(76.7)	
Food and nonfood shares						
Food	0.81	0.78	-0.03***	0.79	0.80	0.01
	(0.01)	(0.01)		(0.01)	(0.01)	
Nonfood	0.19	0.22	0.03***	0.21	0.20	-0.01
	(0.01)	(0.01)		(0.01)	(0.01)	
Observations	454	454		460	460	

Note: Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1.

All expenditures in level are annual, real Birr per adult equivalent. Results

[10] This finding is consistent with Engel's law of food demand that states "as income rises, the proportion of income spent on food falls, even if the actual expenditure on food rises".

based on per-capita expenditure are in Table A3 in Appendix. Point estimates differ but the pattern for wellbeing dynamics is qualitatively the same.

Table 8 presents the dynamics of consumption for households that were above the poverty line in 2012. Approximately 21% of the 2,567 non-poor households fell back to poverty in 2014. The backward movers experienced declines both in their food and non-food consumption. Those who remained non-poor over time spent more on food items but, as Engel's law of food demand implies, their share of food expenditure decreased and the share of non-food expenditures increased. Results in Tables 7 and 8 indicate that the view of poverty based on cross-sectional data is unable to capture the dynamics of consumption and the change in the relative position of households over time. In addition, traditional consumption-based analyses of wellbeing typically do not examine changes in the composition of consumption which can be just as important as the level of consumption in determining wellbeing dynamics. In fact, measuring wellbeing status with consumption aggregates may miss the dynamics of consumption at food and non-food items level.

Table 8: Consumption expenditures of households non-poor in baseline (2012/13)

Expenditures	Backward movers			Always non-poor		
	Wave 1	Wave 2	Diff	Wave 1	Wave 2	Diff
Total	5608	2482	-3126***	7028	6400	-628***
	(193.6)	(38.0)		(181.1)	(164.5)	
Food	4811	1939	-2872***	5695	4995	-700***
	(187.3)	(38.0)		(166.9)	(147.3)	
Nonfood	797	542	-254***	1333	1405	72
	(47.7)	(21.9)		(69.2)	(59.4)	
Food and nonfood shares						
Food	0.85	0.78	-0.07***	0.81	0.78	-0.03***
	(0.01)	(0.01)		(0.01)	(0.01)	
Nonfood	0.15	0.22	0.07***	0.19	0.22	0.03***
	(0.01)	(0.01)		(0.01)	(0.01)	
Observations	543	543		2024	2024	

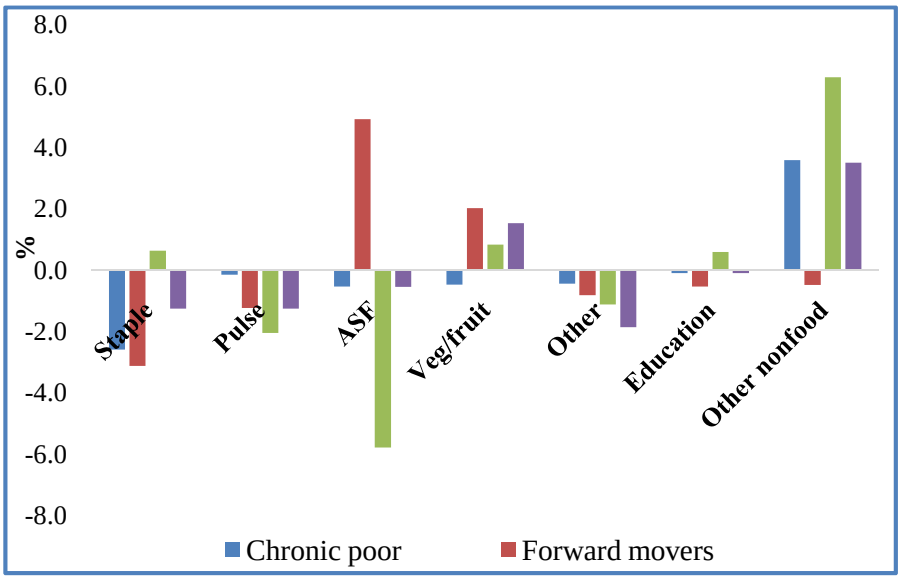
Notes. Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1

All expenditures in level are annual, real Birr per adult equivalent. Results based on per-capita expenditure are in Table A4 in Appendix. Point estimates differ but the pattern for wellbeing dynamics is qualitatively the same.

In Figure 2, we present the change in the share of consumption expenditures on various food and non-food groups over time. A negative change in expenditure share means the household decreases the share of expenditure over time. Examining the changes in expenditure shares, we find that chronically poor households decreased their share of all food and non-food items except for 'other non-food'. As implied by Bennett's law of food demand[11], forward movers spent smaller shares on starchy staples and other foods, but more on nutritious foods like ASF and vegetable and fruits. The opposite is true for backward movers as they spend more on staples but less on nutritious foods like pulses and ASFs. For non-poor individuals, as Engel's law implies, the non-food budget share has increased over time but the food budget share has decreased for all food items, with the exception of fruit and vegetables. Overall, results in Figure 2 imply that even though consumption-based poverty has increased over time (Table 6) and overall consumption has fallen over time (Table 5), many rural Ethiopians have experienced improvements in wellbeing status as reflected in changes in the quality of diet.

[11]Bennett's law of food demand states 'As income rises the proportion of starchy staples in the diet falls

Figure 2: Change in the expenditure share of food and nonfood items by poverty status between 2012 and 2014



4.2 Consumption-based poverty and household demographics

Understanding the relationship between household demographics and poverty may provide further insights for policy design and implementation. For example, policymakers may be interested to know whether poverty status differs with the gender of the household head, the household head's education level, or the proportion of economically active members in the household. Figure 3 depicts the proportions of the population in each poverty dynamics group by gender of the household head. It suggests that wellbeing dynamics in rural Ethiopia does not differ greatly by gender of the household head. However, it does appear there were more forward movers among male headed households and more individuals who were always non-poor among female headed households.

Figure 3: Gender of household head in baseline and poverty transition

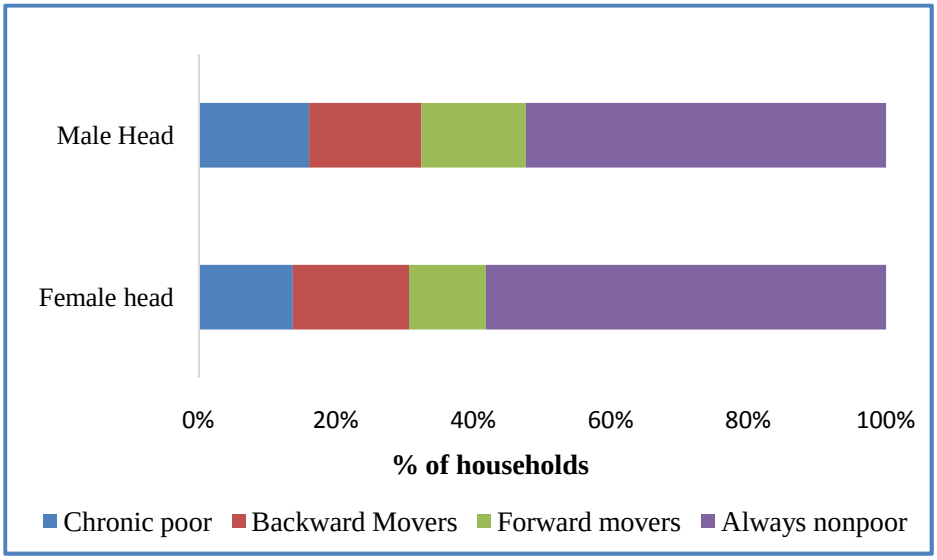
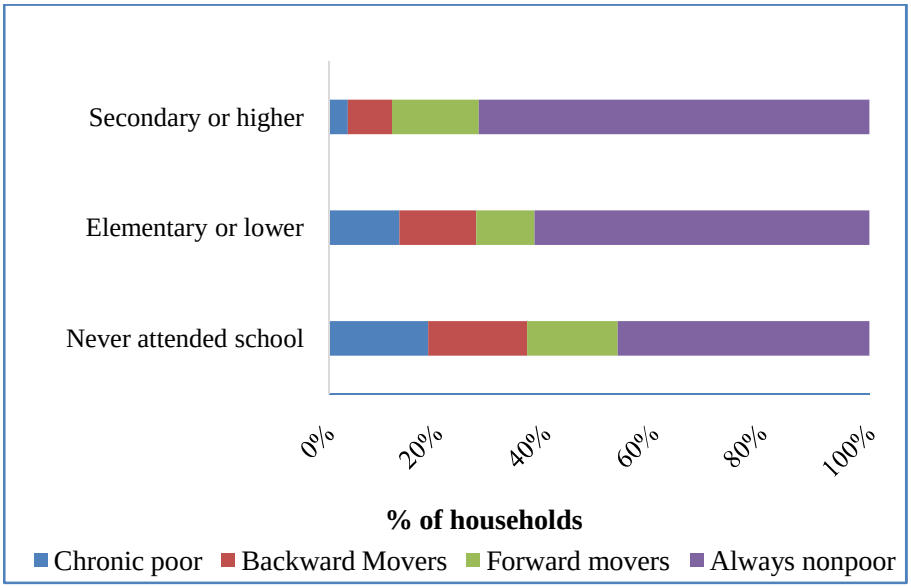


Figure 4 plots household poverty status against household head's education level. First, we classify household heads into two groups: "never attended school" and "attended school". The 'attended school' category is classified further into 'elementary school or lower' and 'secondary school or higher'. A vast majority of household heads who have attended school did not complete primary school (8th grade). Figure 4 indicates that poverty status and a household head's education level have an inverse relationship. While households headed by those with the highest education have the smallest proportion of chronic poor and the largest proportion of non-poor in both waves, households with 'never attended school' heads have the largest proportion of chronic poor and the smallest proportion of non-poor. The proportion of backward movers decreases with household head's education level while there is no clear difference for forward movers. This suggests that households with less educated heads were more likely to fall into poverty but those with better educated heads were not necessarily more likely to escape poverty.

Figure 4: Household head's education level in baseline and poverty transition



In Table 9, we take a slightly different angle and compare the demographic profile of the four poverty transition groups. In order to conserve space, we only present adjusted Wald test results for differences in means between chronic poor and forward movers as well as between backward movers and always non-poor. We find that household composition in wave 1 is different between these groups. Forward movers had smaller households compared to chronic poor while backward movers had larger households than those that were always non-poor. Among household head characteristics, the strongest differences are for education. In general, those households that fell into poverty had less educated heads than those households that were able to remain non-poor. Likewise, those households that were able to escape poverty had heads that were better educated than those that remained poor, though this result was much weaker. Comparing these demographic profiles suggests that education is one important component for transitions into and out of poverty.

Table 9: Baseline demographic characteristics by poverty transition group

	Chronic Poor	Forward Movers	Diff	Backward Movers	Always non-poor	Diff
Household						
Adult Equivalent Size	5.3	4.7	***	5.2	4.5	***
Dependency ratio	1.5	1.6	**	1.3	1.3	***
Number of kids below 6	1.3	1.2	***	1.1	1.1	*
Number of Kids 6-18	2.9	2.4	***	2.9	2.2	***
Rural	0.96	0.96		0.96	0.92	***
Household head						
Religion (1=Christian)	0.71	0.68	*	0.69	0.65	
Religion (1=Muslim)	0.21	0.31		0.29	0.33	
Religion(1=Other)	0.07	0.01	***	0.02	0.02	
Sex (1=Female, 0=else	0.13	0.15		0.11	0.16	
Married (1=Yes, 0=No)	0.88	0.88		0.87	0.88	
Age	44.8	45.4		46.0	43.1	***
Can read and write (1=Yes, 0=No)	0.36	0.42	*	0.42	0.53	***
Education (1=Never school, 0=else)	0.70	0.67	*	0.69	0.52	***
Education (1=Primary, 0=else)	0.29	0.30		0.26	0.41	***
Education (1=Secondary, 0=else)	0.01	0.03	*	0.06	0.07	***
Observations	454	460		543	2024	

4.3 Asset poverty and wellbeing dynamics

In this section, we explore the dynamics of wellbeing using an alternative measure of poverty based on household asset holdings. As Carter & Barrett (2006) and Carter & May (2001) mention, dynamic asset poverty is the latest and fourth generation of poverty measurement approaches. The third generation of poverty measures, dynamic consumption poverty measure, captures what households consume over time but doesn't reflect the dynamic socioeconomic status. We argue that individuals' wellbeing status should be

defined beyond merely what they consume. A stock of durable assets owned by the household, livestock, agricultural tools and equipment, and dwelling characteristics may well reflect the components of wellbeing not captured by consumption expenditures and therefore should be taken into account in the analysis of wellbeing dynamics. Table 10 provides poverty transition matrices based on household asset holdings, for our full panel sample, rural, and small town households.

Table 10: Proportion of poor and non-poor households based on asset poverty line

Wave 1 (2011/12)	Wave 2 (2013/14)		Total
	Non-poor	Poor	
Full sample			
Non-poor	61.0	8.8	*69.8*
	(2.19)	(0.99)	*(1.92)*
Poor	13.6	16.6	*30.2*
	(1.09)	(1.60)	*(1.92)*
Total	*74.6*	*25.4*	*100*
	(1.99)	*(1.99)*	
Rural			
Non-poor	58.7	9.2	*67.9*
	(2.30)	(1.05)	*(2.03)*
Poor	14.5	17.6	*32.1*
	(1.16)	(1.71)	*(2.03)*
Total	*73.2*	*26.8*	*100*
	(2.11)	*(2.11)*	
Small Town			
Non-poor	95.0	2.7	*97.7*
	(1.79)	(1.45)	*(0.73)*
Poor	0.6	1.7	*2.3*
	(0.29)	(0.68)	*(0.73)*
Total	*95.6*	*4.4*	*100*
	(1.78)	*(1.78)*	

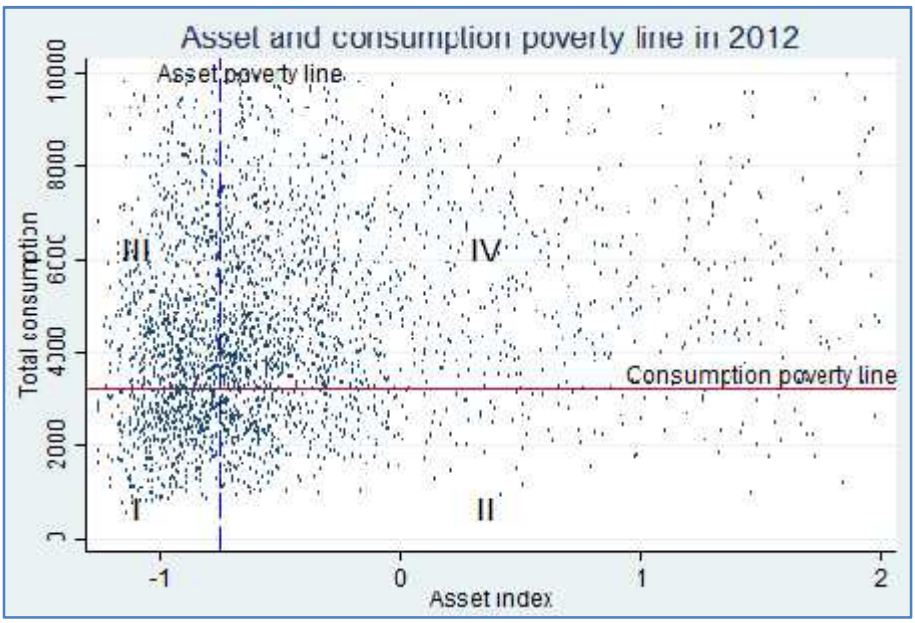
Notes. Point estimates are population weighted proportions. Standard errors adjusted for clustering and stratification are in parentheses. Rural sample includes 3063 households and small town sample includes 418 households.

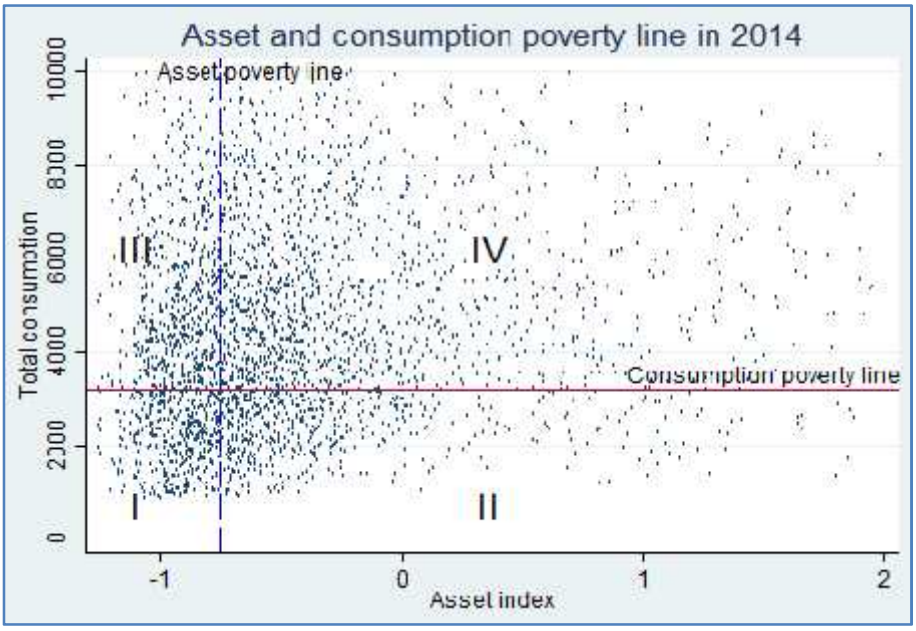
By construction, like consumption-based poverty, 30% of households are asset-poor in 2012 but, unlike consumption-based poverty, the proportion of poor people has declined over time to 25% in 2014. Once again, cross-sectional estimates of poverty underestimate the 'real' poverty prevalence as 39% of the population was 'asset-poor' in either 2012 or 2014. While a similar pattern is observed for consumption-based poverty dynamics, the asset-based dynamics exhibit less movement. Our finding that the prevalence of consumption-based poverty remained the same but the asset-based poverty decreased over time suggests that conclusions drawn from wellbeing dynamics based on consumption expenditures only may be incomplete. From a policy standpoint, it is critical to assess wellbeing dynamics in both consumption and asset spaces to be able to identify a suitable policy instrument.

Next, we compare and contrast asset- and consumption-based poverty both in the cross section and dynamically. Figure 5 depicts the distribution of the asset index and total consumption variables at each point in time. If the asset index and total consumption were highly positively correlated with each other, we would expect to see all observations accumulating around a 45-degree line. Instead, we note a scattered distribution of households both below and above the asset and consumption poverty lines.

However, even though the asset index and consumption expenditures are not strongly correlated, it is possible that poverty classifications based on the two variables may in fact exhibit a correspondence. In Figure 4, the large mass of households in region I and IV in both years implies at least some correspondence in wellbeing status based on the two variables. In both years, approximately 66% of households were classified to identical poverty status categories based on both the asset index and consumption expenditures; 53% were non-poor in both consumption and asset spaces and 13% were poor in both spaces. The remaining 34% of households were poor in one space but non-poor in the other space. This implies there is at least some correspondence between consumption- and asset-based poverty in the cross-section.

Figure 4: Asset and consumption poverty lines in rural and small town areas in 2012 and 2014





Next, we assess the extent to which these two estimates of poverty are correlated dynamically. In particular, we examine whether changes in consumption-based poverty over time tell us anything about changes in asset-based poverty over the same period. We construct two categorical variables each of which categorize households to three groups in both asset and consumption spaces – 'backward movers', 'forward movers' and 'stayed the same' – based on the change in their wellbeing status over time. Table 11presents the cross tabulation of these two variables. In the consumption space, 16% of households worsened, 69% stayed the same and about 15% improved their wellbeing status; a similar pattern holds in the asset space but only 9% households worsened and approximately 14% households improved their wellbeing status. However, among the 16% who fell into poverty in the consumption space, 71% stayed the same in the asset space and another 71% of the forward movers in the consumption space stayed the same in the asset space. Similarly, a large proportion of households that descended into or out of poverty in the asset space saw no change in their status in the consumption space. Although the one-third of the households that worsened or improved in the consumption space exhibit a different trend in the asset space, most of the 'stayers' in the consumption space remained 'stayers' in the asset space as well. In fact, a Pearson's test of independence between changes in asset- and consumption-based poverty indicators rejects the null hypothesis that the two distributions are independent. This suggests that there is at least some co-movement between asset- and consumption-based poverty.

Table 11: Contrasting changes in consumption- and asset-based wellbeing dynamics

Consumption-based poverty	Asset-based poverty			
	Backward movers	**Stayed the same**	**Forward movers**	***Total***
Backward movers	2.0	11.7	2.7	*16.4*
	(0.41)	(1.04)	(0.42)	*(1.18)*
Stayed the same	5.5	55.5	8.0	*69.0*
	(0.67)	(1.63)	(0.75)	*(1.50)*
Forward movers	1.3	10.4	2.9	*14.6*
	(0.32)	(0.96)	(0.52)	*(1.25)*
Total	*8.8*	*77.6*	*13.6*	*100*
	(0.99)	*(1.37)*	*(1.16)*	

Notes. Point estimates are population weighted proportions. Standard errors adjusted for clustering and stratification are in parentheses. In a Pearson's chi-squared test of independence, we reject the null hypothesis of independence, at p=0.001 and a chi-square value of 44.3

Table 12 summarizes the asset index for four different poverty transition groups in both consumption and asset spaces. The first three columns present the distribution of the asset index for four 'asset-poverty' status groups and the next three columns present the distribution for the 'consumption-poverty' status groups. If the asset index and consumption expenditures were perfectly correlated, we would expect the same values of the index for each poverty status group across the two survey waves.

Results indicate that although the values of the asset index are not the same, they do exhibit similar distributions for both asset-based and consumption-based poverty groups. The average asset index is always negative for the chronic poor and positive for 'always non-poor' in both waves. Among the transitory poor, the backward movers in the asset space have a positive asset

index in the first wave and a negative asset index in the second wave but, backward movers in the consumption space saw only a small decrease in their asset index. In contrast, the forward movers exhibit an opposing pattern; forward movers in the asset space move backward in the consumption space as their asset index decreases from 0.09 in 2012 to -0.38 in 2014. This observation suggests that asset poor households may not be consumption poor and vice versa. Overall, the results imply that even though wellbeing dynamics based on an asset index and consumption aggregates do exhibit similar trends, the two variables do not appear to be strongly correlated.

Table 12: Asset index by poverty status groups across waves

Poverty groups	Asset-based poverty			Consumption-based poverty		
	Wave 1	Wave 2	N	Wave 1	Wave 2	N
Chronic poor	-1.24	-1.22	653	-0.61	-0.70	454
	(0.007)	(0.006)		(0.12)	(0.05)	
Forward movers	-1.18	-0.51	486	0.09	-0.38	460
	(0.007)	(0.023)		(0.23)	(0.07)	
Backward movers	0.86	-1.16	315	-0.12	-0.50	543
	(0.37)	(0.008)		(0.15)	(0.05)	
Always non-poor	1.02	1.06	2027	0.62	0.74	2024
	(0.08)	(0.07)		(0.08)	(0.07)	
Total			3481			3481

Notes. Point estimates are the population weighted asset index obtained from the principal component analysis. Standard errors adjusted for clustering and stratification are in parentheses.

5. Conclusion

Our analysis emphasizes the notion that poverty assessments based on household level panel data provide a more complete picture of wellbeing

dynamics, as they can uniquely identify the transitory poor that are not detectable using cross-sectional data. In particular, the prevalence of poverty based on panel data is more than 55% higher than cross-sectional poverty which is around 30% in both 2012 and 2014. Panel data are crucial for assessing progress toward poverty reduction as poverty measures based solely on cross-sectional data significantly underestimate exposure to poverty at some point in time.

Our analysis further contributes to the literature on the dynamics of wellbeing in Ethiopia by looking at changes in the levels and shares of various components of household consumption. Disaggregating the consumption expenditures to various food and non-food groups, our results show that even though consumption-based poverty increased slightly over time in rural and small town areas, a large proportion of the population saw improvement in food consumption, consuming more nutritious foods and fewer staples. It is in this sense that assessing wellbeing dynamics based on aggregate consumption only may not fully capture wellbeing dynamics.

We also assess wellbeing dynamics based on household asset holdings and find that, unlike consumption-based poverty, asset poverty has decreased over time. As asset- and consumption-based poverty measures are mostly uncorrelated, a large chunk of ‘consumption poor’ are ‘asset non-poor’ and vice versa. We argue that since consumption is often temporal and does vary with season but asset accumulation is less subject to seasonal variations and reflects longer run economic status, using asset holdings to measure wellbeing dynamics may provide a more accurate view of the depth and severity of poverty dynamics.

The results also imply that policy interventions targeting poverty reduction may find it worthwhile to consider both consumption- and asset-based wellbeing dynamics in conjunction. While the chronic poor and households that are both asset and consumption poor may need policy interventions comprising immediate relief schemes, the transitory poor and households that are asset poor but consumption non-poor and vice versa may benefit more from long run poverty reduction policies.

Further research is needed to verify and expand on the findings of this study. Future studies could address the limitations from different perspectives. First, the comparison period considered in this paper (2011/12 to 2013/14) could be too short to fully explore the transitions. Future rounds of the ESS will allow for conducting these analyses over a longer time period. In addition, due to data availability, this study only analyzed poverty dynamics in rural areas. The urban context would offer a different setting. The follow-up ESS surveys would be used to address this and provide a more complete picture of poverty dynamics throughout Ethiopia.

References

Abro, Z. A., Alemu, B. A., & Hanjra, M. A. (2014). Policies for Agricultural Productivity Growth and Poverty Reduction in Rural Ethiopia. *World Development*, *59*, 461–474. http://doi.org/10.1016/j.worlddev.2014.01.033

Barrett, C. B. (2005). Rural poverty dynamics: development policy implications. *Agricultural Economics*, *32*, 45–60. http://doi.org/10.1111/j.0169-5150.2004.00013.x

Barrett, C. B., Marenya, P. P., Mcpeak, J., Minten, B., Murithi, F., Oluoch-Kosura, W., Wangila, J. (2006). Welfare dynamics in rural Kenya and Madagascar. *The Journal of Development Studies*, *42*(2), 248–277. http://doi.org/10.1080/00220380500405394

Baulch, B., & Hoddinott, J. (2000). Economic mobility and poverty dynamics in developing countries. *The Journal of Development Studies*, *36*(6), 1–24. http://doi.org/10.1080/00220380008422652

Bezemer, D., & Headey, D. (2008). Agriculture, Development, and Urban Bias. *World Development*, *36*(8), 1342–1364. http://doi.org/10.1016/j.worlddev.2007.07.001

Bogale, A., Hagedorn, K., & Korf, B. (2005). Determinants of poverty in rural Ethiopia, *44*(2), 101–120.

Booysen, F., van der Berg, S., Burger, R., Maltitz, M. von, & Rand, G. du. (2008). Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries. *World Development*, *36*(6), 1113–1130. http://doi.org/10.1016/j.worlddev.2007.10.008

Carter, M., & Barrett, C. (2006a). The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of Development Studies*, *42*(2), 178–199.

Carter, M., & Barrett, C. (2006b). The economics of poverty traps and persistent poverty: An asset-based approach. *Journal of Development Studies*, *42*(2), 178–199.

Carter, M. R., & May, J. (2001). One Kind of Freedom: Poverty Dynamics in Post-apartheid South Africa. *World Development*, *29*(12), 1987–2006. http://doi.org/10.1016/S0305-750X(01)00089-4

CSA. (2012). *Ethiopia - Household Consumption Expenditure (HCE) Survey 2010/2011 Analytical Report*. Ethiopia Central Statistical Agency. Retrieved from http://catalog.ihsn.org/index.php/catalog/3123

CSA. (2015). *Country and Regional Level Consumer Price Indices.* Ethiopia Central Statistical Agency. Retrieved from http://www.csa.gov.et/images/documents/pdf_files/CPI/cpi_decm_2014.

Dang, H. A., & Lanjouw, P. F. (2013). *Measuring Poverty Dynamics with Synthetic Panels Based on Cross-Sections* (SSRN Scholarly Paper No. ID 2285321). Rochester, NY: Social Science Research Network. Retrieved from http://papers.ssrn.com/abstract=2285321

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies*, *36*(6), 25–53. http://doi.org/10.1080/00220380008422653

Duncan, G. J., Gustafsson, B., Hauser, R., Schmauss, G., Messinger, H., Muffels, R., Ray, J. C. (1993). Poverty dynamics in eight countries. *Journal of Population Economics*, *6*(3), 215–234. http://doi.org/10.1007/BF00163068

FAO. (2011). *Food and Agriculture Organization: Ethiopia Country Programming Framework 2012-2015*. Addis Ababa: Food and Agriculture Organization of the United Nations.

Filmer, D., & Pritchett, L. H. (2001). Estimating Wealth Effects without Expenditure Data–or Tears: An Application to Educational Enrollments in States of India. *Demography*, *38*(1), 115–132.

Filmer, D., & Scott, K. (2008). *Assessing Asset Indices*. The World Bank. Retrieved from http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-4605

Harttgen, K., Klasen, S., & Vollmer, S. (2013). An African Growth Miracle? Or: What do Asset Indices Tell Us About Trends in Economic Performance? *Review of Income and Wealth*, *59*, S37–S61. http://doi.org/10.1111/roiw.12016

Lipton, M. (1977). Why poor people stay poor: urban bias in world development. *Cambridge Massachusetts Harvard University Press 1977*. Retrieved from http://www.popline.org/node/497105

Liverpool-Tasie, L. S. O., & Winter-Nelson, A. (2011). Asset versus consumption poverty and poverty dynamics in rural Ethiopia.

Agricultural Economics, *42*(2), 221–233. http://doi.org/10.1111/j.1574-0862.2010.00479.x

Martins, P. (2014). *Structural change in Ethiopia: an employment perspective* (No. WPS6749) (pp. 1–42). The World Bank. Retrieved from http://documents.worldbank.org/curated/en/2014/01/18832342/structural-change-ethiopia-employment-perspective

McKenzie, D. (2005). Measuring inequality with asset indicators. *Journal of Population Economics*, *18*(2), 229–260.

Mengistu, A. (2003). Country Pasture/Forage Resource Profiles: Ethiopia. Retrieved July 11, 2016, from http://www.fao.org/ag/agp/agpc/doc/counprof/ethiopia/ethiopia.htm

Moser, C., & Felton, A. (2007). *The Construction of an Asset Index Measuring Asset Accumulation in Ecuador* (SSRN Scholarly Paper No. ID 1646417). Rochester, NY: Social Science Research Network. Retrieved from http://papers.ssrn.com/abstract=1646417

Sahn, D. E., & Stifel, D. C. (2000). Poverty Comparisons Over Time and Across Countries in Africa. *World Development*, *28*(12), 2123–2155. http://doi.org/10.1016/S0305-750X(00)00075-9

Sahn, D. E., & Stifel, D. C. (2003). Progress Toward the Millennium Development Goals in Africa. *World Development*, *31*(1), 23–52. http://doi.org/10.1016/S0305-750X(02)00121-3

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: How to use principal components analysis. *Health Policy and Planning*, *21*(6), 459–468.

Woolard, I., & Klasen, S. (2005). Determinants of Income Mobility and Household Poverty Dynamics in South Africa. *The Journal of Development Studies*, *41*(5), 865–897. http://doi.org/10.1080/00220380500145313

World Bank. (2015). *Ethiopia Poverty Assessment 2014*. The World Bank. Retrieved from https://openknowledge.worldbank.org/handle/10986/21323

World Bank. (2016). *Ethiopia - Systematic country diagnostic: priorities for ending extreme poverty and promoting shared prosperity* (No. 100592) (pp. 1–144). The World Bank. Retrieved from http://documents.worldbank.org/curated/en/2016/05/26170176/ethiopia-systematic-country-diagnostic-priorities-ending-extreme-poverty-promoting-shared-prosperity.

Appendix

Table A1: Per-capita consumption expenditures of households in rural and small town areas

Expenditures	Full Sample		
	Wave 1 (2011/12)	**Wave 2 (2013/14)**	**Diff**
Total	4324	4028	-295**
	(130.2)	(116.3)	
Food	3530	3163	-367***
	(112.6)	(100.1)	
Nonfood	793	865	72**
	(38.4)	(35.6)	
Food and nonfood shares			
Food	0.82	0.78	-0.04***
	(0.01)	(0.01)	
Nonfood	0.18	0.22	0.04***
	(0.01)	(0.01)	
Observations	3481	3481	

Notes. Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1

All expenditures are expressed in 2014 levels and reflect real annual Birr per-capita.

Table A2: Proportion of poor and non-poor households based on per-capita consumption

Wave 1 (2011/12)	Wave 2 (2013/14)		Total
	Non-poor	Poor	
Full sample			
Non-poor	53.5	16.2	*69.7*
	(2.21)	(1.19)	(*1.91*)
Poor	13.5	16.8	*30.3*
	(1.17)	(1.48)	(*1.91*)
Total	*67.0*	*33.0*	*100*
	(*2.03*)	(*2.03*)	
Rural			
Non-poor	52.4	16.5	*68.9*
	(2.32)	(1.27)	(*2.02*)
Poor	13.8	17.3	*31.1*
	(1.24)	(1.56)	(*2.02*)
Total	*66.2*	*33.8*	*100*
	(*2.15*)	(*2.15*)	
Small Town			
Non-poor	69.5	12.3	*81.8*
	(3.69)	(2.35)	(*2.68*)
Poor	9.8	8.4	*18.2*
	(2.11)	(1.98)	(*2.68*)
Total	*79.3*	*20.7*	*100*
	(*3.33*)	(*3.33*)	

Notes. Point estimates are population weighted proportions. Standard errors adjusted for stratification and clustering are in parentheses.

Rural sample includes 3063 households and small town sample includes 418 households

Table A3: Per-capita consumption expenditures of households poor in baseline (2012/13)

Expenditures	Chronic poor			Forward movers		
	Wave 1	**Wave 2**	**Diff**	**Wave 1**	**Wave 2**	**Diff**
Total	1793	1779	-14	2007	4508	2501***
	(43.4)	(35.8)		(38.6)	(172.4)	
Food	1459	1404	-55	1597	3696	2099***
	(40.4)	(34.7)		(39.5)	(184.1)	
Nonfood	334	375	41***	410	812	402***
	(17.4)	(19.6)		(18.8)	(56.1)	
Food and nonfood shares						
Food	0.81	0.79	-0.02***	0.79	0.80	0.01
	(0.01)	(0.01)		(0.01)	(0.01)	
Nonfood	0.19	0.21	0.02***	0.21	0.20	-0.01
	(0.01)	(0.01)		(0.01)	(0.01)	
Observations	478	478		449	449	

Notes. Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1.
All expenditures in level are annual, real Birr per-capita.

Table A4: Per-capita consumption expenditures of households non-poor in baseline (2012/13)

Expenditures	Backward movers			Always non-poor		
	Wave 1	Wave 2	Diff	Wave 1	Wave 2	Diff
Total	4554	1987	-2567***	5630	5230	-400**
	(178.7)	(30.6)		(141.8)	(132.4)	
Food	3926	1548	-2378***	4546	4069	-477***
	(167.9)	(30.3)		(129.1)	(117.6)	
Nonfood	628	439	-189***	1084	1161	77
	(41.7)	(16.7)		(56.9)	(48.6)	
Food and nonfood shares						
Food	0.86	0.78	-0.08***	0.81	0.78	-0.03***
	(0.01)	(0.01)		(0.01)	(0.01)	
Nonfood	0.14	0.22	0.08***	0.19	0.22	0.03***
	(0.01)	(0.01)		(0.01)	(0.01)	
Observations	530	530		2024	2024	

Notes. Point estimates are population weighted means. Standard errors adjusted for stratification and clustering are in parentheses. Significance level: *** <0.01, ** <0.05, * <0.1
All expenditures in level are annual, real Birr per-capita.

A Profile of Food Insecurity Dynamics in Rural and Small Town Ethiopia[1]

Anna D'Souza[2] and Dean Jolliffe[3]

Abstract

Using panel data from the Ethiopia Socioeconomic Survey (ESS), representative of all people living in rural and small-town areas, this paper describes changing patterns of food security between 2012 and 2014. We examine four measures of food security – two consumption based (calories and dietary diversity) and two experience based (whether food insecurity was experienced in any month, and whether any actions were taken in response).Over all four measures in both years, the share of the food insecure population was never less than 25 percent. Disentangling chronic from transitory food insecurity is important for policy design and for estimating the total food insecurity count over time. For example, the average rate of inadequate dietary diversity was approximately 30 percent in both 2012 and 2014, but the panel data reveal that 46 percent of the rural and small-town population had inadequately diverse diets at some point over the period. While the cross-sectional estimates suggest similar patterns in levels and trends of the measures, the panel data reveal that there is very little co-movement of the measures. For example, observing that someone has improved in terms of dietary diversity does not reveal information as to whether she or he has similarly improved in terms of the experiential-based measures.

Keywords: Ethiopia, food security, poverty
JEL Codes: D12, I3

---

[1] *Acknowledgments:* D'Souza is an Associate professor at Baruch College, City University of New York (CUNY); Jolliffe is a senior economist at the World Bank is also affiliated with the Institute for the Study of Labor (IZA) in Bonn and the National Poverty Center (NPC) at the Ford School of Public Policy, University of Michigan.
The authors are grateful to the UK Department for International Development Ethiopia for generous funding assistance. We thank seminar participants at the Marxe School, Baruch College for comments. We also thank Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw, and Alemayehu Seyoum Taffesse for their generous insight and feedback and Demirew Getachew and Tadele Ferede for their support in dissemination of this paper. Finally, we deeply appreciate all the comments from participants in the Workshop on Dynamics of Wellbeing and the annual Ethiopian Economic Association conference.
[2] Baruch College, City University of New York; Contact: anna.dsouza@baruch.cuny.edu
[3] World Bank; Contact: djolliffe@worldbank.org

1. Introduction

Despite commendable achievements in reaching key Millennium Development Goals, food security in nations across Sub-Saharan Africa is still precarious (United Nations Economic Commission for Africa, African Union, African Development Bank Group, and United Nations Development Program, 2015). Even though Ethiopia in particular has made encouraging progress in reducing poverty and undernourishment, its malnutrition rates remain high (Food and Agricultural Organization [FAO], 2014; World Bank, 2014). For example, the FAO estimates that between 1990–1992 and 2012–2014, the share of the population who are undernourished fell from 75 to 35 percent, partially achieving Millennium Development Goal 1 (FAO, 2014).[4] Yet about 44 percent of children under 5 are stunted, 21 percent severely so, and about 10 percent of children under 5 suffer from wasting, 3 percent severely so (Ethiopia Central Statistical Agency and ICF International, 2012). Critical to nutrition for both children and adults are the three pillars of food security set out by the FAO – availability of, access to, and utilization of food – and their stability over time (FAO, 2006). Given its history of drought, conflict, and other shocks, in Ethiopia food security has been and continues to be a significant concern for large portions of the population, and therefore for government policy.

This paper documents the state of food insecurity in Ethiopia based on information from a large sample of households representative of all rural and small-town areas of Ethiopia. The data, which cover nearly 4,000 households, were collected in 2011/12 and 2013/14. We use the data to explore the nature of food insecurity, static and dynamic, in this vulnerable population: First, we use multiple measures to document the prevalence of food insecurity. Second, we document how the prevalence of food insecurity changed between survey waves and how measures of food security covary over time. Finally, we document the types of variation within and between geographic areas that drives changes in food security and what they say about whether food security is localized or widespread. Thus, using recent,

[4] Undernourishment is defined by per capita calorie consumption below a dietary threshold based on population demographics and activity levels.

representative panel data and multiple measures of food security, this paper complements previous studies of food security in rural Ethiopia.

While food security is typically defined by the three pillars listed above (food availability, access, utilization and the temporal stability of each of these); it is, however, an inherently multidimensional concept. In terms of one of its broadest definitions, "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life"(FAO, 1996). Some indicators capture food safety and the cultural acceptability of the household diet in addition to standard indicators of availability (often at the country level), access (often at the household level), and utilization. More recently, experiential measures have received significant attention; these are designed to capture anxiety over food insecurity through psychological and behavioral questions about the severity of food insecurity. Two examples are the U.S. Department of Agriculture Household Food Security Scale (Bickel, Nord, Price, Hamilton, and Cook, 2000) and the FAO's Food Insecurity Experiential Scale (FIES; Ballard, Kepple, and Cafiero, 2013). The FIES is being used to estimate the prevalence of food insecurity in 147 countries through the Gallup World Poll (Nord, Cafiero, and Viviani, 2016). In its 2013 annual report *The State of Food Insecurity in the World: The Multiple Dimensions of Food Security*, the FAO sets out 30 indicators that capture various dimensions of food security (FAO, 2013).

In this paper we use four measures of food security—two related to household access and utilization of food (quantity and diversity) and two experiential. Identifying and describing the dynamics of food insecurity in vulnerable populations is critical to better targeting during crisis periods like droughts, and more generally to the design of safety net and insurance programs.

For centuries Ethiopia has experienced periods of extreme food insecurity, including famine, most recently in 1983–1985 (Taye, Mariam, and Murray, 2010). Given this history, and similar food crises caused by periods of conflict, there is an extensive literature related to food security, shocks, and

coping mechanisms, especially with regard to the role of food aid. It ranges from cross-sectional studies that draw on small samples from limited geographical areas to larger data sets and panel data studies, which are not always representative of any underlying population.

Hirvonen and Hoddinott (2014) use a large non-representative sample to look at the relationship between diversity in agricultural production and in children's diets. Yamano, Alderman, and Christiaensen (2005) use data from three separate nationally representative cross-sectional surveys conducted in 1995 and 1996 to look at how child nutrition then was affected by harvest failures and food aid.

Some studies have drawn on several waves of panel data and thus are better able to capture long-run dynamics. One rich data set many researchers use is that of the Ethiopian Rural Household Surveys (ERHS), 1989–2009.[5] In a series of papers, Dercon and coauthors use the data to examine the dynamics of poverty – which is closely related to food insecurity – in rural Ethiopia, specifically looking at the impact of various household- and village-level shocks (Dercon, 2004; Dercon, Hoddinott, and Woldehanna, 2006, 2012). These papers highlight how household characteristics may be linked to differences in experiencing or recovering from widespread covariate shocks (factors like drought that adversely affect an entire village) and household-specific idiosyncratic shocks (factors like death or illness that adversely affect only specific households). We examine sources of variation in changes in the food security measures available in our data by comparing the extent to which variation is occurring between or within villages. Changes that stem from between-village differences are more likely to be due to covariate factors; those that stem from within-village differences are more likely to be due to idiosyncratic factors. In either case, as previous studies note, differences in what is driving food insecurity necessitate different policy responses.

Maxwell, Vaitla, and Coates (2014), a study based on panel data from 300 households in rural Ethiopia, is closely related to this paper. They compare

[5] A description of the data is available at https://www.ifpri.org/publication/ethiopian-rural-household-surveys-erhs-1989-2009.

the prevalence of and changes in food security based on seven common measures (the data were tailored to measure food security). The authors find that although prevalence estimates vary by measure, they display similar trends and are reasonably correlated. Differences in the prevalence rates may be attributed to differences in cut-off points (e.g., for a poor diet base on a dietary diversity score); sensitivity of the measures to the severity of food insecurity (e.g., indicators that pick up mild vs. severe food insecurity); and the fact that the measures may be picking up different dimensions of food security.

Applying four food security measures, we find substantial differences both in prevalence rates and in their trends over time. The next section describes the survey data. Section three describes the measures of food security and other household characteristics. Section four presents estimates that provide a snapshot of food insecurity in rural Ethiopia, and section five discusses changes in the prevalence of food insecurity between the first and the second waves of the survey.

2. Survey data

The primary data are from the Ethiopia Socioeconomic Survey (ESS),[6] a panel survey conducted by the Central Statistics Agency of Ethiopia (CSA) in collaboration with the World Bank Living Standards Measurement Study team. Data were first collected from 3,969 households between September 2011 and March 2012.[7] The first wave (ESS1) used two-stage probability sampling and is representative of rural and small-town areas throughout Ethiopia.[8] In the first stage, 290 enumeration areas with probability proportionate to estimated population were selected from rural areas and 43 from small-town areas within five strata based on the administrative divisions

[6] The first wave was initially referred to as the Ethiopia Rural Socioeconomic Survey (ERSS), but this name was changed with wave 2 when the panel was supplemented by an urban subsample. Now the survey is referred to as ESS and each wave is numbered, so ESS1 refers to the first wave of the ESS.

[7] The response rate was 99.3 percent.

[8] The ESS rural sample is a subsample of the Annual Agricultural Sample Survey (AgSS) conducted by the CSA.

in Ethiopia.[9] In the second stage, within each enumeration area 12 households were randomly selected (fixed interval, systematic random sampling).

The second wave of data (ESS2) was collected between September 2013 and April 2014 and covered 5,262 households – 3,776 panel households and 1,486 new urban households.[10] Although ESS2 is representative of the entire country, for this paper we limit our analysis to the households that were interviewed in both waves. Using sample weights, the estimates provide inferences to the populations of rural and small-town areas of Ethiopia.

The household questionnaires cover demographics, education, health, labor, time use, income and assistance, nonfood spending, food consumption and spending, food security, shocks and coping mechanisms, housing, assets, and credit. The community questionnaires cover infrastructure, resources, and significant events, such as drought. This analysis is primarily concerned with the food security, food consumption, and expenditure modules. It is important to note that because food data were collected postharvest, they are likely to reflect seasonal periods of relative food security. This is a particularly important caution because due to Ethiopia's reliance on rain-fed agriculture, there is strong seasonality in its consumption patterns (World Bank, 2014).

3. Measures of food security

We construct four measures of food security: daily calories per adult equivalent (AE); the Food Consumption Score (FCS); actions taken to relieve food insecurity in the past week; and months of food insecurity in the past year. While each of these is measured at the household level, we report estimates of the percent of people who live in households that are food

[9] The strata consist of four regions (Amhara; Oromia; Southern Nations, Nationalities, and Peoples' Region; and Tigray) with a fifth combining data for the remaining administrative regions.

[10] The response rate was 96.2 percent. For households that split, the remaining core household was interviewed.

insecure. This distinction matters when household size and food security status are correlated, which is frequently the case.

Daily calories per AE, a common measure for nutritional analysis, is conceptually linked to the FAO food access pillar. The calories estimate is based on a 7-day recall of 25 broadly defined and commonly consumed foods and beverages. The enumerator solicited information on quantities consumed from purchases, home production, and gifts and other sources from the individual primarily responsible for preparing food. To link food quantities to calories and other nutritional information, we use the 1998 Food Composition Tables developed by the Ethiopian Health and Nutrition Research Institute (EHNRI, now part of the Ethiopian Public Health Institute) and the FAO.[11,12] We then calculate the total AE for each household based on the age and sex composition of members,[13] using equivalence scales developed by the CSA (Ethiopia Central Statistical Agency, 2012). The survey asks about meals served to guests; we incorporate information on the AE of these guests into the total household AE in order to capture accurately the count of individuals sharing in food consumed over the past week.[14][15] Finally, we divide total daily household

[11] We obtained hard copies of the tables from EHNRI. General information on FAO food composition tables is available at http://www.fao.org/docrep/017/ap796e/ap796e.pdf. For foods that were not available in the Ethiopia database, we used the USDA National Nutrient Database for Standard Reference, http://ndb.nal.usda.gov/ndb/doc/index. For kocho, a standard and popular Ethiopian bread, we use nutritional information from Shank and Ertiro (1996), http://www.africa.upenn.edu/eue_web/enset96.htm).

[12] We trim daily per capita food quantity data at the 97th percentile in wave 1, and the 99th in wave 2, which we based on biologically feasible amounts.

[13] Adult equivalence scales capture household composition to account for the varying dietary requirements of individuals of different ages and sexes, as well as economies of scale in consumption (Deaton, 2000).

[14] Ideally we would want to account for meals household members ate away from home, but because the data were not collected in wave 1, we do not incorporate it into our calculations. In wave 2, we have information only on whether any member ate meals away from home and the approximate value of the meals; we do not have the number of meals eaten away from home. Given the growing importance of food away from home in developing countries, this is a shortcoming of the survey.

[15] We top-coded calories at 7,000 per AE for both waves; 7,000 is approximately 94.7 percentile in wave 1 and 96.2 in wave 2.

calories by the household AE (with guests) to get the final measure of daily calories per AE (denoted as calories).

There are two primary concerns related to the calorie estimate: The first is that 25 items is a short list of food items for a consumption survey, and Beegle *et al.* (2012) provide evidence that the number of food items (in addition to recall period and method of collection) greatly influences estimates of consumption. With a short list, the survey may be missing a non-negligible portion of food consumption. However, in mitigation of this concern we note that in rural and small-town Ethiopia, the share of staple food consumption is estimated to be very high, which means that a few food items cover a substantial portion of total calories.

A second concern is that the food items in the survey are relatively broad categories, and Jolliffe (2001) provides evidence that asking about the consumption of food in terms of categories (e.g., meat) produces substantially lower estimates than asking about specific types (e.g., chicken, beef, and goat). This concern is particularly relevant to obtaining the right level of total calories (i.e., the cross-sectional estimate), but much of our analysis is mainly concerned with changes in calories across the waves (the first-difference estimate), and since the food items list was essentially the same in both waves, there is no reason to expect that the bias in levels necessarily contaminates the bias in first differences. Nonetheless, we take these concerns seriously and interpret the calorie data results with caution.

The FCS, developed by the World Food Programme, measures dietary diversity and is often interpreted as a partial measure of dietary quality; it has been used in food security assessments throughout the world and validated against nutritional measures for adults and children (Arimond and Ruel, 2004; Nguyen et al., 2013). The measure is conceptually linked to both the access and utilization pillars of food security. Because we use information on the frequency with which households had consumed foods from 16 foods and food groups over the past week, the measure is not derived from the same data used for the calorie estimates but is from a different section of the questionnaire that follows the standard FCS definition. The FCS is the

weighted sum of the frequencies with which in the previous week a household has consumed foods within eight groups: grains, pulses, vegetables, fruit, meat and fish, milk/dairy, sugar, and oil/fat. The weights are based on the nutrient density of each group.[16] Lower scores indicate a less varied diet, with less potential for micronutrient intake. Low scores are often associated with a large share of calories derived from staple foods (and in many poor countries, oil and fat).

The third measure relates to a household's experience with food access, which is gauged through eight questions based on the number of days in the past week the household (1) relied on less preferred foods, (2) limited the variety of foods eaten, (3) limited portion size at mealtimes, (4) ate fewer meals in a day, (5) restricted adult consumption to benefit small children, (6) borrowed food or relied on help from a friend or relative, (7) had no food of any kind in the household, and (8) went a whole day and night without eating anything. We create a count variable based on these actions against food insecurity (labeled *actions)*; the larger the number, the greater the food insecurity, or the more limited the access to food. All the actions are linked to food-based rather than non-food-based coping strategies, such as selling off assets—households may be sacrificing in other areas that this measure does not capture.

Finally, we create a variable for total months of food insecurity based on the household's response to the question, "In the last 12 months, have you been faced with a situation when you did not have enough food to feed the household" (labeled *months*). These last two measures are experience-based; they complement the calorie and diversity measures, which do not directly reflect a household's actions or subjective feelings about food insecurity.

We also inventory household demographic characteristics: household size, age of household head, and indicators for female head, married head, and heads who have completed primary education. And we create several variables that capture household livelihood, including real annual household consumption,

[16] The food groups and weights (in parentheses) are as follows: starches (2), pulses (3), vegetables (1), fruit (1), meat (4), dairy (4), fats (0.5), and sugars (0.05).

the sum of food and nonfood consumption. The value of food consumption is the sum of the value of food purchased outside the home and the value of food produced at home and gifts.[17] The value of nonfood consumption is the sum of all reported expenditures on nonfood items. All values are in 2013 Ethiopian birr. They have been spatially adjusted for each wave and temporally adjusted based on price indices provided by the CSA. We also create an indicator for access to agricultural land (farm households) and indicators for households that receive assistance through the Productive Safety Net Programme (PSNP), free food assistance programs, and food or cash for work programs.

4. A profile of household food security in rural Ethiopia

Table 1 presents population-weighted summary statistics of key variables by wave, with p-values to denote the statistical significance of differences in means between the two waves. For wave 1 estimates we use wave 1 sample weights, and for wave 2 estimates, wave 2 weights. The weighted sample estimates thereby providing inferences to the population of rural and small-town areas of Ethiopia in 2011/12 and 2013/14, respectively.[18] The effective size of the sample for our analysis is 3,266 panel households.[19] Households have about 5 members and most are headed by males. (Mean values of adult equivalents are 4.2 in both waves; the numbers are slightly larger when guests are taken into account.) In wave 1, the household heads were about 45 years old, and about 13 percent of them had completed primary school. On average, as estimated in the ESS measure of total consumption, about 80 to 90 percent of total expenditures is for food. We observe a decline between

[17] Food produced at home and gifts use median unit-value prices taken from the nearest geographical area in a minimum of 10 unit-price observations

[18] The weighted-estimates provide inferences to the population of households for household size, age of household head, and the indicators for whether the household is: a farm household, female-headed, has a married head, headed by someone who has completed primary education. For all other variables, including in particular the food security measures, the weighted estimates provide inferences to the population of individuals.

[19] We dropped 510 panel households due to missing data on consumption, household demographics and relationships, and housing characteristics.

waves in the mean of real annual total consumption per AE, driven by a decrease in real annual food consumption.[20]

Table 1: Summary Statistics

	Wave 1		Wave 2		P-value of mean difference
	Mean	***S.E.***	***Mean***	***S.E.***	
Household size	5.17	(0.06)	5.13	(0.06)	0.487
Indicator (Female headed household)	0.20	(0.01)	0.22	(0.01)	0.000***
Age of household head	44.59	(0.40)	46.11	(0.39)	0.000***
Indicator (Head married)	0.77	(0.01)	0.75	(0.01)	0.126
Indicator (Head completed primary education)	0.15	(0.01)	0.16	(0.01)	0.158
Indicator (Farm household)	0.89	(0.02)	0.97	(0.01)	0.000***
Real Annual Total Consumption per AE	5957	(405)	4917	(143)	0.001**
Real Annual Food Consumption per AE	4668	(339)	3654	(122)	0.000***
Real Annual Nonfood Consumption per AE	871	(46)	983	(41)	0.018**
Daily calories per AE	2894	(91.98)	2774	(84.95)	0.101
Food consumption score (FCS)	42.64	(0.90)	44.32	(0.85)	0.089*
Actions against food insecurity	3.60	(0.48)	2.14	(0.23)	0.000***
Actions against food insecurity (if actions>0)	10.19	(0.67)	7.80	(0.42)	0.000***
Months of food insecurity	0.97	(0.08)	1.07	(0.09)	0.389

Notes: Population-weighted means and deciles. Calories refer to daily calories per adult equivalent. Diversity refers to the food consumption score. Actions refers to the number of reported actions taken against food insecurity. Months refers to the number of reported months of food insecurity. Number of observations: 3,266. AE = adult equivalents.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

[20] A potential concern with this estimated decline is that the consumer price index measure of inflation may overstate price changes as observed by households in rural and small-town areas. Indeed, when we examine changes in unit values (i.e., expenditure per food item divided by household quantity of food item, which can be viewed as reflecting quality and price changes of food items), their rate of increase is about half the rate found by the CPI measure of inflation.

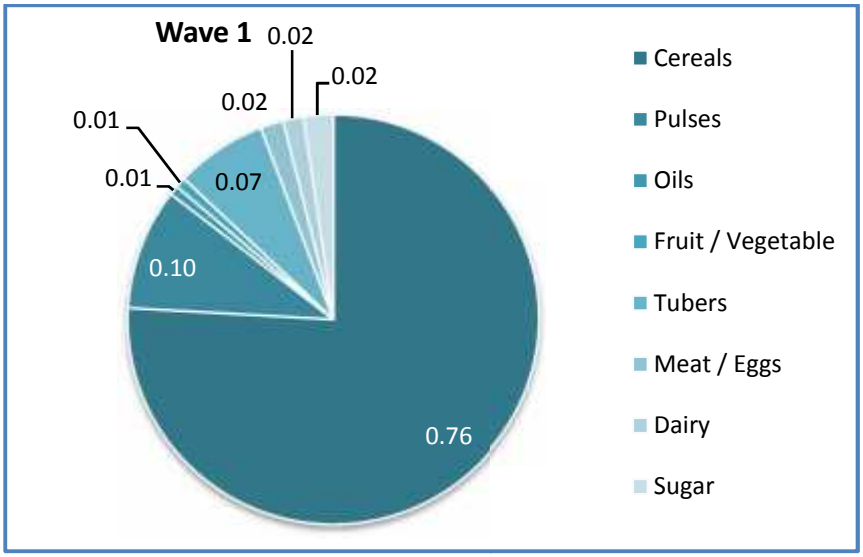
We also observe that the standard error of the estimated mean of total consumption is twice as large in wave 1 than in wave 2.[21] One possible explanation for this decline in the standard error (and the coefficient of variation) is that the enumerators and field protocols improved between waves 1 and 2, which would reduce error and, most likely, reduce observed dispersion. Most households in rural Ethiopia have access to agricultural land; a share of these households sells some of the harvest. Very few households report receiving any form of assistance and there are no observable differences between waves in assistance received.[22] Appendix Figure A1 shows the percent of individuals living in households that report receiving various forms of assistance by wave and consumption quintile. There is marked heterogeneity; somewhat surprisingly, poorer households do not always report more assistance.

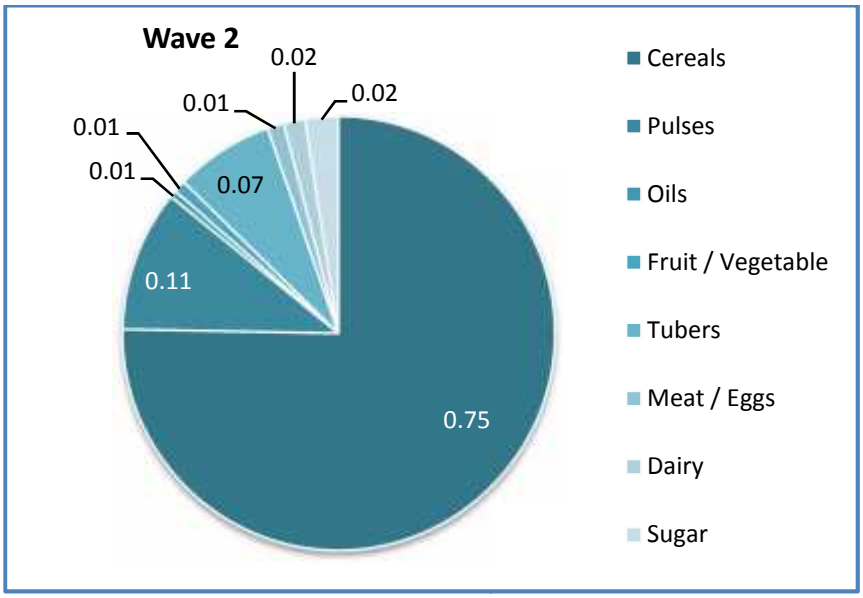
The Ethiopian diet depends largely on cereals (mainly teff, wheat, barley, rice, and sorghum) with both waves of data indicating that on average, 75 percent of calories are from cereals(figure 1). Average food shares for the seven other food categories, such as pulses and oils, were also constant when both waves were treated as cross-sectional data. Figure 2 shows the cumulative consumption frequencies by major food group; the food consumption score reflects these (weighted) frequencies. Most households report eating staple foods (cereals) and oil and fat every day. As households become richer, they are able to diversify their diets, incorporating pulses, vegetables, meat and fish, and dairy. (Berhane, Paulos, Tafere, and Tamru (2011) give a detailed analysis of dietary patterns in Ethiopia.)

[21] The scale-independent coefficient of variation also declines substantially.

[22] We do not include assistance from input for work programs because less than 1 percent of households report receiving such aid.

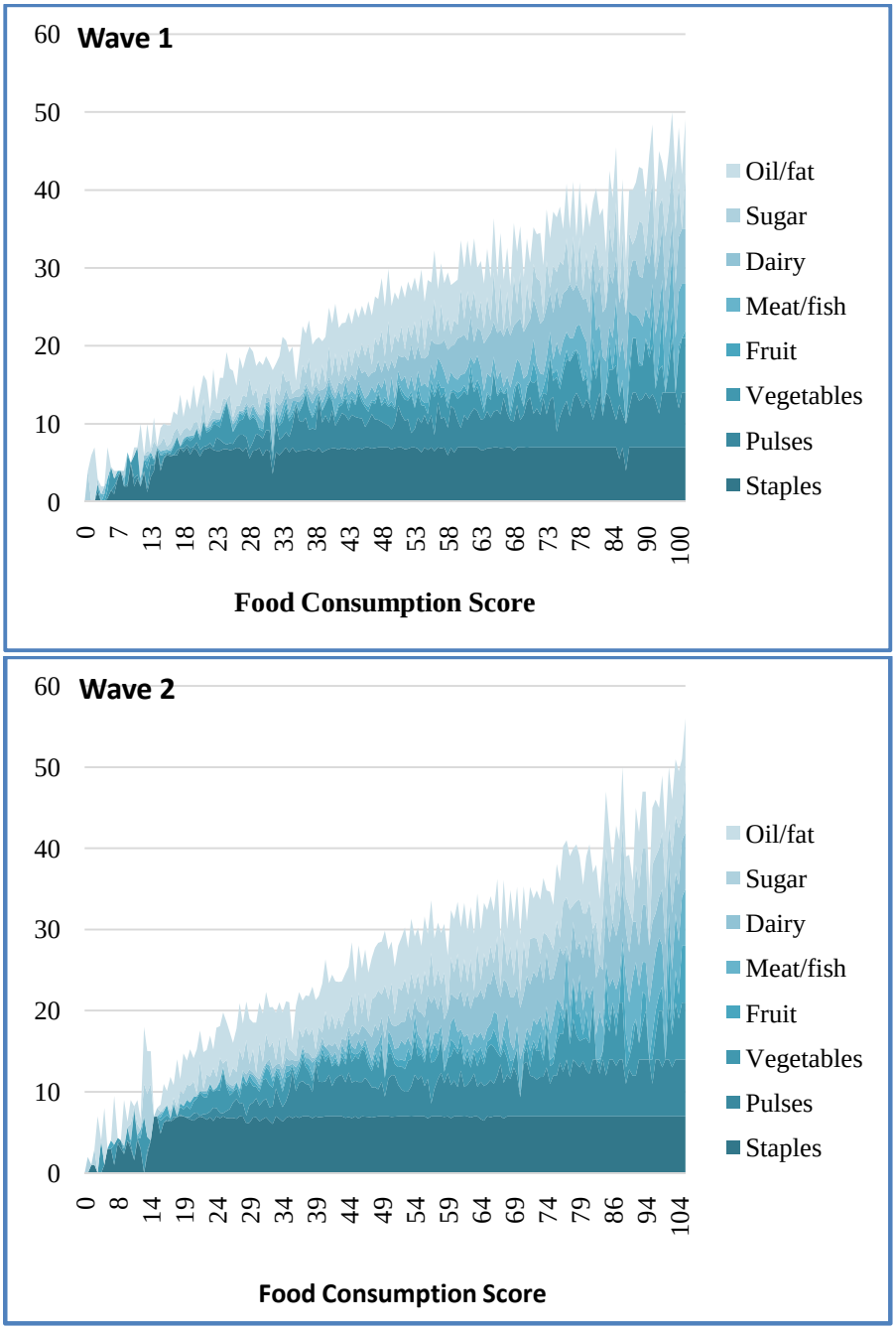
Figure 1: Calorie Shares by Wave





Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

Figure 2: Cumulative Consumption Frequencies by Wave



Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

The mean daily calories per AE was 2,894 in wave 1 and 2,774 in wave 2.[23] The mean FCS was 43 in wave 1 and 44 in wave 2.[24] Table 1 also reveals that the standard errors of both FCSs and calories are essentially unchanged between waves, unlike the standard errors for the expenditure measures. The standard error would be expected to change if the underlying population distribution of FCSs or calories had changed significantly in two years, or if there were significant changes in the quality of the data (e.g., due to measurement error). Thus one possible inference of the stable error message is that there were no significant changes in data quality between the two waves.

In terms of the experiential measures, less than a third of the population live in households who report taking any action against food insecurity (Figure 3). Over the entire survey sample, people lived in households that took about 3.6 actions on average in response to food insecurity in wave 1, and about 2.1 actions in wave 2. This decline is statistically significant. When we subsampled the households that did take actions against food insecurity, there was a statistically significant decline between waves in the number taken. On average, people lived in households that report about one month of food insecurity in both survey rounds.

Table 2 displays averages of the food security measures for each decile of the relevant distribution by wave. For example, during wave 1, people in the top decile for actions were in households that undertook on average 13 actions to alleviate food insecurity; in wave 2, those in that decile undertook on average 5 fewer actions than in wave 1. Across the distribution, changes in FCSs across people are quite uniform but changes in calories are larger for people at the top of the distribution. The patterns for the experiential measures reflect the fact that few people live in households that report positive actions or months.

---

[23] This is comparable to calorie estimates from the most recent WFP report (WFP and Ethiopia Central Statistical Agency, 2014).

[24] These estimates are weighted to produce average calories and FCS for individuals. For example for the FCS, each individual is assigned the value of FCS for their household, and then weights are used to allow for inference to the population of individuals.

Table 2: Household Food Security Distributions

	Calories		Diversity		Actions		Months	
	Wave 1	**Wave 2**	**Wave 1**	**Wave 2**	**Wave 1**	**Wave 2**	**Wave 1**	**Wave 2**
Mean	2894	2774	42.6	44.3	3.6	2.1	1.0	1.1
10th	1239	1163	19.5	21.5	0	0	0	0
20th	1636	1539	27.0	29.5	0	0	0	0
30th	1919	1865	35.0	36.0	0	0	0	0
40th	2234	2138	38.5	39.5	0	0	0	0
50th	2585	2426	42.0	43.0	0	0	0	0
60th	2993	2823	45.5	47.0	0	0	0	0
70th	3409	3226	50.0	52.5	3.0	0	1.0	2.0
80th	3984	3801	57.5	58.5	7.0	3.0	2.0	3.0
90th	5122	4900	66.5	68.0	13.0	8.0	3.0	3.0

Notes: Population-weighted means and deciles. Calories refers to daily calories per adult equivalent. Diversity refers to the food consumption score. Actions refers to the number of reported actions taken against food insecurity. Months refers to the number of reported months of food insecurity. Number of observations: 3,266. AE = adult equivalents.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

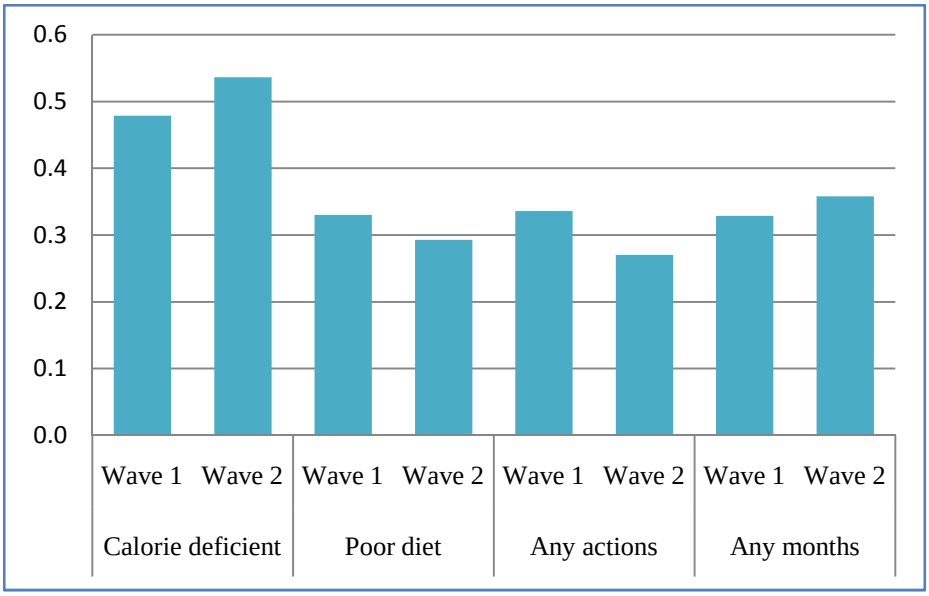
These numbers underscore the importance of exploring changes in food security across people rather than relying on changes in the average values. For example, D'Souza and Jolliffe (2014) show that the impact of food-price increases differs significantly for people across the distribution of food security measures in Afghanistan. And for urban Ethiopians, Alem and Soderbom (2011) show that households with fewer assets and with members who are casual laborers are harder hit by higher food prices.

To estimate the prevalence of food insecurity and to identify the most vulnerable people in rural Ethiopia, we create indicators of food insecurity using cut-off points for the four measures. While there are inherent difficulties in choosing cut-offs, operationally such indicators are typically useful for targeting, monitoring, and evaluation, and so we use them here in providing descriptive information.

We create indicators of calorie deficiency and poor diet based on thresholds set by the World Food Programme (WFP) in its food security assessment of Ethiopia (WFP and CSA, 2014): *Calorie-deficient* households are those with fewer than 2,550 daily calories per AE. *Poor-diet* households are those with an FCS less than 35 (the WFP threshold for poor or borderline versus acceptable diets). We also define indicators for the experiential measures: households that report any action against food insecurity over the past week (labeled "*any action*") and those that report any month of food insecurity over past year (labeled "*any month*").

Figure 3 shows that more than 25 percent of rural and small-town Ethiopians are food-insecure by any measure – though the prevalence rate using calories is markedly higher than rates using the other indicators. These findings are consistent with the high prevalence of poverty and undernourishment found in recent assessments of food security in Ethiopia (FAO, 2015; Rosen, Meade, and Murray, 2015; World Bank, 2014). The most recent WFP food security assessment found that about 74 percent of rural Ethiopians have acceptable diets (WFP and CSA, 2014) and the ESS2 found that about 70 percent of those in rural and small towns had acceptable FCS diets.

Figure 3: Food Insecurity by Wave

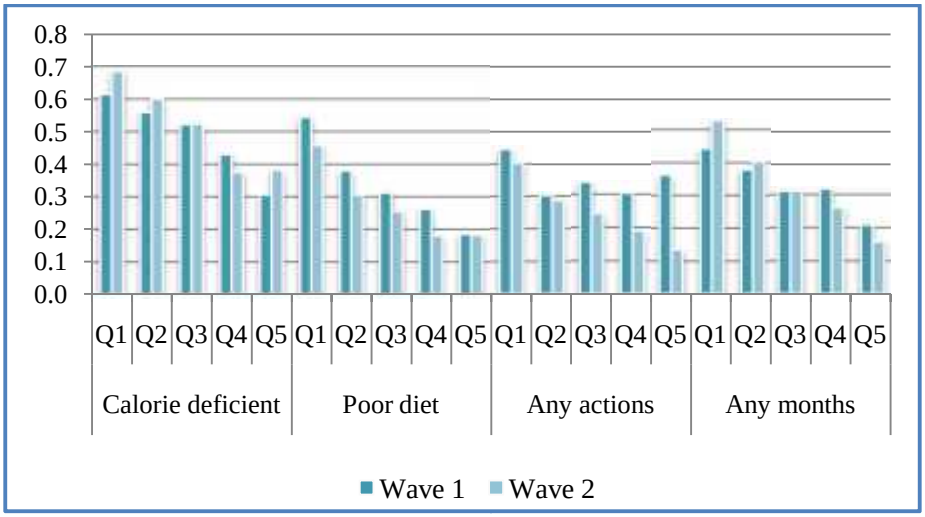


Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

While prevalence rates are similar in both waves and across data sources, they mask large differences in food security based on household economic status. Examining people by consumption quintiles (based on real nonfood monthly consumption per AE), we see that, as expected, people in poorer households have significantly worse food insecurity status relative to people in richer households. This is the case for all measures in both waves except for the any-action indicator in wave 1 (Figure 4).[60] In fact, in the bottom consumption quintile, over half of rural Ethiopians do not meet the minimum daily calorie requirements of 2,550 per AE, and about half have poor diets.

[60] As a proxy for income and livelihood, we use the log of the real value of nonfood consumption per adult equivalent; we do not include food consumption since it is drawn from the same data as the food security measures, so that including it could result in spurious correlations.

Figure 4: Food Insecurity by Consumption Quintile and by Wave



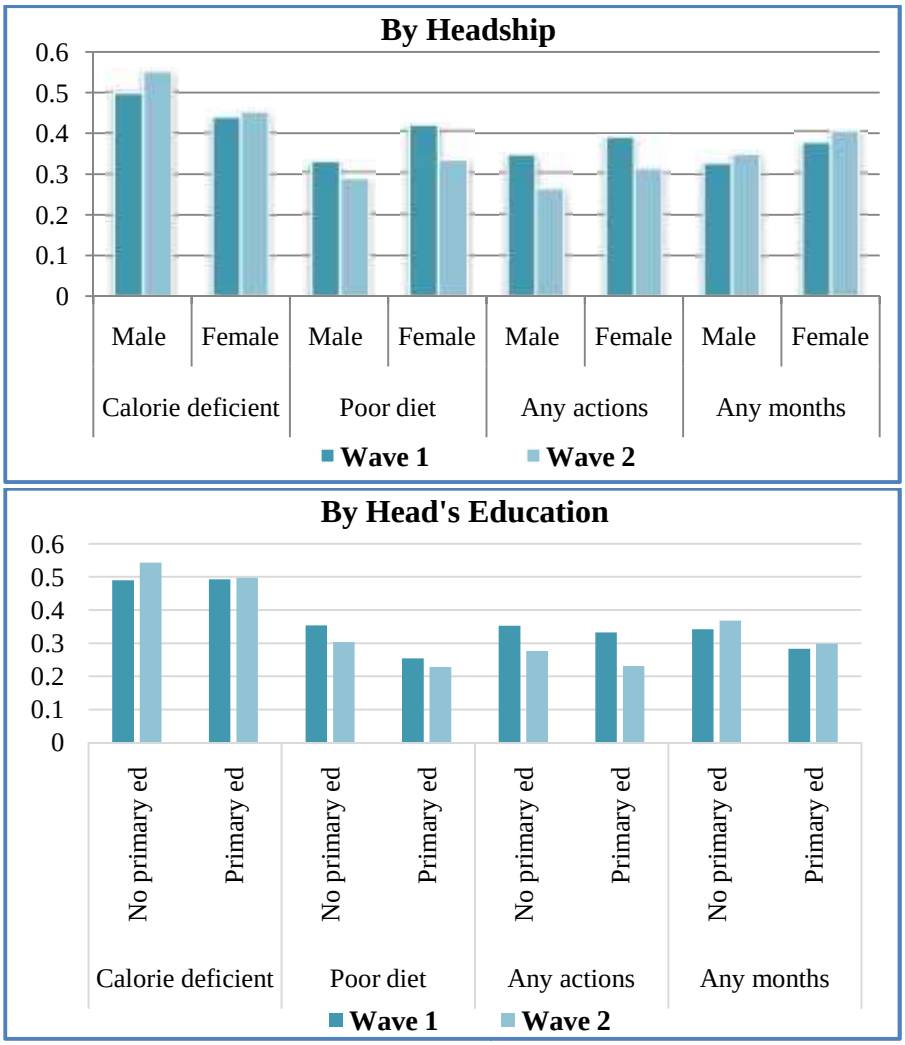
Notes: Population-weighted estimates. Q = quintile. Consumption quintile is based on real per adult equivalent nonfood monthly consumption. Number of observations: 3,266.

Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

Figure 5 shows the prevalence of food insecurity by education and sex of the household head. While the differences are fairly modest, male-headed households have slightly better outcomes, but the differences in terms of whether the head has had primary education are more marked. People in households headed by someone who has some primary education are significantly less likely to have poor diets, to be calorie deficient, or to have experienced any months of food insecurity. Figure 6 explores the prevalence of food insecurity by region. The survey design allows for disaggregated estimates for four regions (Tigray, Amhara, Oromia, and the Southern Nations, Nationalities, and Peoples' [SNNP] Region); the other six administrative regions are grouped together as the Others Region. There are both noticeable regional variations in food insecurity and differential changes in food security over time (Figure 6). This may not be surprising given the topographical diversity within the country and the related differences in seasonal income and consumption patterns (WFP and CSA, 2014). For all indicators except calorie deficiency, the prevalence of food insecurity is highest in the SNNP region; Amhara and the Other Regions

category have the highest prevalence of calorie deficiency. Based on the experiential indicators, Tigray and Amhara display a relatively low prevalence of food insecurity in wave 1, though the situation worsens considerably in wave 2.

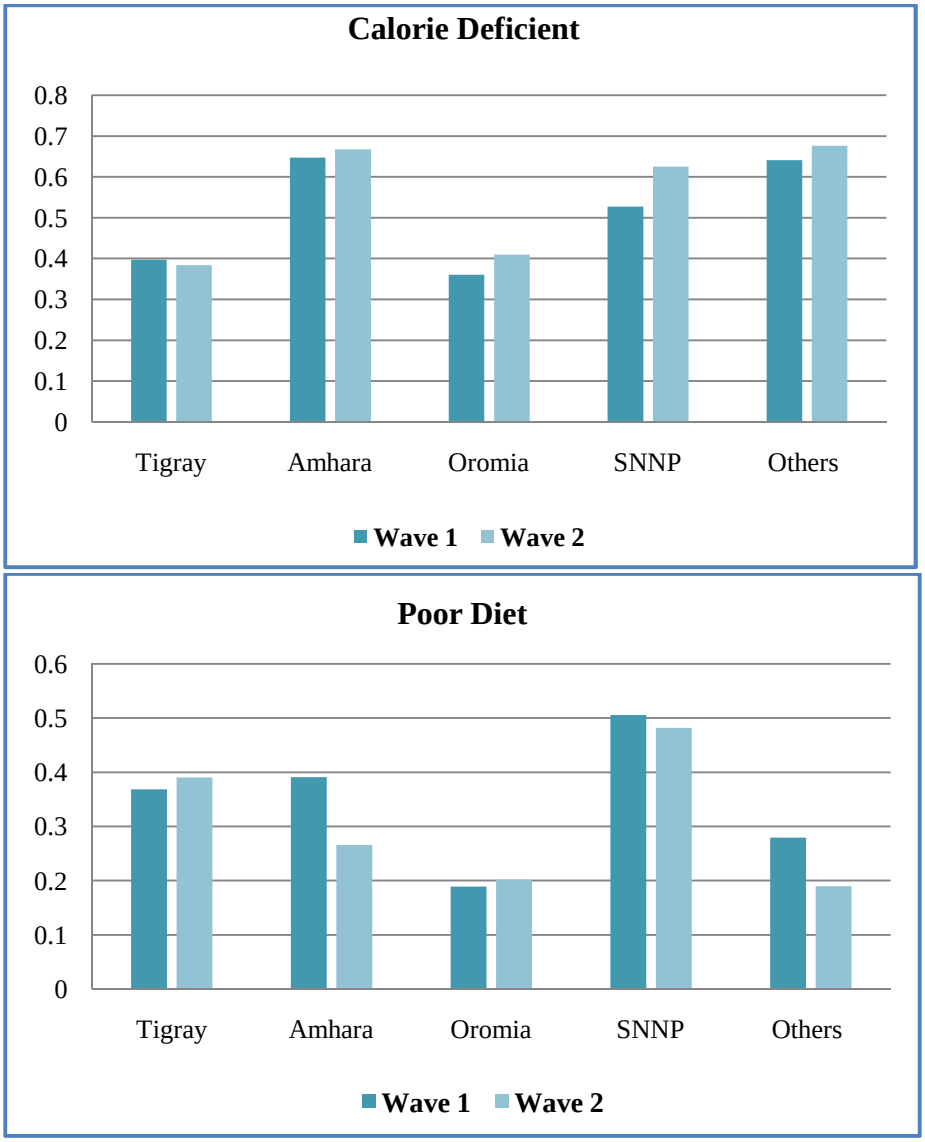
Figure 5: Food Insecurity by Headship and Head's Education and by Wave

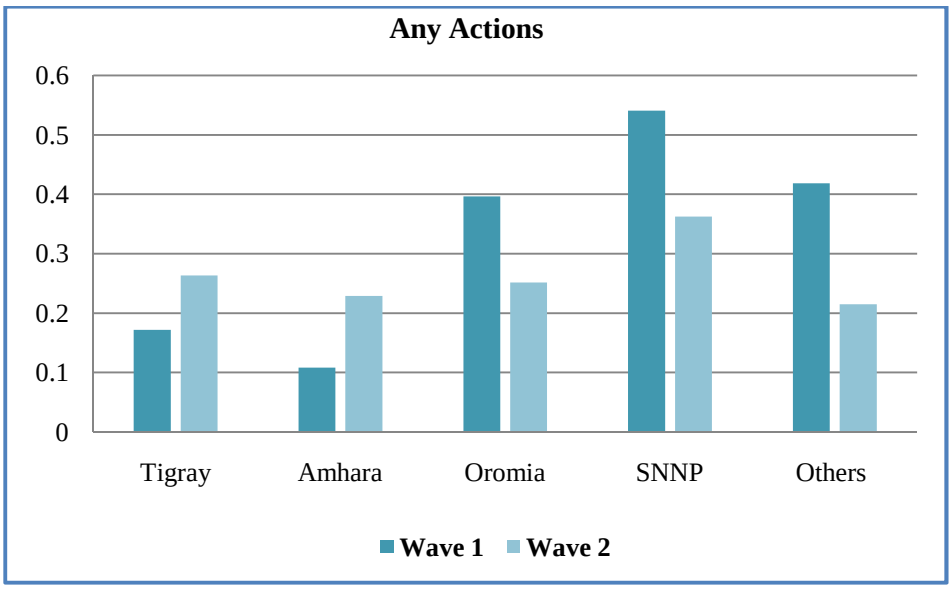


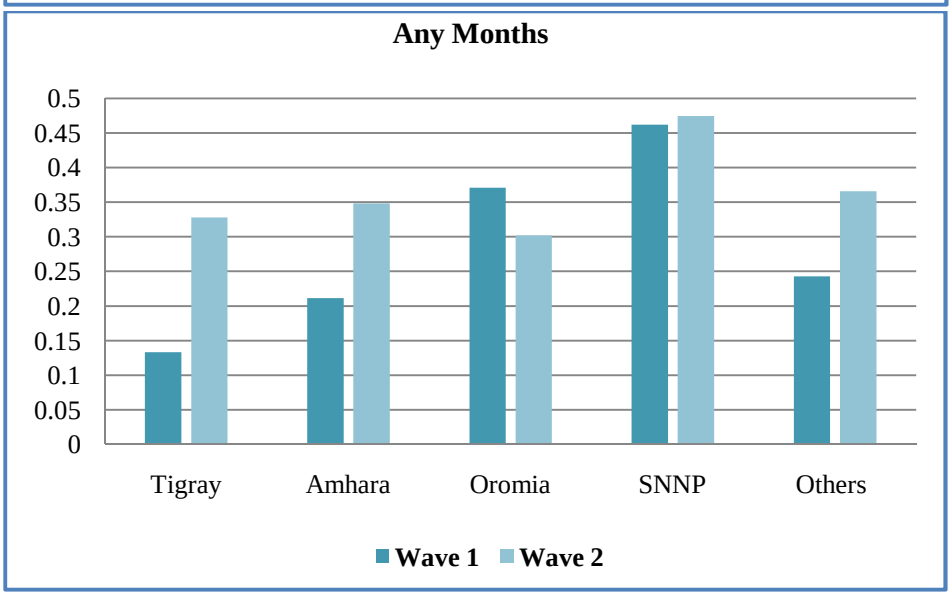
Notes: Population-weighted estimates. ed = education Number of observations: 3,266.

Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

Figure 6: Food Insecurity by Region and Wave







Notes: Population-weighted estimates. SNNP = is Southern Nations, Nationalities, and Peoples' Region; Others includes all other administrative regions. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

5. Transitions in household food security in rural Ethiopia

The results shown for the two waves provide cross-sectional snapshots of the precarious nature of food security for rural and small-town Ethiopians. These snapshots tell us that between 2012 and 2014, more people are calorie-deficient while fewer have poor diets (Figure 3), but they cannot tell us how likely a person is to become food insecure, or how many have transitioned into or out of food insecurity. A major benefit of panel data is the ability to identify the latter, and to help understand what drives these transitions.

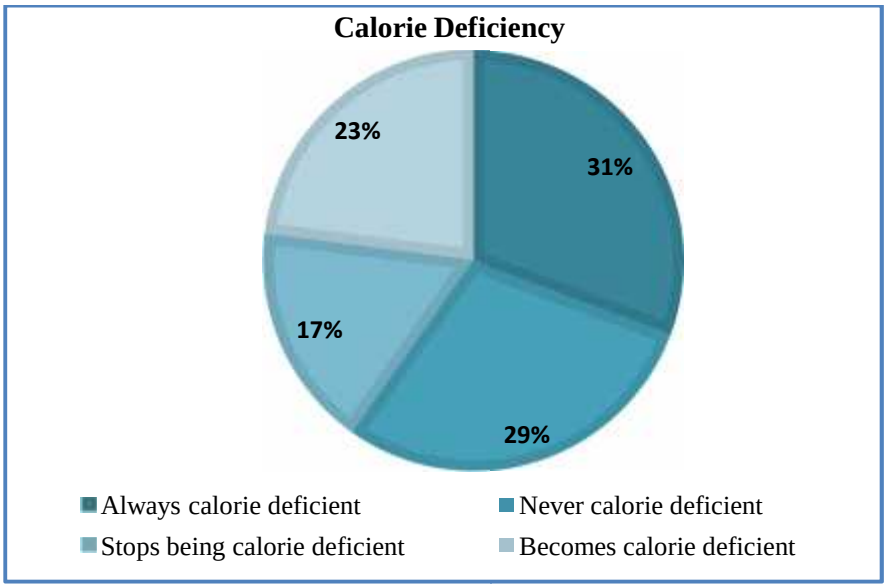
Figures 7 and 8 present transitions in and out of food insecurity, identifying both the chronically insecure and the percent of people whose food security status improves or deteriorates.[61] About 17 percent of people live in households that transition out of calorie deficiency between waves 1 and 2; and similarly, 17 percent transition to an adequately diverse diet. Approximately 19 percent of the people who lived in households that took actions to mitigate food insecurity in wave 1, reported in wave 2 that they did not need to do so. Similarly, 15 percent who reported being food insecure for at least one month in wave 1, reported no months of food insecurity in wave 2.

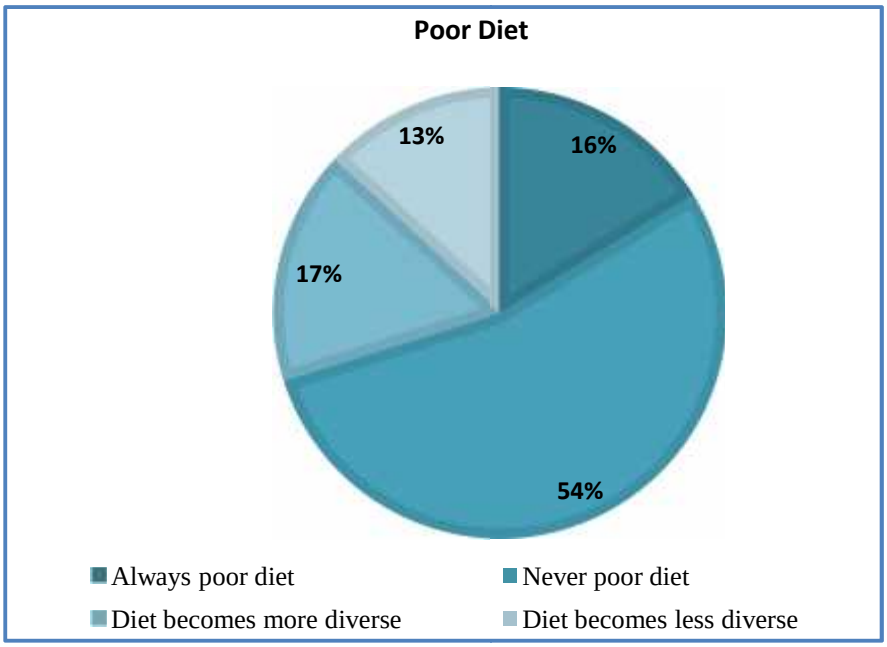
While substantial portions of the population thus indicated improvement over time, there are also many Ethiopians who saw their food security status worsen between waves. Twenty-three percent of the rural and small-town population transitioned from having adequate calories in wave 1 to being calorie-deficient in wave 2. Similarly, 13 percent transitioned into poor dietary diversity status. The pattern of the experiential measure – months of reported food insecurity and any actions taken to relieve food insecurity – is similar to the poor diet indicator: 13 percent of the population took no actions in wave 1, but then started taking actions in wave 2; while 18 percent of the population reported zero months of food insecurity in wave 1, but then in wave 2 experienced at least one month of food insecurity. The proportions whose status deteriorates over time are somewhat smaller than those whose

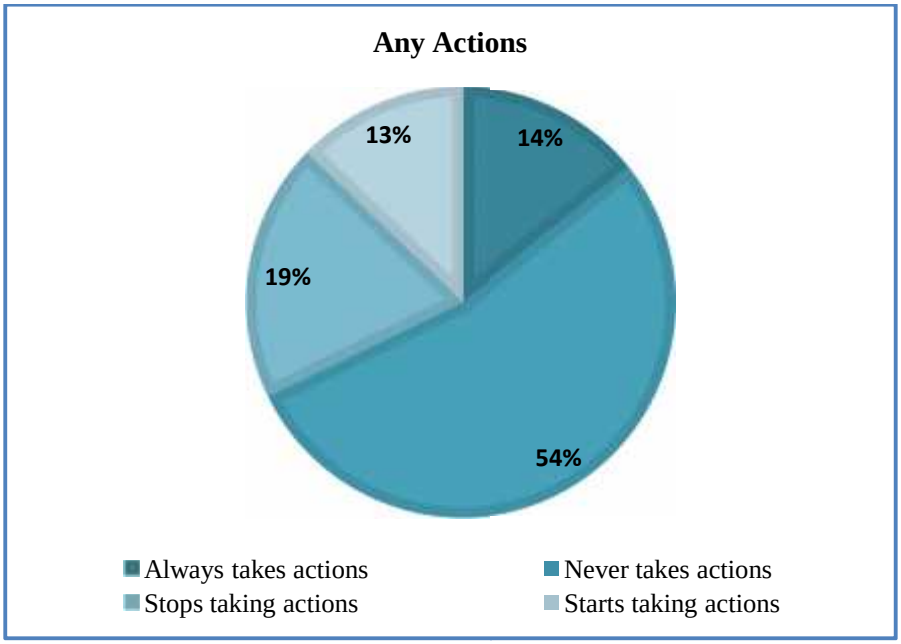
[61] In this section where we examine differences across the two waves, or transitions between the waves, we use the wave 2 weights.

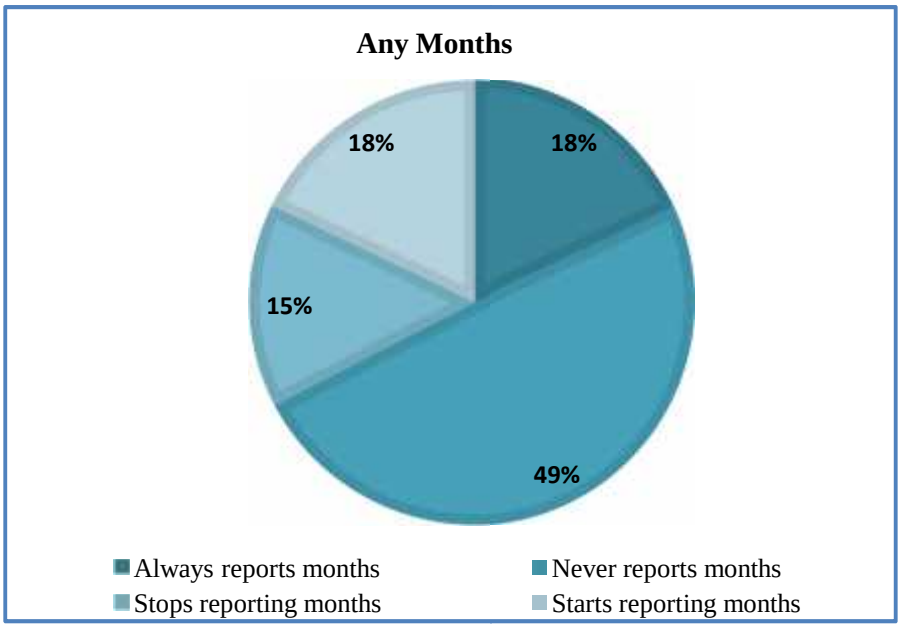
status improves, but what is particularly noteworthy is the large number of individuals whose food insecurity status transitions over time.

Figure 7: Food Insecurity over Time



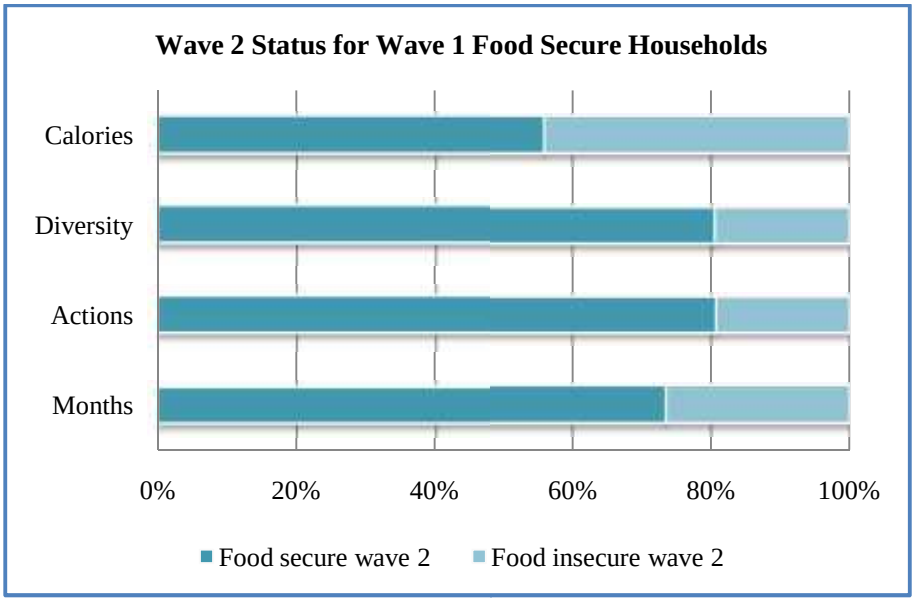


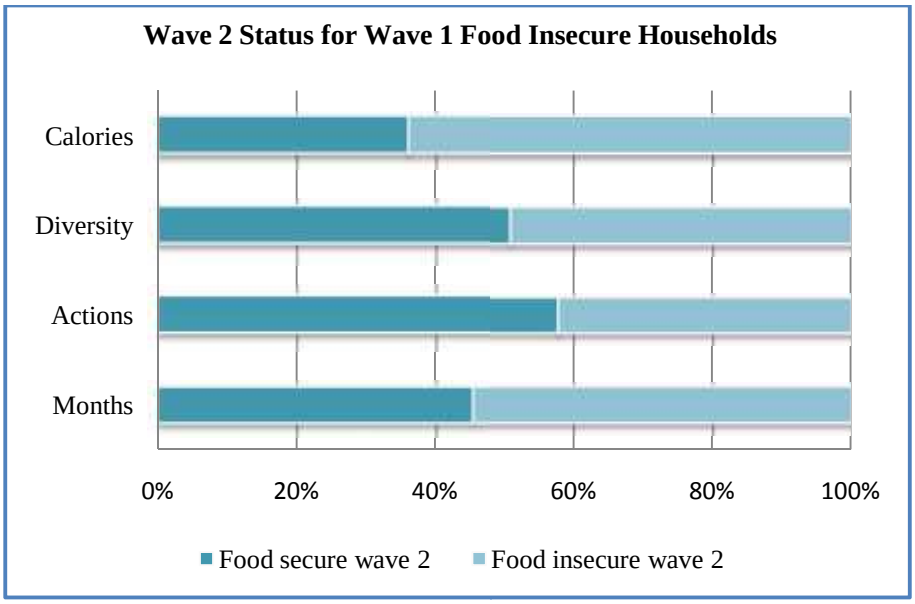




Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

Figure 8: Transitions in Food Insecurity by Measure

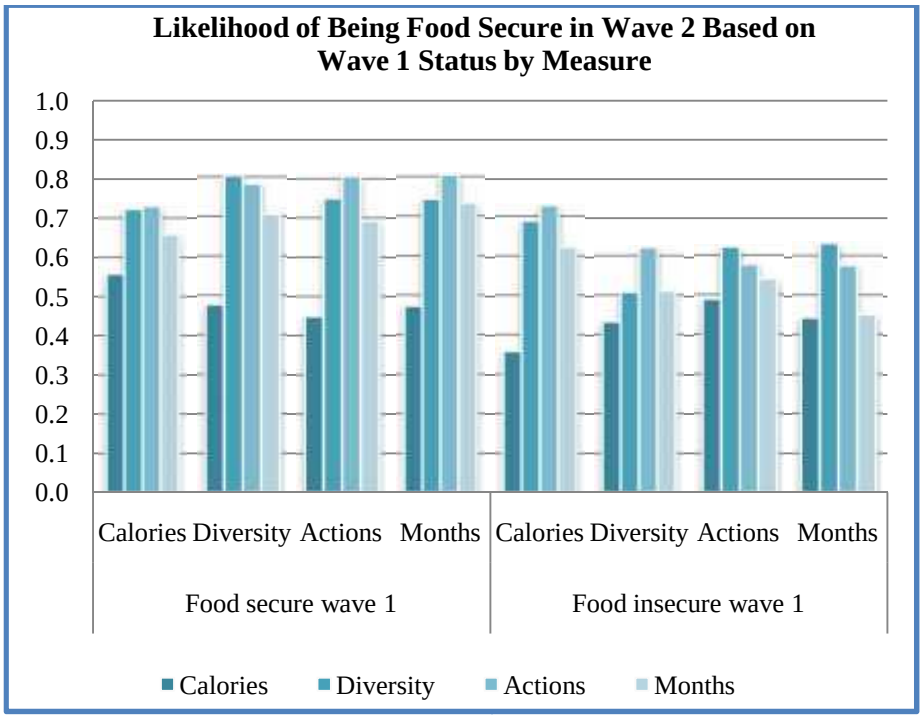


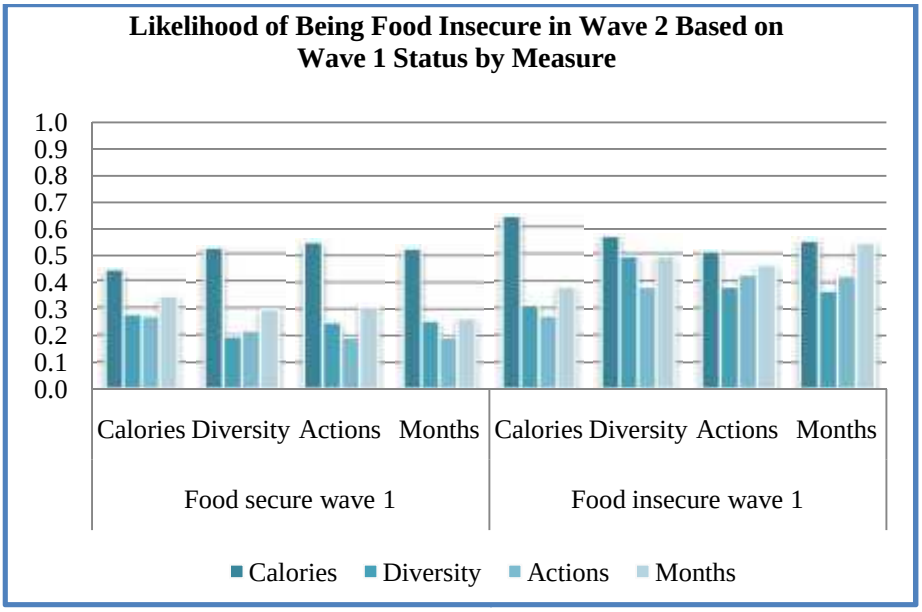


Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

To further explore these transitions, for each food security measure figure 9 reports the likelihood of being food secure or insecure in wave 2 based on whether the person was food secure (top panel) or insecure (bottom panel) in wave 1. Depending on the indicator, people who are food secure in wave 1 are likely to be food secure – to varying degrees – in wave 2. The persistence is greater with dietary diversity and the experiential measures than with calories. The food security status of many Ethiopians does, however, worsen. For people who were food insecure in wave 1, the likelihood that they remain food insecure varies by indicator. Those who were calorie-deficient are more likely than not to continue to be calorie-deficient; however, those with poor diets or any reported months of food insecurity are about equally likely to become food secure as to stay insecure. Households that took actions against food insecurity in wave 1 are less likely to do so in wave 2.

Figure 9: Transitions in Food Insecurity by and Across Measures





Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

In addition to comparing food security status over time based on a single measure, we examine the co-movement of food insecurity indicators over time. Table 3, which shows whether food security worsens, is constant, or improves over time for combinations of indicators helps answer the question of whether improvement in one indicator of food security suggests similar improvement in other indicators. It also helps identify whether indicators are dependent on or independent of each other. For most combinations, observing improvement in one measure of food security for an individual appears to tell an observer very little about whether the person has similarly improved in another measure.

For example, the (sample design-corrected) Pearson test of independence between changes in food security as measured by changes in FCS and in the reported number of months experiencing food insecurity has a p-value of 0.27. This suggests a failure to reject the null hypothesis of independence, which means that an improvement in FCS tells us nothing about whether the count of food-insecure months is improving or worsening. Similarly, the p-value of the test of independence for changes in FCS and in the number of

actions taken in response to food insecurity is 0.65, which also means that the first difference in FCS is independent of the first difference in the number of actions taken to alleviate food insecurity.

Table 3: Comovements in Food Insecurity Status

		Worsened	*Constant*	*Improved*	*Total*
		Poor diet status			
Calorie deficiency status	Worsened	0.03	0.17	0.03	0.23
	Constant	0.08	0.42	0.11	0.60
	Improved	0.02	0.12	0.04	0.17
	Total	0.13	0.70	0.17	1.00
		Any actions status			
Calorie deficiency status	Worsened	0.03	0.16	0.04	0.23
	Constant	0.07	0.40	0.12	0.60
	Improved	0.02	0.12	0.04	0.17
	Total	0.13	0.68	0.19	1.00
		Any months status			
Calorie deficiency status	Worsened	0.05	0.15	0.03	0.23
	Constant	0.10	0.41	0.09	0.60
	Improved	0.04	0.11	0.03	0.17
	Total	0.18	0.67	0.15	1.00
		Any months status			
Poor diet status	Worsened	0.03	0.08	0.02	0.13
	Constant	0.11	0.49	0.10	0.70
	Improved	0.04	0.10	0.03	0.17
	Total	0.18	0.67	0.15	1.00
		Any actions status			
Poor diet status	Worsened	0.01	0.09	0.02	0.13
	Constant	0.09	0.47	0.14	0.70
	Improved	0.02	0.12	0.03	0.17
	Total	0.13	0.68	0.19	1.00
		Any actions status			
Any months status	Worsened	0.05	0.12	0.01	0.18
	Constant	0.07	0.48	0.13	0.67
	Improved	0.01	0.08	0.06	0.15
	Total	0.13	0.68	0.19	1.00

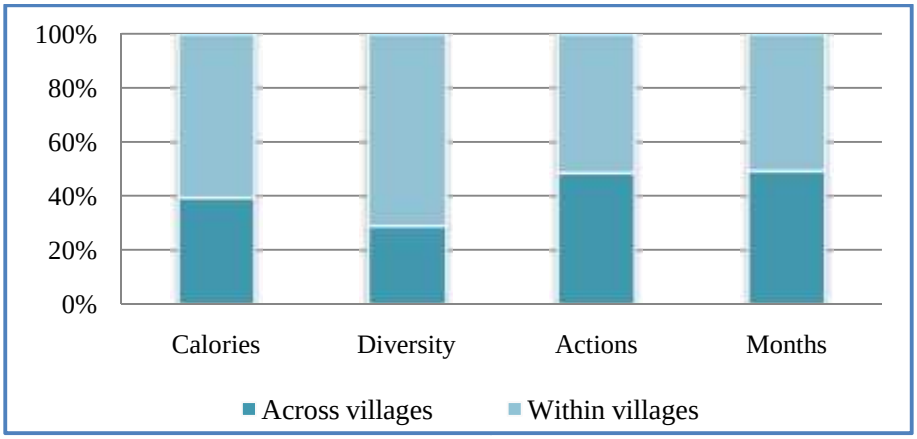
Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

An important exception to this finding is that there is statistical dependence in the first difference of the experiential measures. For example, a decline in the reported number of months experiencing food insecurity is correlated with a decline in the reported number of actions taken to counter food insecurity, suggesting that these measures may be picking up some common dimension of food insecurity.

Finally, we examine the geographic sources of variation of changes (in first differences) for our food security measures: calories, FCS, and the two experiential measures. For each measure, the figure 10 presents the proportion of the variance that is occurring within villages and the proportion occurring between villages. A lack of variation in first-difference measures within villages suggests that all food security shocks are (like droughts) covariate: if someone in a village has a marked decline in FCS, everyone in that village has the same decline. Similarly, if all of the variation is within a village and none between villages, then all change appears to be idiosyncratic or not shared at all by neighbors within villages. One possible example of an idiosyncratic shock would be death of a household member.

From Figure 10 it appears that the majority of variation is occurring within villages; for calories and FCS, more than 60 percent of the variation is within-village. For the two experiential measures, the within-village variation explains a slightly smaller proportion of total variation but it is still the main source of the variation. As a whole, the results suggest that drivers of changes in food insecurity appear to be both covariate and idiosyncratic, with the idiosyncratic component significantly more important. Other research, such as Dercon *et al.* (2006), has found that households in rural Ethiopia typically experience both covariate and idiosyncratic shocks that affect current consumption and in some cases have long-lasting effects. Additionally, Yilma *et al.* (2014), who examine how coping mechanisms relate to the nature of a shock in rural Ethiopia, find that when confronted with covariate shocks households reduce food consumption and draw on savings; however, confronted with idiosyncratic health shocks, they draw on savings and borrow.

Figure 10: Variations of Changes in Food Security



Notes: Population-weighted estimates. Number of observations: 3,266.
Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

6. Conclusion

In this paper, we use data from the ESS, a panel survey that is representative of rural and small towns in Ethiopia, to examine patterns of food security over time and across households. Understanding the drivers of food insecurity is crucial in Ethiopia, where much of the population either lives with or is vulnerable to food insecurity and poverty. We found, using multiple measures, that a large share of the rural Ethiopian population is food insecure, and that this share was much larger when viewed over a 2-year period since there is considerable movement into and out of food insecurity. We also found that the changes in food security are driven by differences both between and within villages, with the latter being more important in terms of calories and nutritional diversity. Finally, we found little co-movement in food insecurity status. The measures may have been picking up different dimensions of food security or may suffer from measurement error.

Our results underscore the importance of research that carefully examines the measurement of the multidimensional concept of food security, such as Maxwell *et al.* (2014) specifically for Ethiopia, and Carletto, Zezza, and Banerjee (2013) more generally. Such research is crucial for identifying public and private solutions to both transitory and chronic food insecurity.

References

Alem, Y., and Soderbom, M. (2011). "Household-level consumption in urban Ethiopia: the effects of a large food price shock," *World Development*, 40(1): 146-162.

Arimond, M., and Ruel, M. T. (2004). "Dietary diversity is associated with child nutritional status: evidence from 11 Demographic and Health Surveys," *The Journal of Nutrition*, 134(10): 2579-2585.

Ballard, T., Kepple, A. W., and Cafiero, C. (2013). *The Food Insecurity Experience Scale: Development of a Global Standard for Monitoring Hunger Worldwide*. Retrieved on December 15, 2016 from: http://www.fao.org/fileadmin/templates/ess/voh/FIES_Technical_Paper_v1.1.pdf

Beegle, K., De Weerdt, J., Friedman, J., and Gibson, J. (2012). "Methods of household consumption measurement through surveys: experimental results from Tanzania," *Journal of Development Economics* 98 (1): 3–18.

Berhane, G., Paulos, Z., Tafere, K., and Tamru, S. (2011). "Foodgrain consumption and calorie intake patterns in Ethiopia, "*IFPRI ESSP II Working Paper 23*. Washington, DC: IFPRI.

Bickel, G., Nord, M., Price, C., Hamilton, W., and Cook, J. (2000). *Guide to Measuring Household Food Security*. United States Department of Agriculture. Food and Nutrition Service. Retrieved on December 15, 2016 from: https://www.fns.usda.gov/guide-measuring-household-food-security-revised

Carletto, C., Zezza, A., and Banerjee, R. (2013). "Towards better measurement of household food security: harmonizing indicators and the role of household surveys,"*Global Food Security*, 2: 30-40.

D'Souza, A., and Jolliffe, D. (2014). "Food insecurity in vulnerable populations: coping with food price shocks in Afghanistan," *American Journal of Agricultural Economics*, 96(3): 790-812. doi:10.1093/ajae/aat089.

Deaton, A. (2000). *The Analysis of Household Surveys*, Baltimore, MD: The Johns Hopkins University Press.

Dercon, S. (2004). "Growth and shocks: evidence from rural Ethiopia," *Journal of Development Economics, 74*(2), 309-329. doi:http://dx.doi.org/10.1016/j.jdeveco.2004.01.001.

Dercon, S., Hoddinott, J., and Woldehanna, T. (2006). "Consumption, vulnerability, and shocks in rural Ethiopia, 1999-2004, "*Ethiopian Journal of Economics*, 15(1): 56-85.

Dercon, S., Hoddinott, J., and Woldehanna, T. (2012). "Growth and chronic poverty: evidence from rural communities in Ethiopia." *Journal of Development Studies*, 48(2): 238-253.

Ethiopia Central Statistical Agency. (2012). *Household Consumption and Expenditure (HCE) Survey 2010/11 Analytical Report*. Retrieved on December 15, 2016 from Addis Ababa: http://catalog.ihsn.org/index.php/catalog/3123

Ethiopia Central Statistical Agency, and ICF International. (2012). *Ethiopia Demographic and Health Survey 2011*. Retrieved on December 15, 2016 from:https://dhsprogram.com/pubs/pdf/FR255/FR255.pdf

Food and Agricultural Organization (FAO). (1996). *Rome Declaration on World Food Security*, Rome: FAO. Retrieved on December 15, 2016 from http://www.fao.org/docrep/003/w3613e/w3613e00.htm

Food and Agricultural Organization (FAO). (2013). *The State of Food Insecurity in the World: The Multiple Dimensions of Food Security*. Retrieved on December 15, 2016 from: http://www.fao.org/docrep/018/i3434e/i3434e.pdf.

Food and Agricultural Organization (FAO). (2014). *The Post-2015 Development Agenda and the Millennium Development Goals: Country Achievements 2014*, Retrieved on December 15 2016 from: http://www.fao.org/post-2015-mdg/awards/country-achievements-2014/en/.

Food and Agricultural Organization (FAO). (2015). *The State of Food Insecurity in the World: Meeting the 2015 International Hunger Targets: Taking Stock of Uneven Progress*, Retrieved on December 15, 2016 from: http://www.fao.org/3/a-i4646e.pdf.

Nord, M., Cafiero, C., and Viviani, S. (2016). "Methods for estimating comparable prevalence rates of food insecurity experiences by adults in 147 countries and areas," *Journal of Physics: Conference Series.* 722(1): 1-6.

Hirvonen, K., and Hoddinott, J. (2014). "Agricultural production and children's diets: evidence from rural Ethiopia," *IFPRI Working Paper 69*, Washington, DC: IFPRI.

Jolliffe, D. (2001). "Measuring absolute and relative poverty: the sensitivity of estimated household consumption to survey design," *Journal of Economic and Social Measurement* 27: 1–23.

Maxwell, D., Vaitla, B., and Coates, J. (2014). "How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia," *Food Policy*, 47: 107-116, doi:http://dx.doi.org/10.1016/j.foodpol.2014.04.003

Nguyen, P. H., Avula, R., Ruel, M. T., Saha, K. K., Ali, D., Tran, L. M., Rawat, R. (2013), "Maternal and child dietary diversity are associated in Bangladesh, Vietnam, and Ethiopia," *The Journal of Nutrition*, 143(7): 1176-1183, doi:10.3945/jn.112.172247.

Rosen, S., Meade, B., and Murray, A. (2015). *International Food Security Assessment, 2015-25*, Retrieved on December 15, 2016 from: https://www.ers.usda.gov/publications/pub-details/?pubid=37265

Shank, R., and Ertiro, C. (1996). *A Linear Model for Predicting Enset Plant Yield and Assessment of Kocho Production in Ethiopia*, Retrieved on December 15, 2016 from: http://www.africa.upenn.edu/eue_web/enset96.htm

Taye, A., Mariam, D. H., and Murray, V. (2010). "Interim report: review of evidence of the health impact of famine in Ethiopia, "*Perspectives in Public Health*, 130(5):222-226.

United Nations Economic Commission for Africa, African Union, African Development Bank Group, and United Nations Development Program. (2015). *MDG Report 2015: Lessons Learned in Implementing the MDGs*. Retrieved on December 15, 2016 from:http://reliefweb.int/report/world/mdg-report-2015-lessons-learned-implementing-mdgs-assessing-progress-africa-toward

Weismann, D., Bassett, L., Benson, T., and Hoddinott, J. (2009). *Validation of the World Food Programme's Food Consumption Score and Alternative Indicators of Household Food Security*, Retrieved on December 15, 2016 from: programmes-food-consumption-score-and-alternative-indicators

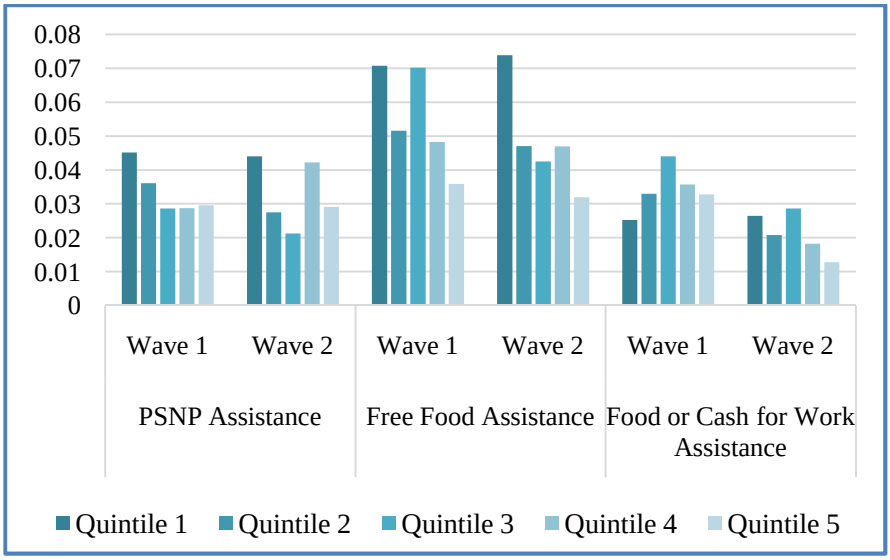
World Bank. (2014). *Ethiopia Poverty Assessment*, Washington, DC: World Bank. Retrieved on December 15, 2016 from: https://openknowledge.worldbank.org/handle/10986/21323

World Food Programme (WFP) and Ethiopia Central Statistical Agency. (2014). *Comprehensive Food Security and Vulnerability Analysis (CFSVA): Ethiopia*. Retrieved on December 15, 2016 from:http://documents.wfp.org/stellent/groups/public/documents/ena/wfp265490.pdf?_ga=1.59828389.900803756.1491095419

Yamano, T., Alderman, H., and Christiaensen, L. (2005). "Child growth, shocks, and food aid in rural Ethiopia," *American Journal of Agricultural Economics*, 87(2): 283-288.

Yilma, Z., Mebratie, A., Sparrow, R., Abebaw, D., Dekker, M., Alemu, G., and Bedi, A. S. (2014). "Coping with shocks in rural Ethiopia, "*The Journal of Development Studies*, 50(7) 1-16. doi:10.1080/00220388.2014.909028

Appendix Figure 1: Assistance by Quintile and by Wave



Notes: Population-weighted estimates. Quintiles are based on real nonfood monthly consumption per AE. Number of observations: 3,266.

Source: Ethiopia Rural Socioeconomic Surveys, 2011/12, 2013/14.

Dynamics of Wasting and Underweight in Ethiopian Children

Chris Cintron[1], Ilana Seff[2] and Sarah Baird[1]

Abstract

In Ethiopia, 9.7 percent of rural and 28.7 percent of small-town children are wasted and underweight, and undernutrition is responsible for a large percentage of childhood deaths. We use two waves of panel data, from the 2012 and 2014 Ethiopia Socioeconomic Surveys, to assess the dynamics of weight-for-height z-score, wasting, weight-for-age z-score, and underweight among children aged 6-59 months. Ordinary least squares (OLS) and fixed effects regression models are used to examine the associations of individual, household, and community factors with each outcome. The cross-sectional results, which generally parallel previous findings, suggest that child's sex, recent illnesses, household assets, and livestock ownership are correlated with nutritional status. However, many associations disappear after controlling for fixed effects; only recent illness and community access to a main road are consistently significant determinants of changes in nutrition status. Thus, changing factors traditionally identified as correlates of undernutrition may not be enough to improve children's nutrition. Further panel analysis, conditional on baseline nutrition status, shows that drivers of change are asymmetrical—a finding important for policy development.

Keywords: Ethiopia, child malnutrition, wasting, underweight, panel data analysis
JEL Classification: C33, I10, I31

---

[1] Department of Global Health, George Washington University Washington, DC, USA
[2] Department of Population and Family Health, Columbia University Mailman School of Public Health, New York, NY, USA
Acknowledgements: The authors are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding; to Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw, and Alemayehu Seyoum Taffesse for useful insights and feedback; to Demirew Getachew and Tadele Ferede for their help in disseminating this paper; and to two anonymous referees for excellent comments.

1. Introduction

Undernutrition is responsible for an estimated 3.1 million child deaths annually, most of which occur in low- and middle-income countries (Black *et al.*, 2013). Other serious consequences of childhood undernutrition are deficiencies in physical and mental development, higher susceptibility to disease, inhibited educational attainment, and diminished lifetime earning potential (Caulfield *et al.*, 2004; Victora *et al.*, 2008; Black *et al.* 2013). Accordingly, eradicating hunger and halving the proportion of underweight children were among the United Nations (UN) Millennium Development Goals for 2015 (MDGs), and continued reductions in all forms of malnutrition are set forth in the Sustainable Development Goals for 2030 (SDGs; UN 2015, UN-DESA 2016).

In addition to immediate impacts on health and survival, childhood nutritional status has been linked to educational outcomes, adult health, and economic productivity. Early childhood exposure to protein and calorie-boosting supplements in Guatemalan villages in the 1970s was positively associated with grade attainment and progression through school for women, and with reading comprehension and nonverbal cognitive tests scores for both men and women (Maluccio *et al.*, 2009). Men of the same cohort were also found to have higher hourly wages as adults if they had been exposed to the supplement before age 3 (Hoddinott et al., 2008). Data from Brazil, Guatemala, India, Philippines, and South Africa demonstrate that weight-for-age z-scores(WAZ) at age 2 are positively associated with adult height, body-mass index, years of schooling, birthweight of first offspring, and income (Victora et al., 2008).

Common indicators of undernutrition in children aged 6-59 months are stunting, wasting, and underweight, which are defined by comparing height- and weight-related z-scores with the WHO reference population.[3] Stunting

[3] The 2006 WHO child growth standards are derived from the WHO Multicenter Growth Reference Study carried out between 1997 and 2003. The study collected growth and other relevant data on 8,500 ethnically diverse, healthy, breastfed children in Brazil, Ghana, India, Norway, Oman, and the United States.

is defined by a height-for-age z-score (HAZ) below 2, which indicates chronic undernutrition and restricted growth; wasting is defined by a weight-for height z-score (WHZ) below 2 and suggests acute undernutrition or rapid weight loss (Black et al., 2008); and underweight is defined by a WAZ below 2, which can result from stunting or wasting. The MDGs used underweight as a general indicator of nutritional status and health (Black *et al.*, 2008, UN 2015). Stunting, wasting, and underweight are considered severe when z-scores are below 3.

In Ethiopia, reducing child undernutrition is a top national priority (Government of Ethiopia, 2013). Despite substantial progress over the last decade, large proportions of Ethiopian children under5 are still stunted (44.4%), wasted (9.7%), or underweight (28.7%), which together contribute to 51% of childhood deaths (Government, 2013). Understanding the determinants of childhood undernutrition in Ethiopia is paramount to achieving further reductions and accomplishing nutrition agenda goals, particularly where prevalence remains high.

Numerous cross-sectional studies have analyzed the social and economic determinants of stunting and underweight in Ethiopia (Edris, 2007; Haidar and Kogi-Makau, 2009; Alemayehu *et al.*, 2015; Degarege, Degarege, and Animut 2015; Degarege, Hailemeskel, and Erko 2015; Fekadu *et al.*, 2015), but fewer have used panel data or focused on wasting. Quisumbing (2003) and Hagos *et al.* (2014) did conduct studies in Ethiopia that undertook wasting or underweight analysis but with longer intervals between data points, different methods of sample selection, and ultimately different goals than this paper. Quisumbing (2003) used four waves of panel data from 15 Ethiopian villages to examine the effects of food aid on children's nutrition, specifically looking at differences by type of food aid (food-for-work vs. free distribution) and children's sex; both aid types had positive impacts on children's weight-for-height but differences by sex were insignificant. Using four waves of panel data to assess how climate and food production affected children's nutrition, Hagos *et al.* (2014) found that rainfall, temperature, and ecological zones were predictive of stunting and underweight but not of wasting.

Accurate targeting of nutrition interventions is necessary to efficiently prevent or alleviate undernutrition in children, thereby improving associated short and long-term outcomes. The cross-sectional and panel studies in Ethiopia mentioned above and those from other lower-middle-income countries (LMICs) have identified sometimes conflicting determinants of wasting and underweight. An analysis covering Bangladesh, Ethiopia, and Vietnam found household food insecurity to be highly and significantly positively associated with underweight prevalence in children under 5 (U5) in all three countries but with U5 wasting only in Bangladesh(Ali *et al.*, 2013). In other LMICs, household factors associated with wasting or underweight include inadequate toilet facilities and drinking water sources, large family size, possession of various household assets, and family wealth quintile (Gupta *et al.*, 2011; Ndiku *et al*., 2011; Rannan-Eliya *et al.*,2013; Aheto, 2015; and Arndt *et al.*, 2016). Associated individual factors are recent episodes of diarrheal disease, maternal education/literacy, maternal age, child's age, and child's sex (Aheto, 2015; Rannan-Eliya *et al.*, 2013). Studies in rural Senegal and Kenya also found wasting and underweight to be associated with child's sex, though the disparities favored females in the former and males in the latter (Gupta *et al.*, 2011; Ndiku *et al.* 2011).

Macroeconomic factors like natural disasters and food price shocks have been associated with negative nutrition outcomes, particularly for the poor, women, and children (Darnton-Hill and Cogill, 2010). Food price shocks were associated with U5 underweight or wasting in Mozambique, Malawi, and Bangladesh, though specific effects varied by context and household asset ownership, child's sex, and possibly receipt of food aid (Torlesse *et al.*, 2003; Hartwig and Grimm, 2012; Arndt *et al.*, 2016). Cash-transfer programs have had mixed results, generally improving HAZ but having varied or insignificant impacts on WHZ and WAZ (de Groot *et al.*, 2015).

Determinants observed in other LMICs generally hold true in Ethiopia, particularly diarrheal disease, parental education, and family size. With regard to U5 wasting, household income, breastfeeding behaviors, mother's ability to use money, a case of diarrheal disease in the last two weeks, parental education, family size, family possession of a cooperative bank

savings account, maternal access to a health facility, and receiving food aid were each found to be significantly and independently associated in at least one study in Ethiopia (Quisumbing, 2003; Edris, 2007; Egata *et al.*; Alemayehu *et al.*, 2015; Degarege, Hailemeskel, and Erko, 2015; Fekadu *et al.*, 2015). Applying the same criteria for U5 underweight status, associations were found with household income, living in a female-headed household, being female, breastfeeding, having a toilet in the household, age of 12-23 months, mother's ability to use money, most common complementary foods, diarrheal disease episode in the last two weeks, parental education, family size, and living in highland or midland ecological zones (Edris, 2007; Haidarand Kogi-Makau, 2009; Hagos *et al.*, 2014; Alemayehu *et al.*, 2015; Degarege, Hailemeskel, and Erko 2015; Fekadu *et al.*, 2015).

Interestingly, while several studies suggested the season during which data were collected might explain observed prevalence of wasting, studies of this specific question generated mixed results. While Egata *et al.* (2013) found no significant association, Ferro-Luzzi *et al.* (2001) found WHZ declines among U5s during lean seasons in Southern Ethiopia, particularly for girls, and Abay and Hirvonen (2016) found significant seasonal differences in WHZ and WAZ related to whether market access is good or poor.

This paper contributes to the literature on determinants and dynamics of U5 wasting and underweight in Ethiopia by analyzing the two waves of panel data collected for the 2011/2012 and 2013/2014 Ethiopian Socioeconomic Surveys (ESS Waves 1 and 2).[4] At two-year intervals the ESS captures information on individual nutrition status, socioeconomic assets, and community/external factors. Using these data, we first analyze the cross-sectional correlates of wasting and underweight in Ethiopian rural and small-town children aged 6-59 months in 2012 and 2014. We then analyze wasting and underweight dynamics in a cohort of children aged 6-41 months in Wave 1 and 24-59 months in Wave 2. These analyses identify the individual, household, and community factors associated with nutrition status at given

[4] For analysis of stunting dynamics based on the same data, see Seff, Baird, and Jolliffe, 2016.

points in time and with changes in status over time. Our findings should help inform future efforts to improve Ethiopia's child nutrition and health outcomes.

In general, our cross-sectional results support previous findings. At the individual level, children's sex, maternal literacy, and recent illnesses were significantly associated with nutrition outcomes in most of our models. A variety of household characteristics were also repeatedly significant, such as sex and age of household head, possession of a solid roof, and livestock ownership. One community characteristic, presence of a health post, in Wave 2 was also significantly associated with all outcome variables.

Unlike the cross-sectional analysis, the fixed effects model lets us control for unobservable time-invariant factors and obtain a sense of what drives changes within individuals. This analysis of the dynamic associations between individual, household, and community characteristics and children's nutritional outcomes provides insights well-suited for informing policy; by controlling for potential confounders, we can better identify factors and populations to target with policies and interventions. However, this still should be interpreted as an association, not a causal relationship.

After controlling for fixed effects in our panel analysis, fewer factors remained significant. Illness in the last two months was significantly associated with negative changes in WHZ, wasting, WAZ, and underweight status. However, community access to a main road was associated with positive changes in WHZ and underweight status. After baseline status was controlled for, factors driving changes to or from undernourished states varied. For instance, children wasted at baseline were generally more responsive than non-wasted children to household changes they saw improvements in WHZ when they gained a solid roof or food assistance, and a decreased likelihood of wasting when they gained an improved water source or toilet; non-wasted children were not significantly affected by such changes.

In what follows, section 2 describes the study setting and data; section 3 details the analytic methodology, rationale, and limitations; section 4 discusses analysis results; and section 5 concludes.

2. Setting and Data

2.1 Study Setting

Ethiopia is the second most populous country in Africa, home to an estimated 88.4 million people, 84% of whom live in rural areas (Government, 2013). Aspiring to improve health and nutrition enroute to achieving the MDGs and reaching middle-income country status, Ethiopia implemented its first National Nutrition Program (NNP) in 2008 and its second in 2013. Demographic and Health Survey (DHS) data show improvements in childhood nutrition between 2000 and 2011, with underweight falling from 42.1% to 28.7% and wasting from 12.9% to 9.7% (Government, 2013). Nevertheless, underweight and wasting in Ethiopia are more prevalent than the regional averages for Sub-Saharan Africa (UNICEF 2014).

2.2 Data

The ESSs used here were conducted through a partnership of the Central Statistics Agency of Ethiopia and the World Bank Living Standards Measurement Study—Integrated Surveys of Agriculture team. In Wave 1, a stratified, two-stage sampling design was used to select first 290 rural and 43 small town enumeration areas (EA) and then 12 households from each EA; 3,969 households consented to interviews. Excluding 9 zones which were not sampled, Wave 1 is nationally representative for rural and small-town households and regionally representative of the four most populous regions of Amhara, Oromiya, SNNP, and Tigray. Wave 2re-interviewed 3,776 of the households from Wave 1, losing 5% of respondents to attrition.[5] We utilize data from the household and community questionnaires administered January to March 2012 for Wave 1 and February to April 2014 for Wave 2,

[5] ESS Wave 2 in 2013-2014 included all households sampled in Wave 1 and an additional 100 urban EAs. The latter were excluded from the analysis.

and from the livestock questionnaire administered in November/December of 2011 and 2013.

Within the panel of households, analysis was restricted to those with children aged 6-59 months (U5) in both waves to make the findings comparable to previous studies. Thus the analysis covered 2,480 children in Wave 1 and 2,202 in Wave 2. We also identified a cohort of 1.048 children who were 6-41 months during Wave 1 and 24-59 months during Wave 2—thus 6-59 months during both baseline and follow up. This cohort (the panel sample) allows for tracking of the dynamics in and out of wasting and underweight and drawing inferences on what drives changes.

2.3 Dependent and Independent Variables

The four outcomes of interest in this analysis are the dependent variables WHZ, WAZ, and binary indicators of wasting and underweight. Weight, height, and age in months were collected by interviewers for all children aged 6-59 months in Wave 1 and 6-83 months in Wave 2. Dates of birth were confirmed; follow-up questioning clarified discrepancies between reported and age imputed from date of birth. Weight was recorded in kilograms to the first decimal point using a hanging Salter-type scale. Height/length was recorded in centimeters to the first decimal point using a Shorrboard. Length was measured from a recumbent position for those aged 6-24 months and standing upright for all others. WHZ and WAZ were calculated using the 2006 WHO child growth standards recommended for international settings. As WHO recommends, outliers were excluded; WAZ less than -6 or greater than 5, and WHZ less than -5 or greater than 5were not included in the final sample (WHO, 2009). Children with WHZ below -2 are classified as wasted and those with WAZ below -2 as underweight. While research suggests the binary indicators of wasting and underweight are less efficient, there is no evidence suggesting any meaningful insight can be gleaned from an increase in WAZ from 3.5 to 4.5, for example (Royston et al., 2006), so the analysis comprehensively examines both outcomes.

Our aim is to identify which individual, household, and community factors are significantly associated with each outcome of interest. Independent variables tested were identified by previous studies and other relevant factors on which the ESS collected data. Individual variables include a continuous variable for child's age in months (6-59) and binary variables for child's sex, being the grandchild of the household head, living biological parents, mother's literacy, and occurrence of illnesses in the past two months. Because a nonlinear relationship has been demonstrated between child age in months and anthropometric z-scores, in all models we control for age in months, months squared, and months cubed (Cummins, 2013; Victora *et al.*, 2010).[6] While previous studies typically used mother's education, we instead examine mother's literacy as the majority of women surveyed have never attended school and are illiterate.

Numerous household variables are available for analysis due to the breadth of ESS coverage. The household questionnaire allowed for continuous variables of family size, age of household head, and average number of months of food insecurity[7], along with binary variables for sex of household head, receiving food aid[8], and self-reported experiences of shocks. Using principal component analysis, an asset index was constructed from a list of 35 household assets that when aggregated reflect a household's wealth. Additional binary variables signaling whether a household has a dirt floor, a solid roof[9], access to an improved toilet facility[10], and access to an improved

[6] Our data confirms the nonlinear relationship.

[7] Average number of months of food insecurity was determined by asking households that reported dealing with this situation at least once in the previous 12 months, "In which months of the last 12 did you experience [a situation when you did not have enough food to feed the household]?"

[8] Food aid includes the household or an individual household member receiving food or cash assistance through either food-for-work or free food programs.

[9] A solid roof is one made of iron or concrete.

[10] Improved toilet facilities are private or shared flush toilets and ventilated or non-ventilated pit latrines. Unimproved facilities are a bucket or field/forest (no facilities). WHO/JMP standards for improved sanitation facilities treat structurally improved facilities as unimproved if they are shared by more than one household (WHO, 2006).

source of drinking water[11] are included separately because the literature suggests these assets may have an independent effect on nutrition. Shocks include death or illness of a household member, losses of livestock, experience of a natural disaster[12], and increases in the price of food items or agricultural inputs in the past 12 months. The livestock questionnaire provided a final set of household variables; it asked households to report numbers owned of several types of animals. Binary variables were constructed for whether households owned at least one female cow, egg-laying hen, or milking cow.

Community variables were derived from the questionnaires completed by keyinformants with knowledge of EA infrastructure, organizations, and resources. Access to a main road, a large weekly market, a store selling basic medicines, a staffed health post, and Productive Safety Net Program (PSNP) operation within the kebele (smallest local administrative unit) make up the community variables, all of which are binary.

3. Methods

3.1 Cross-sectional Analysis

We first describe the cross-sectional methods used to examine for each wave which factors are associated with wasting, WHZ, underweight status, and WAZ. Associations are estimated for each dependent variable using OLS regression separately for each wave using the following model:

Model 1 $$Y_i = \beta_0 + \beta_1 X_{ihc} + \beta_2 X_{hc} + \beta_3 X_c + f_r + \varepsilon_{ic} \quad \textbf{(1)}$$

In the wasting and underweight versions of the model, Y_i is a binary indicator of wasting or underweight; in the WHZ and WAZ versions, Y_i is a

[11] Improved water sources are water piped into a dwelling, a yard, or a plot; a public tap or standpipe; a tubewell or borehole; a protected dug well or spring; bottled water; and rainwater. Unimproved sources are unprotected springs or dug wells, carts with small tanks, tanker-trucks, and surface water (WHO, 2006).

[12] Drought, flood, landslide, earthquake, fire, and heavy rains that prevented work.

continuous variable between -6 and 6.[13] All other components of the model are the same in each version: X is a set of characteristics where *i* represents the individual; *h*, signifies the household, and *c*, the community; β is a vector of coefficients to be estimated; f_r is a set of regional dummies; and ε_{ic} is the error term, clustered at the EA level due to the ESS two-stage sampling design. Use of wave-specific household weights make the results representative of rural and small-town areas in Ethiopia in 2012 and 2014. The OLS cross-sectional model is intended to test whether at a given point in time different combinations of individual, household, and community factors are associated with nutritional status. We first look at individual, household, and community factors separately before combining them.

3.2 Panel Analysis

Next, we use a fixed-effects model to exploit the panel data structure to examine factors associated with changes in the four outcomes of interest between the two waves.[14]As noted above, unlike the cross-sectional analysis, the fixed-effects modellets us control for unobservable time-invariant factors and obtain a sense of what drives changes within individuals. In analyzing the dynamic associations between individual, household, and community characteristics and children's nutritional outcomes, we can better identify factors and populations to target with policies and interventions. We also examine changes in the four outcome variables after controlling for baseline nutritional status because factors driving changes into or out of undernourished states may differ—catch-up growth in malnourished children can operate differently from the growth patterns of healthy children (Hassan, 2016). Stratifying fixed-effects analyses by baseline nutrition status allows

[13] The binary variable models were also run with logit regression, and results were qualitatively the same as with OLS regression.

[14] Hausman tests were performed to test whether omitted variables were correlated with the variables in the model. All tests were statistically significant at $p<0.01$—the omitted variables were not randomly distributed with respect to the error term. This indicates that a fixed- and not random-effect model is the appropriate choice.

us to ascertain whether programs targeting prevention of malnutrition need different components from those targeting its reduction.[15]

An important limitation of fixed-effects analysis is that it only examines individuals who experienced changes in status between the two waves and cannot estimate the effect of any time-invariant observed variables, such as gender or ethnic group. Additionally, some variables may be capable of changing over time but simply do not for numerous reasons; for example, the literacy status of very few mothers changes between waves. Accordingly, the fixed-effects model covers only independent variables for which 10% or more of the sample experienced a change between Waves 1 and 2.[16]

To estimate these changes within the children who were measured in both waves—those aged 6-41 months old in Wave 1 and 24-59 months old in Wave 2 whose information for all covariates was complete—the following fixed effects model was used:

Model 2 $$Y_{it} = \beta_1 X_{it} + \beta_2 X_{ht} + \beta_3 X_{ct} + f_i + \varepsilon_{itc} \quad \textbf{(2)}$$

As in the cross-sectional model, here Y_{it} is a binary outcome indicator for child *i* at time *t* in the wasting and underweight versions of the model and a continuous variable in the WHZ and WAZ versions. All other model components are the same in each version: X_i is a vector of individual characteristics, X_h of household characteristics; and X_c of community characteristics; f_i is an individual fixed effect; and ε_{itc} is the error term, all at time *t*. Standard errors are again clustered at the EA level and panel weights from Wave 2 are used to make the results representative of rural and small-town children age 6-41 months in 2012.

[15] One weakness of stratifying the analysis by baseline nutrition status is the resulting smaller sample size.

[16] Variables excluded here are grandchild of household head, maternal literacy, male household head, dirt floor, TV ownership, stove ownership, milking goat ownership, commercial bank, and PSNP presence.

4. Results

4.1 Descriptive Statistics

Table 1 illustrates all outcomes and independent variables analyzed, by year of analysis and for children aged 6-59 months during each wave. Prevalence of wasting was 11% in both waves, marginally higher than the rural prevalence of 10.2 percent reported in Ethiopia's 2011 mini-DHS survey (Central Statistical Agency [Ethiopia] and ICF, 2012). Underweight prevalence was 26.9% in Wave 1 and 24.9% in Wave 2, both lower than the DHS finding of 28.7%. The average WHZ was -0.321 in Wave 1 and -0.400 in Wave 2, while average WHA was -1.277 and -1.268. Figure 1 shows changes in the distributions for WAZ and WHZ between waves.

A few findings stand out in Table 1. As noted, maternal literacy was very low at 24.1% in Wave 1 and 23.3% in Wave 2. Average household size rose from 6.08 members to 6.28, a subtle but statistically significant change. There were also significant changes in the number of households with solid roofs, improved water sources, and improved toilets, the former two increasing between waves and the last decreasing. The prevalence of many self-reported shocks declined between waves, most notably subjective food price shocks, which were more than twice as common in Wave 1 (27.4%) as in Wave 2 (12.8%).[17] Prevalence of livestock ownership was mostly stable, the largest change being a 4% increase in female cow ownership (68.6% to 72.5%). The community characteristic which underwent the greatest change was main road access, which went up from 50.3% to 64.8%.

4.2 Cross-Sectional Analysis

WHZ

Table 2 presents the OLS cross-sectional regression results predicting children's WHZ scores. All children between 6-59 months are included in each wave. Column (1) shows the relative impacts of individual

[17] This decline in subjective estimates of food price shocks is supported by objective stabilization of food prices in 2014 (Woldehanna and Tafere 2015).

characteristics[18], column (2) the impact of household characteristics, column (3) community characteristics, and column (4) the full model. Tables 3-5 follow the same format for other outcomes. For all four outcomes, differences in the effects of covariates are observed across waves. Given that both waves comprise children aged 6-59 months, the majority of these observed differences are likely due to *time* rather than *age* differences.

Starting with individual characteristics, having been ill in the last two months had a significant negative association with WHZ in the full models of both waves. This finding, and recent illness also being significantly associated with negative outcomes in the following models, supports previous research in Ethiopia and elsewhere.

Moving to household characteristics, living in a male-headed household, household head age, and having a dirt floor were negatively associated with WHZ in Wave 1. The negative association for male-headed households was repeated in Wave 2, contradicting findings in a previous study.[19] Having a solid roof and an improved toilet were positively associated with WHZ in the full models, each serving as a proxy for wealth and contributing to improved hygiene and sanitation. Two livestock-related household characteristics were significant in both models: ownership of female cows and of laying hen. As expected, both were positively associated with WHZ, the latter strongly, since owning livestock could indicate wealth and have a direct or indirect (economic) influence on nutrition.

Wasting

Being male and experiencing illness in the last two months were significantly associated with wasting in the full model for Wave 1, but neither was significant in Wave 2 (Table 3). Supporting the findings of

[18] The variables "Father is alive" and "Mother is alive" were removed from the model. The percentage of living fathers did not change between waves, while attrition resulted in only children with living mothers being in Wave 2 (collinearity).

[19] A small regional study in northern Ethiopia by Haidar and Kogi-Makau (2009) found lower prevalence of stunting and underweight among 6-59-month-olds in male-headed than female-headed households; wasting prevalence was roughly the same.

numerous studies, having an improved water source was significantly negatively associated with wasting in the household and full models of Wave 1, but not in Wave 2. Having a solid roof was significantly negatively associated with wasting in the full model of Wave 2, reflecting its positive association with WHZ from Table 2. Female cow ownership was significantly negatively associated with wasting in the Wave 2 household model, but despite the strong association observed with WHZ in Table 2, no significant association was found between laying hen ownership and wasting. This implies that laying hen ownership is positively associated with weight-for-height but not enough to produce a change away from the wasting threshold. Curiously, self-reported natural disaster shocks in Wave 1 and food price shocks in Wave 2 were negatively associated with wasting, and community presence of a health post positively associated in Wave 2.

WAZ

Being male was significantly negatively associated with WAZ in the full models of both waves (Table 4), as was having been ill in the last two months, with large coefficients and high significance ($p<0.01$). Having a solid roof was positively associated with WAZ in the household and full models of both waves, as was score on the asset index. Female cow ownership stands out among all household findings for the high significance levels and relatively large coefficients in its positive association with WAZ in both models of each wave. Laying hen ownership was also significantly and positively associated in the household and full models of Wave 2. These and earlier findings suggest that, directly or indirectly, livestock ownership is an important determinant of childhood nutritional status in rural and small-town Ethiopia. A loss of livestock was significantly associated positively with WAZ in the full model of Wave 2—a curious finding given the direction of the association.[20]

Household characteristics with negative significant associations followed familiar patterns: In Wave 2 male-headed households and age of the

[20] Negative shocks from loss of livestock is, by definition, restricted to households that owned livestock in the past 12 months. Therefore, this finding is probably linked to the fact that we are subsampling on a “wealthier” group of individuals.

household head age were negatively associated with WAZ in both models, as were two communities characteristic: PSNP operation within the kebele, and the presence of a health post. Both were significant only in Wave 2, PSNP in the community model and the health post in the full model. Since the PSNP aims to serve the poorest communities, the negative association with WAZ likely reflects accurate targeting rather than negative impact. The same target group explains the association of a health post with lower WAZ, since this level of facility is usually found only in the poorest communities (Government, 2013).

Underweight

Using Model 1, illness in the last two months was significant and positive in both models of both waves (Table 5). As with wasting, being male was significantly positively associated with underweight status in the full model of Wave 1. Being the grandchild of the household head had a significant negative association with underweight in the full model of Wave 1; in Wave 2, having a literate mother had a similar significant negative association in Wave 2, but only in the individual model.

Significant associations between household characteristics and underweight status closely mirrored those for WAZ (Table 4)—moreso than was true of the wasting and WHZ results. Across all models and waves, having a solid roof had a significant negative association with underweight. Milking cows and laying hens were negatively associated with underweight in both models of Wave 2, again suggesting a significant relationship between livestock assets and nutritional status. In both models and waves, the asset index was also negatively associated with underweight. Positive associations were also familiar, with male-headed households and household head age strongly significant in both models of Wave 2 and death or illness of a household member significant in both models of Wave 1. Of community characteristics, only health post presence was significant, this time positively associated with underweight in Wave 2.

4.3 Panel Analysis

With regard to nutritional status across time, individuals surveyed in both ESS waves fall into four categories; as shown in Table 6, only 1.92% of the panel sample (18 U5 children) were wasted at both baseline and follow-up; 13.02% (121) were wasted in Wave 1 but recovered by Wave 2; 7.07% (66) were not wasted in Wave 1 but became wasted by Wave 2; and 77.99% (725) were not wasted at either point. Given the acute nature of wasting, it is possible (though not probable), that many children fell in and out of wasting status at multiple points during the two-year survey period—unlike being underweight, which can relate to either wasting or stunting and is a more general malnutrition indicator. That would explain why in the sample more children, 12.23% (128) were underweight at both baseline and follow-up: 16.18% (170) were underweight in Wave 1 but recovered by Wave 2, 11.29% became underweight between waves, and 60.3% (632) were not underweight at either point. That more children recovered from wasting or underweight status between waves than fell into either is a positive indicator for children's nutrition in Ethiopia, but it also raised the question of why some children became less well-nourished or remained malnourished.

WHZ

Table 7 presents the fixed effects regression results predicting changes in children's WHZ scorebased on Equation 2. Children aged 6-41 months in Wave 1 and 24-59 months in Wave 2 comprise the sample population, which is weighted to make results representative of rural and small-town areas. As in the cross-section tables, the fixed effects results are subdivided into individual, household, and community, and the full model. Tables 8-10 follow the same format for their outcome variables, as do Tables 7a-10a, with additional subdivisions by baseline status.

Controlling for fixed effects, we found two characteristics significantly associated with changes in WHZ. The association with illness in the past two months was negative in the full model, as it was in the full models of the cross-sectional WHZ results. The combination of these findings suggests that recent illness was an important risk factor for lower WHZ at both points

in time as well as across time (we will discuss this after examining the remaining outcomes). The second significant variable found was main road access, a community characteristic not significant in any cross-sectional results but here positively associated with WHZ. In Table 7a, main road access continues to have a significant positive association for the wasted at baseline subgroup, suggesting that improving community access to outside services via main roads may have broad benefits for children's WHZ. Among other significant factors (Table 7a) were changes in possession of a solid roof and receipt of food assistance, which were both positively associated with WHZ in children wasted at baseline. In contrast, death or illness of a household member had a significant negative impact on WHZ among those wasted at baseline—an unfortunate yet unsurprising finding, slightly buoyed by the fact that this factor did not drag down the WHZ of children not wasted at baseline.

Wasting

With Model 2 (Table 8), while having a solid roof was significantly associated with such positive outcomes as higher WHZ and lower likelihood of wasting in our cross-sectional models, we found a significant positive association between solid roof ownership and wasting in our fixed effects models, as well as among those not wasted at baseline (Table 8a).[21] More intuitive are the results for gaining an improved toilet and water source (Table 8a): after controlling for fixed effects, those who gained these household assets and were wasted at baseline were more likely to recover than those who did not. Experiencing a food price shock in the last 12 months was, oddly, also strongly predictive of recovery from wasting; death or illness of a household member was strongly predictive of remaining wasted.

WAZ and underweight

Table 9 presents the fixed effects regression results predicting changes in children's WAZ and table 10 for underweight status, both using Model 2. Illness in the last two months was significantly negatively associated with

[21] These results may be spurious due to the small sample of those gaining or losing access to a solid roof.

WAZ after controlling for fixed effects, with high significance and a relatively large coefficient in both individual and full models. In both models, illness was also significantly positively associated with underweight. Such associations, found in cross-sectional and fixed effects analysis for all outcome variables, strongly suggest recent illness is a serious risk factor for Ethiopian children being or becoming undernourished. Interestingly, after controlling for baseline underweight status (Tables 9a and 10a), recent illness is only significantly associated with a negative change in WAZ among children not underweight at baseline.

Together, these finding raise serious questions about responses to illness in U5s, if medical attention is sought, if feeding decreases, if unsafe or otherwise ineffective remedies are attempted, and so on. These questions warrant both further research in rural and small-town Ethiopian contexts and consideration by policy makers addressing U5 nutrition, health, and healthcare.

In addition to recent illness, several other factors were associated with changes in WAZ (Table 9a). After controlling for fixed effects, individuals not underweight at baseline were more likely to see WAZ decrease when they received food aid or lived in a community with a health post. Children underweight at baseline were more likely to see WAZ decrease when a household member died or was seriously ill. Among children not underweight at baseline, the family gaining a laying hen or community access to a main road appeared to be support their remaining at a healthy weight. Combined with the earlier findings for WHZ and wasting, making communities more accessible via connection to a main road may be a strategy for improving or protecting children's nutritional status.

6. Conclusions

Our cross-sectional findings generally agree with previous studies, particularly those using data from Ethiopia. Male children, those with male and older household heads, and those experiencing illness in the last two months were significantly more likely to have negative nutrition outcomes

(lower WAZ or WHZ scores or a higher likelihood of wasting and underweight).Meanwhile, having a solid roof, a female cow, or a laying hen repeatedly were significantly associated with positive outcomes. Most community characteristics were insignificant, but having a health post was significantly associated with negative outcomes for all variables, probably because they are located in poorer communities.

Some differences from previous studies are worth noting, however. First, we find better WHZ, WAZ, and underweight outcomes for children in female-headed households, unlike regional studies in Ethiopia (Alemayehu *et al.*, 2015; Haidar and Kogi-Makau 2009) and Kenya (Ndiku *et al.*, 2012). However, the reason for female headship can provide insight into household's wellbeing. In our sample, the majority of female household heads are monogamously married (rather than widowed) and may be receiving financial transfers from their migrant worker husbands, which would help give the household's financial stability and the ability to invest more in child health. There is also a body of literature that documents the relatively higher investments female household heads make in the health of young household members compared to male household heads (Mikalitsa 2015**).**

Second, we saw no significant association between any outcomes and household size, though studies that did (Degarege, Degarege, and Animut 2015; Degarege, Hailemeskel, and Erko 2015) also included older children in their analyses[22]—context cannot be ignored when assessing problems, and solutions.

In our panel analysis, illness in the last two months was significantly associated with negative outcomes for WHZ, wasting, WAZ, and underweight after controlling for fixed effects, which reinforces our cross-sectional findings. These results warrant both further research on responses to illness in young children in rural Ethiopia and consideration by those involved with children's health, nutrition, and related policies. The finding

[22] It is also possible that order to affect child malnutrition household sizes need to increase or decrease by a larger magnitude.

that community access to a main road was associated with positive outcomes for WHZ and underweight suggests that making rural communities more accessible may be another strategy for improving children's health and nutrition. Findings from Northwest Ethiopia by Stifel and Minten (2015) that the more remote a household, the greater the decline in household food security and U5 dietary diversity, seem to support this possibility. Finally, our finding that receipt of food aid in the last 12 months was significantly associated with positive outcomes for children who were wasted or underweight at baseline suggests that accurately targeted food aid may be an effective intervention.

With the caveat that these findings represent associations not causal relationships, we offer the following suggestions. Foremost, responses to illness in young children warrant investigation to determine what actions households and health centers take, and how these responses relate to the negative nutritional outcomes we observed. Similarly, more research is needed on the differences between male and female-headed households with regard to children's nutrition. The combination of our findings and those obtained from the proposed research could then inform nutrition-related guidelines for health centers, community health workers, and households. Main road access is also worth further investigation given its demonstrated association with improved nutritional outcomes. It is likely that increased accessibility also improves economic outcomes in rural communities and would therefore further Ethiopia's progress on related SDGs and national goals. Finally, our findings suggest that different policy approaches may be appropriate for preventing or treating undernutrition. Children undernourished at baseline were more sensitive to household changes such as asset ownership and food aid than those who were adequately nourished. Therefore, while new efforts to improve living standards may simultaneously lift undernourished children to healthier states, emphasis should also be placed on preventing undernutrition altogether, to make children more resilient to external changes.

References

Abay, K., and Hirvonen, K. (2016). “Does market access mitigate the impact of seasonality on child growth? Panel data evidence from North Ethiopia”, Innocenti Working Paper No.2015-05, Florence: UNICEF Office of Research.

Aheto, J. (2015). "Analysing malnutrition prevalence and its determinants among under-five children in Ghana: Multilevel methods", *Maternal and Child Nutrition*, 2: 1-127.

Alemayehu, M., Tinsae, F., Haileslassie, K., Seid, O., Gebregziabher, G., and Yebyo, H. (2015). "Undernutrition status and associated factors in under-5 children, in Tigray, Northern Ethiopia", *Nutrition*, 31(7-8*: 964-970.

Ali, D., Saha, K. K., Nguyen, P. H., Diressie, M. T., Ruel, M. T., Menon, P., and Rawat, R. (2013). "Household food insecurity is associated with higher child undernutrition in Bangladesh, Ethiopia, and Vietnam, but the effect is not mediated by child dietary diversity", *The Journal of Nutrition*, 143(12): 2015-2021.

Arndt, C., Hussain, M., Salvucci, V., and Østerdal, L. (2016). “Effects of food price shocks on child malnutrition: The Mozambican experience 2008/2009”, *Economics & Human Biology*, 22: 1-13.

Black, R. E., Allen, L. H., Bhutta, Z. A., Caulfield, L. E., de Onis, M., Ezzati, M., Mathers, C., and Rivera, J. (2008), "Series: Maternal and child undernutrition: global and regional exposures and health consequences", *The Lancet*, 371(9608):243-260.

Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., de Onis, M., Ezzati, M., Grantham-McGregor, S., Katz, J., Martorell, R., and Uauy, R. (2013), "Maternal and child undernutrition and overweight in low-income and middle-income countries", *The Lancet*, 382 (9890): 427-451.

Caulfield, L. E., de Onis, M., Blössner, M., and Black, R. E. (2004). "Undernutrition as an underlying cause of child deaths associated with diarrhea, pneumonia, malaria, and measles", *The American Journal of Clinical Nutrition*, 80(1): 193-198.

Central Statistical Agency [Ethiopia] and ICF International. (2012). Ethiopia Demographic and Health Survey 2011. Addis Ababa, Ethiopia and

Calverton, Maryland, USA: Central Statistical Agency and ICF International.

Cummins, J. R. (2013). *On the Use and Misuse of Child Height-for-Age Z-score in the Demographic and Health Surveys*. Working paper 201417, Department of Economics, University of California, Davis.

Darnton-Hill, I., and Cogill, B. (2010). "Maternal and young child nutrition adversely affected by external shocks such as increasing global food prices", *The Journal of Nutrition*, 140(1): 162S-169S.

de Groot, R., Palermo, T., Handa, S., Ragno, L. P., and Peterman, A. (2015). "Cash transfers and child nutrition: what we know and what we need to know", Office of Research Working Paper, Available: http://www.unicef-irc.org/publications/782, accessed 27 February 2016.

Degarege, A., Hailemeskel, E., and Erko, B. (2015). "Age-related factors influencing the occurrence of undernutrition in northeastern Ethiopia", *BMC Public Health*, vol. 15(1);1-7.

Degarege, D., Degarege, A., and Animut, A. (2015). "Undernutrition and associated risk factors among school age children in Addis Ababa, Ethiopia", *BMC Public Health*, 15(1): 1-9.

Edris, M. (2007). "Assessment of nutritional status of preschool children of Gumbrit, North West Ethiopia", *Ethiopian Journal of Health Development*, 21(2): 125-129.

Egata, G., Berhane, Y., and Worku, A. (2013). "Seasonal variation in the prevalence of acute undernutrition among children under five years of age in east rural Ethiopia: a longitudinal study", *BMC Public Health*, 13(1):864-872.

Fekadu, Y., Mesfin, A., Haile, D., and Stoecker, B. J. (2015). "Factors associated with nutritional status of infants and young children in Somali Region, Ethiopia: a cross-sectional study", *BMC Public Health*, 15(1):1-9.

Ferro-Luzzi, A., Morris, S. S., Taffesse, S., Demissie, T., and D'amato, M. (2001). "Seasonal undernutrition in rural Ethiopia", IFPRI Research Report 118. Washington, D.C., Rome, and Addis Ababa: International Food Policy Research Institute and Istituto Nazionale dellaNutrizione in collaboration with Ethiopian Health and Nutrition Research Institute.

Government of the Federal Democratic Republic of Ethiopia. (2013). *National Nutrition Programme: June 2013-June 2015*, Addis Ababa: Government.

Gupta, N., Gehri, M., and Stettler, N. (2007). "Early introduction of water and complementary feeding and nutritional status of children in northern Senegal", *Public Health Nutrition*, 10(11): 1299-1304.

Hagos, S., Lunde, T., Mariam, D. H., Woldehanna, T., and Lindtjørn, B. (2014). "Climate change, crop production and child under nutrition in Ethiopia; a longitudinal panel study", *BMC Public Health*, 14(1): 884-893.

Haidar, J., and Kogi-Makau, W. (2009). "Gender differences in the household-headship and nutritional status of pre-school children", *East African Medical Journal*, 86(2): 69-73.

Hartwig, R., and Grimm, M. (2012). "An assessment of the effects of the 2002 food crisis on children's health in Malawi", *Journal of African Economies*, 21(1): 124-165.

Hassan, A. (2016). *Food Security and Child Malnutrition: The Impact on Health, Growth, and Well-Being*. Apple Academic Press. Retrieved February 22, 2017 from: https://books.google.com/books?id=Z3auDQAAQBAJ.

Hoddinott, J., Maluccio, J. A., Behrman, J. R., Flores, R., and Martorell, R. (2008). "Effect of a nutrition intervention during early childhood on economic productivity in Guatemalan adults", *The Lancet*, 371(9610): 411-416.

Maluccio, J. A., Hoddinott, J., Behrman, J. R., Martorell, R., Quisumbing, A. R., and Stein, A. D. (2009). "The impact of improving nutrition during early childhood on education among Guatemalan adults", *The Economic Journal*, 119(537): 734-763.

Mikalitsa, S. M. (2015). "Intrahousehold allocation, household headship and nutrition of under-fives: a study of western Kenya", *African Journal of Food, Agriculture, Nutrition and Development*, 15(1): 9708-9721.

Ndiku, M., Jaceldo-Siegl, K., Singh, P., and Sabaté, J. (2011). "Gender inequality in food intake and nutritional status of children under 5 years old in rural Eastern Kenya", *European Journal of Clinical Nutrition*, 65(1): 26-31.

Quisumbing, A. R. (2003). "Food aid and child nutrition in rural Ethiopia", *World Development*, 31: 1309-1324.

Rannan-Eliya, R., Hossain, S. M., Anuranga, C., Wickramasinghe, R., Jayatissa, R., and Abeykoon, A. T. (2013). "Trends and determinants of childhood stunting and underweight in Sri Lanka", *Ceylon Medical Journal*, 58(1): 10-18.

Royston, P., Altman, D., and Saurbrei, W. (2006). Dichotomizing continuous predictors in multiple regression: a bad idea."*Statistics in Medicine*, 25: 127-141.

Seff, I., Baird, S., & Jolliffe, D. (2017). Dynamics of child malnutrition in rural and small town Ethiopia. *Mimeo.*

Stifel, D. & Minten, B. (2015). "Market access, welfare, and nutrition: evidence from Ethiopia", ESSP II Working Paper 77. Washington, D.C. and Addis Ababa, Ethiopia; International Food Policy Research Institute (IFPRI) and Ethiopian Development Research Institute (EDRI).

Torlesse, H., Kiess, L., and Bloem, M. (2003). "Association of household rice expenditure with child nutritional status indicates a role for macroeconomic food policy in combating malnutrition", *Journal of Nutrition*, 133(5): 1320-1325.

UNICEF. (2014). *The State of the World's Children 2015: Reimagine the Future: Innovation for Every Child*, New York, NY: UNICEF.

United Nations. (2015). *The Millennium Development Goals Report*, New York, NY: United Nations.

United Nations Department of Economics and Social Affairs. (2016). "Goal 2: End hunger, achieve food security and improved nutrition and promote sustainable agriculture, "https://sustainabledevelopment.un.org/sdg2, accessed 29 January 2016.

Victora, C. G., Adair, L., Fall, C., Hallal, P. C., Martorell, R., Richter, L., and Sachdev, H. S. (2008). "Series: Maternal and child undernutrition: consequences for adult health and human capital", *The Lancet*, 371(9609): 340-357.

WHO and UNICEF. (2006). *Core Questions on Drinking-Water and Sanitation for Household Surveys*. Geneva: WHO.

WHO. (2009). *WHO AnthroPlus for Personal Computers Manual Software for assessing growth of the world's children and adolescents*. Geneva: WHO. Accessed February 22, 2017athttp://www.who.int/growthref/tools/en/.

Woldehanna, T., and Tafere, Y. (2015). "Food price volatility in Ethiopia: public pressure and state response."*IDS Bulletin*, 46(6).

Tables

Table 1: Descriptive Statistics as means and (standard deviations)

	Wave 1 6-59 mo. mean (sd)	**Wave 2** 6-59 mo. mean (sd)
Outcomes		
Weight-for-height z-score	-0.321	-0.400
	(1.481)	(1.445)
Wasted	0.110	0.112
	(0.313)	(0.315)
Weight-for-age z-score	-1.277	-1.268
	(1.408)	(1.288)
Underweight	0.269	0.249
	(0.444)	(0.432)
Individual Characteristics		
Age in months	32.320	33.000
	(15.410)	(15.020)
Age in months, squared	1281.800	1314.400
	(1010.900)	(995.900)
Age in months, cubed	56664.900	57985.600
	(57683.800)	(57524.500)
Male	0.527	0.499
	(0.499)	(0.500)
Grandchild	0.058	0.047
	(0.234)	(0.211)
Father is alive	0.980	0.982
	(0.140)	(0.133)
Mother is alive	0.992	1.000
	(0.088)	0.000
Mother is literate	0.241	0.233
	(0.428)	(0.423)
Ill in last 2 months	0.213	0.248
	(0.409)	(0.432)

Table 1 (cont.): Household Characteristics

Household size	6.078	6.282
	(2.065)	(2.039)
Male household head	0.896	0.916
	(0.306)	(0.277)
Age of household head	38.450	38.570
	(11.720)	(11.050)
Dirt floor	0.978	0.977
	(0.146)	(0.149)
Solid roof	0.372	0.454
	(0.483)	(0.498)
Improved toilet	0.623	0.579
	(0.485)	(0.494)
Improved water source	0.455	0.599
	(0.498)	(0.490)
Asset Index	5.540	5.334
Descriptive Statistics as means and (standard deviations)		
	(2.537)	(2.642)
Months of food insecurity , last 12m	0.996	1.058
	(1.587)	(1.672)
Received food assistance, last 12m	0.074	0.078
	(0.262)	(0.268)
Food price shock, last 12m	0.274	0.128
	(0.446)	(0.334)
Natural disaster, last 12m	0.204	0.123
	(0.403)	(0.328)
Agricultural inputs price shock, last 12m	0.188	0.101
	(0.391)	(0.301)
Loss of livestock, last 12m	0.088	0.050
	(0.283)	(0.219)
Household member death/illness, last 12m	0.150	0.110
	(0.357)	(0.313)
Female cow ownership	0.686	0.725
	(0.464)	(0.447)
Laying hen ownership	0.472	0.465
	(0.499)	(0.499)
Milking cow ownership	0.237	0.229
	(0.425)	(0.420)

Table 1 (cont.): Community Characteristics

Main road access	0.503	0.648
	(0.500)	(0.478)
Large weekly market	0.441	0.507
	(0.497)	(0.500)
Place to buy basic medicines	0.381	0.438
	(0.486)	(0.496)
Health post	0.913	0.902
	(0.281)	(0.298)
PSNP operates in kebele	0.366	0.334
	(0.482)	(0.472)
Observations	2480	2202

Note: Observations are weighted to make results representative of all rural and small town areas in Ethiopia during Wave 1 (2012) and Wave 2 (2014).

Table 2: Linear regression results predicting weight-for-height z-score, 6-59 months (standard errors in parentheses)

	Wave 1				Wave 2			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Male	-0.128			-0.127	-0.083			-0.107
	(0.085)			(0.083)	(0.085)			(0.082)
Grandchild	0.037			0.276	0.220			0.101
	(0.245)			(0.272)	(0.216)			(0.221)
Mother is literate	0.190			0.105	0.108			0.042
	(0.140)			(0.145)	(0.107)			(0.109)
Ill in last 2 months	-0.208*			-0.182*	-0.171			-0.218**
	(0.113)			(0.101)	(0.108)			(0.106)
Household size		0.014		0.023		0.029		0.035
		(0.028)		(0.028)		(0.025)		(0.025)
Male household head		-0.276*		-0.234		-0.339**		-0.315**
		(0.154)		(0.153)		(0.131)		(0.142)
Age of household head		-0.008		-0.011*		-0.004		-0.006
		(0.006)		(0.006)		(0.004)		(0.004)
Dirt floor		-0.565*		-0.560*		-0.243		-0.187
		(0.320)		(0.327)		(0.216)		(0.218)
Solid roof		0.074		0.076		0.156		0.195*
		(0.121)		(0.122)		(0.115)		(0.111)
Improved toilet		-0.162		-0.159		0.202*		0.195*
		(0.129)		(0.127)		(0.114)		(0.114)

Table 2 (cont.): Linear regression results predicting weight-for-height z-score, 6-59 months (standard errors in parentheses)

Improved water source	-0.065	-0.067	-0.079	-0.075
	(0.116)	(0.120)	(0.108)	(0.107)
Asset Index	0.042	0.039	0.034	0.033
	(0.026)	(0.025)	(0.022)	(0.022)
Months of food insecurity, last 12m	-0.007	-0.011	0.041	0.045
	(0.034)	(0.034)	(0.036)	(0.035)
Received food assistance, last 12m	-0.225	-0.255	-0.073	-0.132
	(0.163)	(0.160)	(0.193)	(0.191)
Food price shock, last 12m	0.019	0.008	0.134	0.095
	(0.117)	(0.119)	(0.153)	(0.158)
Natural disaster, last 12m	0.211	0.172	-0.104	-0.017
	(0.171)	(0.154)	(0.173)	(0.175)
Agricultural inputs price shock, last 12m	0.042	0.067	-0.132	-0.104
	(0.150)	(0.154)	(0.182)	(0.168)
Loss of livestock, last 12m	-0.225	-0.220	0.121	0.156
	(0.160)	(0.158)	(0.232)	(0.225)
Household member death/illness, last 12m	-0.200	-0.181	0.066	0.102
	(0.133)	(0.132)	(0.161)	(0.161)
Female cow ownership	0.069	0.059	0.222*	0.200
	(0.118)	(0.115)	(0.135)	(0.130)
Laying hen ownership	-0.042	-0.030	0.265***	0.272***
	(0.117)	(0.117)	(0.097)	(0.094)
Milking cow ownership	0.010	0.006	-0.145	-0.145
	(0.160)	(0.157)	(0.119)	(0.121)

Table 2 (cont.): Linear regression results predicting weight-for-height z-score, 6-59 months (standard errors in parentheses)

Main road access			-0.012	-0.002			0.112	0.130
			(0.137)	(0.134)			(0.119)	(0.108)
Large weekly market			0.052	0.038			0.039	0.045
			(0.134)	(0.133)			(0.119)	(0.113)
Place to buy basic medicines			-0.036	-0.056			-0.134	-0.159
			(0.146)	(0.148)			(0.130)	(0.124)
Health post			-0.242	-0.194			-0.229	-0.295*
			(0.249)	(0.240)			(0.160)	(0.173)
PSNP operates in kebele			0.115	0.174			-0.101	-0.064
			(0.155)	(0.139)			(0.132)	(0.120)
Observations	2020	2020	2020	2020	2015	2015	2015	2015
Adjusted R2	0.008	0.019	0.003	0.025	0.029	0.054	0.030	0.063

Notes: ***** p<0.01, ****** p<0.05, ***** p<0.1. OLS regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. All columns control for child's age in months, months squared, and months cubed.

Table 3: Linear regression results predicting wasting status, 6-59 months (standard errors in parentheses)

	Wave 1				Wave 2			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Male	0.030			0.034*	0.015			0.020
	(0.019)			(0.019)	(0.020)			(0.019)
Grandchild	-0.014			-0.057	0.024			0.068
	(0.053)			(0.062)	(0.048)			(0.055)
Mother is literate	0.006			0.022	-0.048**			-0.026
	(0.025)			(0.028)	(0.023)			(0.021)
Ill in last 2 months	0.051**			0.049**	0.030			0.037
	(0.026)			(0.025)	(0.028)			(0.026)
Household size		-0.003		-0.003		0.004		0.002
		(0.006)		(0.006)		(0.006)		(0.006)
Male household head		0.050*		0.041		0.038		0.045
		(0.028)		(0.029)		(0.030)		(0.030)
Age of household head		0.001		0.002		0.000		0.000
		(0.001)		(0.001)		(0.001)		(0.001)
Dirt floor		0.034		0.040		0.013		-0.003
		(0.034)		(0.034)		(0.049)		(0.049)
Solid roof		-0.026		-0.029		-0.049**		-0.058***
		(0.025)		(0.024)		(0.021)		(0.021)
Improved toilet		0.037		0.033		-0.039		-0.038

Table 3 (cont.): Linear regression results predicting wasting status, 6-59 months (standard errors in parentheses)

	(0.023)	(0.024)	(0.027)	(0.026)
Improved water source	-0.044*	-0.049**	-0.029	-0.026
	(0.024)	(0.024)	(0.023)	(0.023)
Asset Index	-0.006	-0.006	-0.004	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Months of food insecurity, last 12m	0.000	0.001	-0.005	-0.006
	(0.009)	(0.009)	(0.008)	(0.007)
Received food assistance, last 12m	0.026	0.027	0.015	0.013
	(0.041)	(0.043)	(0.051)	(0.049)
Food price shock, last 12m	-0.037	-0.040	-0.081**	-0.081**
	(0.028)	(0.027)	(0.038)	(0.037)
Natural disaster, last 12m	-0.056*	-0.053*	-0.002	-0.011
	(0.030)	(0.028)	(0.036)	(0.038)
Agricultural inputs price shock, last 12m	0.030	0.029	0.047	0.043
	(0.032)	(0.034)	(0.039)	(0.035)
Loss of livestock, last 12m	0.037	0.039	-0.018	-0.028
	(0.032)	(0.030)	(0.043)	(0.041)
Household member death/illness, last 12m	0.036	0.033	-0.007	-0.013
	(0.036)	(0.036)	(0.035)	(0.035)
Female cow ownership	-0.020	-0.019	-0.050*	-0.046
	(0.025)	(0.025)	(0.029)	(0.028)
Laying hen ownership	-0.018	-0.018	-0.024	-0.022
	(0.023)	(0.023)	(0.022)	(0.021)

Table 3 (cont.): Linear regression results predicting wasting status, 6-59 months (standard errors in parentheses)

Milking cow ownership		-0.010		-0.012		0.014		0.017
		(0.027)		(0.028)		(0.028)		(0.028)
Main road access			0.008	0.007			-0.004	0.002
			(0.025)	(0.023)			(0.025)	(0.022)
Large weekly market			-0.014	-0.015			-0.040	-0.037
			(0.025)	(0.025)			(0.025)	(0.024)
Place to buy basic medicines			0.014	0.016			0.021	0.026
			(0.026)	(0.026)			(0.026)	(0.026)
Health post			0.018	0.007			0.049*	0.069**
			(0.029)	(0.028)			(0.026)	(0.032)
PSNP operates in kebele			-0.016	-0.014			0.028	0.024
			(0.028)	(0.025)			(0.026)	(0.025)
Observations	2020	2020	2020	2020	2015	2015	2015	2015
Adjusted R2	0.014	0.025	0.008	0.031	0.016	0.034	0.017	0.043

Notes:* ** p<0.01, ** ** p<0.05, * * p<0.1. OLS regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. All columns control for child's age in months, months squared, and months cubed.

Table 4: Linear regression results predicting weight-for-age z-score, 6-59 months (standard errors in parentheses)

	Wave 1				Wave 2			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Male	-0.226***			-0.240***	-0.103			-0.127*
	(0.067)			(0.069)	(0.069)			(0.067)
Grandchild	0.000			0.079	-0.098			0.052
	(0.145)			(0.214)	(0.140)			(0.145)
Mother is literate	0.117			0.013	0.227**			0.057
	(0.134)			(0.135)	(0.104)			(0.102)
Ill in last 2 months	-0.402***			-0.397***	-0.255***			-0.293***
	(0.111)			(0.100)	(0.091)			(0.087)
Household size		0.005		0.005		-0.019		-0.016
		(0.029)		(0.029)		(0.023)		(0.023)
Male household head		-0.260*		-0.240		-0.307**		-0.273*
		(0.149)		(0.150)		(0.138)		(0.140)
Age of household head		-0.001		-0.003		-0.011**		-0.011**
		(0.004)		(0.005)		(0.004)		(0.005)
Dirt floor		-0.100		-0.101		-0.262		-0.232
		(0.396)		(0.371)		(0.203)		(0.205)
Solid roof		0.194*		0.195*		0.184**		0.213**
		(0.106)		(0.105)		(0.089)		(0.088)
Improved toilet		-0.138		-0.119		0.093		0.087
		(0.104)		(0.099)		(0.097)		(0.097)

Table 4 (cont.): Linear regression results predicting weight-for-age z-score, 6-59 months (standard errors in parentheses)

Improved water source	0.084	0.127	0.057	0.057
	(0.104)	(0.105)	(0.095)	(0.094)
Asset Index	0.062***	0.063***	0.045***	0.043***
	(0.023)	(0.024)	(0.015)	(0.016)
Months of food insecurity, last 12m	-0.008	-0.001	0.018	0.021
	(0.035)	(0.034)	(0.031)	(0.031)
Received food assistance, last 12m	-0.144	-0.171	-0.147	-0.179
	(0.120)	(0.121)	(0.216)	(0.206)
Food price shock, last 12m	0.161	0.115	-0.069	-0.086
	(0.116)	(0.116)	(0.144)	(0.144)
Natural disaster, last 12m	0.269*	0.252	-0.209	-0.150
	(0.153)	(0.157)	(0.170)	(0.178)
Agricultural inputs price shock, last 12m	-0.057	-0.052	-0.077	-0.052
	(0.157)	(0.165)	(0.195)	(0.192)
Loss of livestock, last 12m	-0.202	-0.192	0.367*	0.380*
	(0.194)	(0.189)	(0.218)	(0.213)
Household member death/illness, last 12m	-0.212	-0.187	-0.049	-0.003
	(0.131)	(0.127)	(0.126)	(0.132)
Female cow ownership	0.288**	0.274**	0.308***	0.295***
	(0.121)	(0.121)	(0.096)	(0.097)
Laying hen ownership	-0.060	-0.059	0.198**	0.208**
	(0.105)	(0.105)	(0.090)	(0.091)

Table 4 (cont.): Linear regression results predicting weight-for-age z-score, 6-59 months (standard errors in parentheses)

Milking cow ownership		-0.034		-0.046		0.024		0.026
		(0.140)		(0.140)		(0.133)		(0.133)
Main road access			-0.081	-0.072			0.082	0.098
			(0.116)	(0.113)			(0.099)	(0.091)
Large weekly market			0.034	0.052			-0.006	-0.007
			(0.122)	(0.117)			(0.101)	(0.091)
Place to buy basic medicines			0.109	0.106			0.046	-0.021
			(0.125)	(0.119)			(0.097)	(0.092)
Health post			-0.054	0.071			-0.216*	-0.263**
			(0.243)	(0.219)			(0.116)	(0.121)
PSNP operates in kebele			0.076	0.102			-0.182*	-0.046
			(0.144)	(0.156)			(0.107)	(0.104)
Observations	2162	2162	2162	2162	2121	2121	2121	2121
Adjusted R2	0.035	0.049	0.016	0.067	0.041	0.084	0.033	0.095

**Notes: ***** p<0.01, ****** p<0.05, ***** p<0.1. OLS regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. All columns control for child's age in months, months squared, and months cubed.

Table 5: Linear regression results predicting underweight status, 6-59 months (standard errors in parentheses)

	Wave 1				Wave 2			
	Individual	Household	Community	Full Model	Individual	Household	Community	Full Model
	1	2	3	4	1	2	3	4
Male	0.060**			0.064***	0.019			0.028
	(0.023)			(0.023)	(0.025)			(0.025)
Grandchild	-0.045			-0.130*	0.006			-0.036
	(0.057)			(0.075)	(0.054)			(0.062)
Mother is literate	-0.054			-0.016	-0.079***			-0.026
	(0.038)			(0.040)	(0.030)			(0.029)
Ill in last 2 months	0.066**			0.063**	0.071**			0.081***
	(0.032)			(0.029)	(0.031)			(0.031)
Household size		-0.002		-0.005		0.002		0.000
		(0.008)		(0.008)		(0.006)		(0.007)
Male household head		0.055		0.039		0.109***		0.093**
		(0.044)		(0.045)		(0.039)		(0.041)
Age of household head		0.002		0.003		0.003***		0.004***
		(0.001)		(0.002)		(0.001)		(0.001)
Dirt floor		-0.011		-0.018		0.066		0.061
		(0.118)		(0.115)		(0.071)		(0.072)
Solid roof		-0.063**		-0.064**		-0.073***		-0.081***
		(0.030)		(0.030)		(0.027)		(0.028)
Improved toilet		0.030		0.027		-0.025		-0.023
		(0.032)		(0.032)		(0.033)		(0.033)

Table 5 (cont.): Linear regression results predicting underweight status, 6-59 months (standard errors in parentheses)

Improved water source	-0.028	-0.035	-0.024	-0.022
	(0.033)	(0.032)	(0.030)	(0.030)
Asset Index	-0.016**	-0.014**	-0.014***	-0.014**
	(0.007)	(0.006)	(0.005)	(0.006)
Months of food insecurity, last 12m	0.005	0.003	-0.011	-0.011
	(0.011)	(0.011)	(0.009)	(0.009)
Received food assistance, last 12m	0.011	0.019	-0.007	0.000
	(0.043)	(0.044)	(0.052)	(0.049)
Food price shock, last 12m	-0.042	-0.036	0.022	0.024
	(0.034)	(0.034)	(0.046)	(0.045)
Natural disaster, last 12m	-0.086*	-0.087*	0.074	0.066
	(0.044)	(0.047)	(0.050)	(0.051)
Agricultural inputs price shock, last 12m	0.051	0.047	0.072	0.064
	(0.045)	(0.047)	(0.055)	(0.056)
Loss of livestock, last 12m	0.018	0.014	-0.070	-0.072
	(0.052)	(0.052)	(0.068)	(0.067)
Household member death/illness, last 12m	0.080*	0.078*	0.029	0.019
	(0.041)	(0.040)	(0.038)	(0.038)
Female cow ownership	-0.048	-0.044	-0.061**	-0.058**
	(0.038)	(0.038)	(0.029)	(0.030)
Laying hen ownership	-0.017	-0.018	-0.071**	-0.074**
	(0.032)	(0.033)	(0.032)	(0.031)

Table 5 (cont.): Linear regression results predicting underweight status, 6-59 months (standard errors in parentheses)

Milking cow ownership		-0.052		-0.053		-0.010		-0.009
		(0.041)		(0.042)		(0.034)		(0.034)
Main road access			-0.006	-0.007			-0.023	-0.025
			(0.037)	(0.035)			(0.028)	(0.026)
Large weekly market			-0.025	-0.028			0.003	0.001
			(0.037)	(0.035)			(0.030)	(0.027)
Place to buy basic medicines			-0.031	-0.029			-0.029	-0.008
			(0.039)	(0.036)			(0.030)	(0.029)
Health post			0.042	0.020			0.080*	0.092**
			(0.058)	(0.059)			(0.042)	(0.044)
PSNP operates in kebele			-0.017	-0.018			0.039	-0.003
			(0.045)	(0.046)			(0.032)	(0.029)
Observations	2162	2162	2162	2162	2121	2121	2121	2121
Adjusted R2	0.027	0.046	0.018	0.056	0.026	0.062	0.020	0.069

Notes:* ***** p<0.01, ****** p<0.05, ***** p<0.1. OLS regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. All columns control for child's age in months, months squared, and months cubed.

Table 6: Dynamics of wasting and underweight in Panel A

Wasting					
	Always wasted	Started wasted	Ended wasted	Never wasted	Total
%	1.92	13.02	7.07	77.99	
Observations	18	121	66	725	929

Underweight					
	Always underweight	Started underweight	Ended underweight	Never underweight	Total
%	12.23	16.18	11.29	60.3	
Observations	128	170	118	632	1048

Notes: The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. Number of observations are weighted using adjusted panel weights from ESS2. Columns are mutually exclusive.

Table 7: Fixed-effects regression results predicting a change in weight-for-height z-score for Panel A (standard errors in parentheses)

	Individual	Household	Community	Full Model
	1	2	3	4
Ill in last 2 months	-0.240			-0.294**
	(0.147)			(0.143)
Household size		-0.009		-0.025
		(0.088)		(0.084)
Age of household head		0.002		0.002
		(0.021)		(0.022)
Solid roof		-0.231		-0.177
		(0.190)		(0.201)
Improved toilet		-0.091		-0.046
		(0.108)		(0.114)
Improved water source		0.007		-0.022
		(0.157)		(0.151)
Asset Index		0.029		0.030
		(0.034)		(0.033)
Months of food insecurity, last 12m		0.005		0.008
		(0.048)		(0.046)
Received food assistance, last 12m		-0.027		-0.094
		(0.259)		(0.263)
Food price shock, last 12m		0.132		0.162
		(0.157)		(0.158)
Natural disaster, last 12m		-0.173		-0.212
		(0.241)		(0.233)
Agricultural inputs price shock, last 12m		0.188		0.171
		(0.160)		(0.165)
Loss of livestock, last 12m		0.378		0.398
		(0.290)		(0.289)
Household member death/illness, last 12m		-0.052		-0.059
		(0.213)		(0.194)
Female cow ownership		0.120		0.137
		(0.183)		(0.186)
Laying hen ownership		0.118		0.130
		(0.126)		(0.128)

Table 7 (cont.): Fixed-effects regression results predicting a change in…

Milking cow ownership		-0.284		-0.266
		(0.215)		(0.204)
Main road access			0.281*	0.278*
			(0.166)	(0.160)
Large weekly market			0.052	0.036
			(0.198)	(0.186)
Place to buy basic medicines			-0.006	-0.084
			(0.166)	(0.158)
Health post			0.110	0.089
			(0.207)	(0.198)
Observations	1994	1994	1994	1994
Adjusted R2	0.005	0.016	0.013	0.035

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 7a: Fixed-effects regression results predicting a change in WHZ, by baseline status (standard errors in parentheses)

	Wasted at Baseline				Not Wasted at Baseline			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Ill in last 2 months	-0.603*			-0.355	-0.054			-0.096
	(0.321)			(0.326)	(0.099)			(0.109)
Household size		0.102		0.068		0.031		0.020
		(0.122)		(0.142)		(0.073)		(0.073)
Age of household head		-0.053		-0.077*		0.005		0.008
		(0.042)		(0.045)		(0.014)		(0.014)
Solid roof		1.237**		1.283**		-0.242*		-0.200
		(0.518)		(0.496)		(0.142)		(0.158)
Improved toilet		0.411		0.628		0.033		0.072
		(0.399)		(0.407)		(0.113)		(0.113)
Improved water source		0.236		0.223		-0.165		-0.185
		(0.319)		(0.298)		(0.112)		(0.116)
Asset Index		-0.065		-0.047		0.046		0.046
		(0.076)		(0.074)		(0.030)		(0.030)
Months of food insecurity, last 12m		0.090		0.096		0.011		0.013
		(0.078)		(0.076)		(0.042)		(0.041)
Received food assistance, last 12m		0.903***		0.631**		-0.301		-0.346
		(0.302)		(0.316)		(0.216)		(0.213)
Food price shock, last 12m		0.188		0.386		0.112		0.111
		(0.307)		(0.305)		(0.156)		(0.160)
Natural disaster, last 12m		-0.290		-0.406		-0.269		-0.266
		(0.261)		(0.285)		(0.216)		(0.209)

Table 7a. (cont.): Fixed-effects regression results predicting a change in WHZ, by baseline status (standard errors in parentheses)

Agricultural inputs price shock, last 12m		0.290		0.245		0.196		0.184
		(0.427)		(0.502)		(0.122)		(0.123)
Loss of livestock, last 12m		0.436		0.496		0.308		0.286
		(0.529)		(0.557)		(0.213)		(0.207)
Household member death/illness, last 12m		-1.030***		-1.120***		0.318**		0.303**
		(0.268)		(0.290)		(0.135)		(0.133)
Female cow ownership		0.129		0.093		0.027		0.039
		(0.357)		(0.371)		(0.143)		(0.147)
Laying hen ownership		-0.153		-0.079		0.134		0.143
		(0.384)		(0.366)		(0.114)		(0.116)
Milking cow ownership		-0.380		-0.243		-0.274		-0.262
		(0.320)		(0.319)		(0.196)		(0.191)
Main road access			0.170	0.384*			0.236	0.237
			(0.268)	(0.197)			(0.156)	(0.146)
Large weekly market			0.079	0.289			-0.007	-0.043
			(0.334)	(0.210)			(0.186)	(0.167)
Place to buy basic medicines			-0.265	-0.729***			0.064	-0.006
			(0.253)	(0.245)			(0.156)	(0.140)
Health post			-0.724*	0.037			0.077	0.061
			(0.364)	(0.376)			(0.195)	(0.173)
Observations	247	247	247	247	1747	1747	1747	1747
Adjusted R2	0.736	0.824	0.730	0.844	0.067	0.109	0.078	0.118

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 8: Fixed-effects regression results predicting a change in wasting status for Panel A (standard errors in parentheses)

	Individual	Household	Community	Full Model
	1	2	3	4
Ill in last 2 months	0.058			0.068*
	(0.037)			(0.035)
Household size		0.009		0.012
		(0.021)		(0.020)
Age of household head		-0.004		-0.004
		(0.005)		(0.005)
Solid roof		0.133***		0.132***
		(0.049)		(0.051)
Improved toilet		0.037		0.029
		(0.033)		(0.036)
Improved water source		-0.050		-0.043
		(0.033)		(0.032)
Asset Index		-0.003		-0.003
		(0.010)		(0.010)
Months of food insecurity, last 12m		0.009		0.008
		(0.013)		(0.013)
Received food assistance, last 12m		-0.061		-0.052
		(0.054)		(0.054)
Food price shock, last 12m		-0.050		-0.062
		(0.039)		(0.039)
Natural disaster, last 12m		-0.036		-0.018
		(0.047)		(0.044)
Agricultural inputs price shock, last 12m		0.007		0.016
		(0.045)		(0.045)
Loss of livestock, last 12m		-0.042		-0.058
		(0.067)		(0.065)
Household member death/illness, last 12m		0.016		0.017
		(0.060)		(0.056)
Female cow ownership		0.029		0.026
		(0.044)		(0.044)
Laying hen ownership		-0.002		-0.009
		(0.026)		(0.027)
Milking cow ownership		0.014		0.014
		(0.049)		(0.047)
Main road access			-0.048	-0.041
			(0.038)	(0.037)
Large weekly market			-0.045	-0.034
			(0.043)	(0.039)
Place to buy basic medicines			0.053	0.065*
			(0.038)	(0.037)
Health post			-0.036	-0.009
			(0.038)	(0.039)
Observations	1994	1994	1994	1994
Adjusted R2	0.038	0.053	0.048	0.071

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 8a: Fixed-effects regression results predicting a change in wasting status, by baseline status (standard errors in parentheses)

	Wasted at Baseline				Not Wasted at Baseline			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Ill in last 2 months	0.077			-0.027	0.014			0.021
	(0.087)			(0.084)	(0.018)			(0.020)
Household size		-0.013		0.008		-0.005		-0.005
		(0.036)		(0.045)		(0.011)		(0.010)
Age of household head		0.009		0.014		-0.006		-0.006*
		(0.010)		(0.010)		(0.004)		(0.003)
Solid roof		0.021		-0.015		0.083**		0.093**
		(0.105)		(0.101)		(0.039)		(0.040)
Improved toilet		-0.278*		-0.310*		0.000		-0.004
		(0.163)		(0.173)		(0.029)		(0.027)
Improved water source		-0.160**		-0.140*		-0.017		-0.012
		(0.080)		(0.076)		(0.025)		(0.024)
Asset Index		-0.004		0.002		-0.004		-0.004
		(0.024)		(0.022)		(0.007)		(0.006)
Months of food insecurity, last 12m		0.002		0.005		0.000		0.000
		(0.022)		(0.023)		(0.008)		(0.008)
Received food assistance, last 12m		-0.045		-0.040		-0.020		-0.020
		(0.110)		(0.143)		(0.034)		(0.032)
Food price shock, last 12m		-0.219**		-0.266***		-0.013		-0.023
		(0.090)		(0.099)		(0.032)		(0.032)
Natural disaster, last 12m		0.066		0.117		-0.012		-0.002
		(0.088)		(0.085)		(0.043)		(0.040)

Table 8a (cont.): Fixed-effects regression results predicting a change in wasting status, by baseline status (standard errors in parentheses)

Agricultural inputs price shock, last 12m		-0.121		-0.095		0.011		0.021
		(0.145)		(0.171)		(0.031)		(0.030)
Loss of livestock, last 12m		0.025		0.012		-0.018		-0.034
		(0.140)		(0.146)		(0.048)		(0.047)
Household member death/illness, last 12m		0.216**		0.271***		-0.057		-0.056
		(0.085)		(0.099)		(0.038)		(0.038)
Female cow ownership		0.176*		0.179*		0.040		0.040
		(0.090)		(0.098)		(0.031)		(0.031)
Laying hen ownership		-0.104		-0.098		0.004		-0.004
		(0.086)		(0.084)		(0.017)		(0.019)
Milking cow ownership		0.165		0.151		0.013		0.017
		(0.124)		(0.117)		(0.032)		(0.031)
Main road access			-0.055	-0.075			-0.020	-0.017
			(0.067)	(0.055)			(0.031)	(0.028)
Large weekly market			-0.058	-0.103			-0.022	-0.009
			(0.077)	(0.072)			(0.036)	(0.032)
Place to buy basic medicines			-0.059	0.123			0.058*	0.067**
			(0.094)	(0.075)			(0.030)	(0.030)
Health post			0.102	-0.015			-0.007	0.008
			(0.094)	(0.139)			(0.018)	(0.022)
Observations	247	247	247	247	1747	1747	1747	1747
Adjusted R2	0.820	0.871	0.821	0.877	0.068	0.089	0.085	0.109

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 9: Fixed-effects regression results predicting a change in weight-for-age z-score for Panel A (standard errors in parentheses)

	Individual	Household	Community	Full Model
	1	2	3	4
Ill in last 2 months	-0.377***			-0.373***
	(0.118)			(0.115)
Household size		-0.063		-0.082
		(0.071)		(0.071)
Age of household head		0.006		0.007
		(0.018)		(0.017)
Solid roof		0.048		0.021
		(0.186)		(0.184)
Improved toilet		0.084		0.064
		(0.101)		(0.103)
Improved water source		-0.103		-0.124
		(0.118)		(0.118)
Asset Index		0.005		0.008
		(0.026)		(0.026)
Months of food insecurity, last 12m		0.041		0.038
		(0.039)		(0.038)
Received food assistance, last 12m		0.037		0.040
		(0.149)		(0.162)
Food price shock, last 12m		-0.208		-0.157
		(0.153)		(0.152)
Natural disaster, last 12m		0.004		-0.011
		(0.124)		(0.129)
Agricultural inputs price shock, last 12m		0.037		0.026
		(0.126)		(0.131)
Loss of livestock, last 12m		0.079		0.110
		(0.246)		(0.241)
Household member death/illness, last 12m		-0.201		-0.147
		(0.185)		(0.177)
Female cow ownership		0.279		0.273
		(0.188)		(0.185)
Laying hen ownership		-0.067		-0.043
		(0.108)		(0.109)
Milking cow ownership		-0.015		-0.018
		(0.122)		(0.121)
Main road access			0.081	0.131
			(0.095)	(0.094)
Large weekly market			-0.068	-0.066
			(0.114)	(0.113)
Place to buy basic medicines			-0.085	-0.085
			(0.115)	(0.117)
Health post			-0.093	-0.132
			(0.154)	(0.166)
Observations	2115	2115	2115	2115
Adjusted R2	0.027	0.021	0.010	0.041

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted

to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 9a: Fixed-effects regression results predicting a change in WAZ, by baseline status (standard errors in parentheses)

	Underweight at Baseline				Not Underweight at Baseline			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Ill in last 2 months	-0.354			-0.330	-0.226**			-0.255***
	(0.290)			(0.274)	(0.094)			(0.094)
Household size		0.094		0.106		-0.032		-0.054
		(0.121)		(0.108)		(0.066)		(0.064)
Age of household head		-0.018		-0.026		0.004		0.009
		(0.051)		(0.054)		(0.016)		(0.016)
Solid roof		0.080		0.053		-0.087		-0.137
		(0.400)		(0.409)		(0.159)		(0.165)
Improved toilet		-0.147		-0.131		0.162		0.137
		(0.193)		(0.203)		(0.106)		(0.105)
Improved water source		0.069		0.046		0.029		0.017
		(0.254)		(0.250)		(0.106)		(0.108)
Asset Index		-0.037		-0.026		0.022		0.022
		(0.054)		(0.053)		(0.026)		(0.026)
Months of food insecurity, last 12m		0.117*		0.111*		0.030		0.027
		(0.065)		(0.065)		(0.035)		(0.035)
Received food assistance, last 12m		0.944**		0.735*		-0.257**		-0.215*
		(0.391)		(0.420)		(0.127)		(0.113)
Food price shock, last 12m		-0.431*		-0.296		-0.194		-0.188
		(0.251)		(0.275)		(0.118)		(0.119)
Natural disaster, last 12m		-0.143		-0.240		0.030		0.065
		(0.297)		(0.294)		(0.121)		(0.127)

Agricultural inputs price shock, last 12m		-0.122		-0.124		-0.066		-0.071
		(0.280)		(0.280)		(0.128)		(0.130)
Loss of livestock, last 12m		-0.002		-0.026		0.287*		0.295*
		(0.466)		(0.448)		(0.158)		(0.164)
Household member death/illness, last 12m		-0.528*		-0.493*		0.093		0.157
		(0.307)		(0.292)		(0.148)		(0.149)
Female cow ownership		0.072		0.051		0.258		0.265
		(0.264)		(0.243)		(0.168)		(0.165)
Laying hen ownership		0.134		0.166		-0.016		-0.009
		(0.231)		(0.229)		(0.098)		(0.097)
Milking cow ownership		-0.254		-0.167		-0.052		-0.067
		(0.332)		(0.322)		(0.115)		(0.116)
Main road access			0.166	0.172			0.085	0.114
			(0.204)	(0.204)			(0.094)	(0.090)
Large weekly market			-0.245	-0.224			-0.098	-0.124
			(0.226)	(0.265)			(0.117)	(0.123)
Place to buy basic medicines			-0.383**	-0.394*			0.053	0.047
			(0.172)	(0.200)			(0.118)	(0.114)
Health post			-0.217	0.028			-0.207	-0.261*
			(0.351)	(0.410)			(0.133)	(0.146)
Observations	594	594	594	594	1521	1521	1521	1521
Adjusted R2	0.320	0.361	0.326	0.379	0.183	0.197	0.181	0.215

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 10: Fixed-effects regression results predicting a change in underweight status for Panel A (standard errors in parentheses)

	Individual	Household	Community	Full Model
	1	2	3	4
Ill in last 2 months	0.071*			0.069*
	(0.040)			(0.039)
Household size		0.011		0.018
		(0.025)		(0.025)
Age of household head		-0.004		-0.004
		(0.005)		(0.005)
Solid roof		-0.038		-0.043
		(0.065)		(0.066)
Improved toilet		-0.011		-0.013
		(0.045)		(0.043)
Improved water source		0.038		0.048
		(0.040)		(0.040)
Asset Index		0.001		0.002
		(0.009)		(0.009)
Months of food insecurity, last 12m		0.006		0.038
		(0.011)		(0.011)
Received food assistance, last 12m		-0.008		0.040
		(0.048)		(0.049)
Food price shock, last 12m		0.010		-0.157
		(0.057)		(0.056)
Natural disaster, last 12m		-0.016		-0.010
		(0.044)		(0.044)
Agricultural inputs price shock, last 12m		-0.026		0.026
		(0.056)		(0.056)
Loss of livestock, last 12m		-0.032		0.110
		(0.072)		(0.071)
Household member death/illness, last 12m		0.064		-0.147
		(0.056)		(0.055)
Female cow ownership		-0.048		-0.050
		(0.061)		(0.058)
Laying hen ownership		-0.001		-0.006
		(0.040)		(0.040)
Milking cow ownership		-0.009		-0.016
		(0.050)		(0.051)
Main road access			-0.039	-0.055*
			(0.031)	(0.029)
Large weekly market			-0.009	-0.011
			(0.042)	(0.040)
Place to buy basic medicines			-0.085	-0.009
			(0.035)	(0.036)
Health post			0.024	0.034
			(0.048)	(0.051)
Observations	2115	2115	2115	2115
Adjusted R2	0.019	0.016	0.015	0.024

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted

to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Table 10a: Fixed-effects regression results predicting a change in underweight status, by baseline status (standard errors in parentheses)

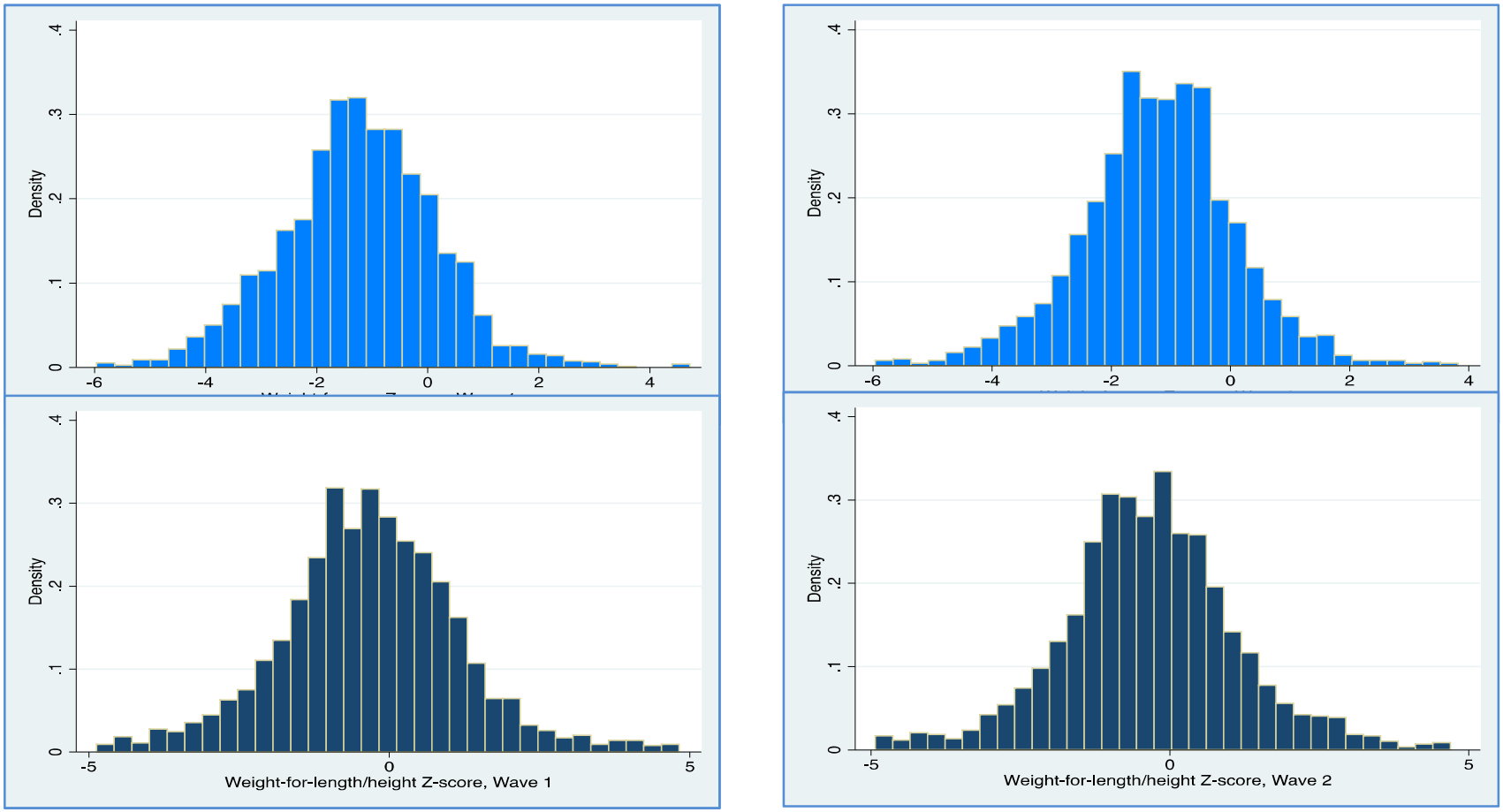
	Underweight at Baseline				Not Underweight at Baseline			
	Individual	**Household**	**Community**	**Full Model**	**Individual**	**Household**	**Community**	**Full Model**
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Ill in last 2 months	0.061			0.016	0.011			0.009
	(0.083)			(0.096)	(0.037)			(0.032)
Household size		0.029		0.028		-0.019		-0.013
		(0.060)		(0.061)		(0.019)		(0.018)
Age of household head		-0.009		-0.009		0.002		0.001
		(0.016)		(0.017)		(0.004)		(0.004)
Solid roof		-0.097		-0.089		0.008		0.012
		(0.132)		(0.133)		(0.054)		(0.058)
Improved toilet		0.057		0.062		-0.036		-0.041
		(0.086)		(0.091)		(0.034)		(0.034)
Improved water source		0.039		0.044		-0.027		-0.009
		(0.086)		(0.090)		(0.043)		(0.046)
Asset Index		0.007		0.007		-0.001		0.000
		(0.020)		(0.020)		(0.009)		(0.009)
Months of food insecurity, last 12m		-0.022		-0.021		0.002		(0.010)
		(0.021)		(0.021)		(0.010)		(0.010)
Received food assistance, last 12m		-0.230		-0.254*		0.083		0.076
		(0.153)		(0.152)		(0.056)		(0.050)
Food price shock, last 12m		0.133		0.135		-0.033		-0.027
		(0.097)		(0.110)		(0.046)		(0.046)
Natural disaster, last 12m		0.044		0.038		-0.003		-0.007
		(0.111)		(0.108)		(0.040)		(0.040)

Agricultural inputs price shock, last 12m		0.043		0.031		0.005		0.007
		(0.107)		(0.111)		(0.060)		(0.061)
Loss of livestock, last 12m		0.018		0.024		-0.103		-0.100
		(0.091)		(0.093)		(0.067)		(0.065)
Household member death/illness, last 12m		0.130		0.115		-0.001		-0.007
		(0.097)		(0.101)		(0.051)		(0.051)
Female cow ownership		0.003		0.005		-0.033		-0.032
		(0.090)		(0.090)		(0.046)		(0.047)
Laying hen ownership		0.002		-0.005		-0.058*		-0.064**
		(0.080)		(0.081)		(0.031)		(0.031)
Milking cow ownership		0.082		0.077		0.002		-0.009
		(0.116		(0.118)		(0.053)		(0.051)
Main road access			-0.023	0.004			-0.067***	-0.074***
			(0.080)	(0.079)			(0.025)	(0.024)
Large weekly market			0.010	-0.014			0.004	0.008
			(0.094)	(0.098)			(0.036)	(0.037)
Place to buy basic medicines			-0.014	-0.036			-0.019	-0.003
			(0.062)	(0.067)			(0.031)	(0.034)
Health post			0.127	0.068			0.059	0.062
			(0.129)	(0.147)			(0.045)	(0.048)
Observations	594	594	594	594	1521	1521	1521	1521
Adjusted R2	0.390	0.405	0.388	0.401	0.176	0.193	0.193	0.209

Notes: *** p<0.01, ** p<0.05, * p<0.1. Fixed effect regressions with standard errors (in parentheses) adjusted for clustering and stratification. Observations are weighted to be representative of all rural and small town children. The panel sample consists of individuals 6-41 months at baseline and 24-59 months at follow-up, and thus were 6-59 months at both baseline and follow-up. The set of independent variables included in each column was restricted to those variables for which at least 10% of the sample experienced a change between Waves 1 and 2. Variables excluded due to this criterion include grandchild of household head, maternal literacy, male household head, dirt floor, and PSNP presence. All columns control for child's age in months, months squared, and months cubed.

Figures

Figure 1: Weight-for-age and weight-for-height z-scores, waves 1 and 2



Nonfarm Enterprises in Rural Ethiopia: Improving Livelihoods by Generating Income and Smoothing Consumption?

Julia Kowalski[1], Alina Lipcan[2], Katie McIntosh[2], Remy Smida[3], Signe Jung Sørensen[4], Ilana Seff[5], and Dean Jolliffe[6]

Abstract

In developing countries highly dependent on agriculture, non-farm enterprises (NFEs) are often lauded as income diversification opportunities, helping to smooth income in the farming off-seasons. Using data from the first wave of the Ethiopia Socioeconomic Survey (ESS), a nationally representative survey of rural and small town Ethiopia, we explore the role NFEs play in seasonal income generation, consumption smoothing, and risk mitigation. We find that NFEs are in fact pro-cyclical with agriculture, with the most productive months of NFE operation coinciding with the harvest season and crop sales. This pro-cyclicality appears to be driven by demand-side factors, where increases in community income through crop sales generate higher demand for NFE goods and services. We also find no evidence that households operating NFEs are better able to ward off incidence or duration of food insecurity in the face of shocks, suggesting NFEs do not insure temporally vulnerable households against risks.

Keywords: Ethiopia, LSMS, non-farm enterprises, income diversification
JEL Codes: I32, E21, O12

---

[1] Bank of England, London, UK
[2] Oxford Policy Management, Oxford, UK
[3] Brunswick Group, London, UK
[4] Ark Education Partnerships Group, London, UK
[5] Department of Population and Family Health, Columbia University; Mailman School of Public Health, New York, NY, USA
[6] World Bank, Washington, DC, USA

Acknowledgements: The authors are grateful to the UK Department for International Development Ethiopia and Tim Conway for generous funding assistance. The authors would also like to thank Tassew Woldehanna, Assefa Admassie, Solomon Shiferaw, and Alemayehu Seyoum Taffesse for their generous insight and feedback and Demirew Getachew and Tadele Ferede for their support in the dissemination of this paper. We also thank two anonymous referees for excellent comments.

1. Introduction

Accounting for an estimated 35-50% of rural household earnings in the developing world and an average of 34% of rural earnings across Africa (Haggblade *et al.*, 2010), the rural nonfarm sector matters for development. Nonfarm enterprises (NFEs), in particular, have been hailed as an instrument of rural growth (Davis *et al.*, 2010; Prahalad, 2005). Studies throughout sub-Saharan Africa also show that NFE operation is positively correlated with household welfare, though the direction of causality is still unclear (Fox & Sohnesen, 2012). The growth-wielding potential of NFEs have made them an integral component of the development research agenda in recent years.[7]

In Ethiopia, studies show that participation in NFEs has risen from 23% in 1998 to 34% in 2006 (Loening *et al.* 2008).[8] Growth in the nonfarm sector coincides with recent positive economic developments in the country, which has seen rapid economic expansion in recent years. Annual per capita GDP growth rates ranged from 4.0% to 9.8% over the past ten years (African Development Bank Group, 2014), and the country's poverty headcount ratio has fallen from 45.5% in 1995 to 29.6% in 2011 (World Bank, 2014). The question exists as to what role nonfarm enterprises might have played in bringing about this progress. Moreover, the Ethiopian government has included developing the micro and small enterprise sector as an objective of its Growth and Transformation Plan (MoFED, 2010).

1.1. NFEs, seasonality, and risk mitigation

One claim made in the literature about NFEs, which we explore in this paper in the context of Ethiopia, suggests they may represent an income smoothing opportunity (Loening *et al.*, 2008). This claim is driven by the potential of NFEs to provide diversified income sources when agricultural earnings are

[7]See numerous studies conducted over the past two decades on NFEs in west Africa using IRD-DIAL's innovative 1-2-3 surveys.

[8]NFEs are defined as any income generating business a household operates which does not involve the primary production of crops or livestock. Included in this definition of NFEs are activities that add value to primary production, such as the processing of agricultural by-products.

low, thereby mitigating income risk (Davis et al., 2010). Agricultural production is highly seasonal, creating substantial income fluctuations throughout the year. Although households engaged in agriculture can generate sizeable income streams to support consumption during the harvest season when yields are high, these income streams diminish as agricultural activity declines. This often leaves households vulnerable to food insecurity during the lean season. NFEs are hypothesized to provide an opportunity for households to smooth consumption, insofar as returns from nonfarm activity are uncorrelated or negatively correlated with the returns to agricultural production (Haggblade *et al.*, 2010). This would enable households to draw upon alternative income sources outside of the agricultural season to sustain their consumption levels. By generating household income during the agricultural off-season, NFE ownership may also create a buffer for households to rely on in the face of negative shocks, thus reducing vulnerability.

NFEs may also provide further means of risk diversification in the face of aggregate shocks to agricultural production, such as drought. Aggregate shocks weaken the alleviating role of informal mutual assistance networks, and in the absence of well-functioning insurance markets, nonfarm enterprises may act as insurance mechanisms for households. Thus, when agricultural income falls short, households can channel their capital and labor into NFEs and utilize this alternative method of income generation to replace lost agricultural income in part or in full. The risk-mitigating opportunities that NFEs may provide are also linked to the issue of food security; they may reduce a household's within-year variability of the capacity to purchase or produce food. Therefore, food security can be improved if households have access to alternative income sources in the face of low agricultural earnings or agricultural shocks (Owusu *et al.*, 2010; Ali and Peerlings, 2012; Barrett *et al.*, 2001).

Alternatively, since agricultural production still represents the largest rural economic activity in developing countries, the rural nonfarm sector may display strong dependency links to the agricultural economy (Haggblade *et al.*, 1989; Reardon *et al.*, 1994). Therefore, just as the growth of the nonfarm

sector may depend on the growth of agricultural productivity, the income generating, and thus consumption smoothing, potential of NFEs may depend on the timing of and profits generated by agricultural production. Strong links with the agricultural economy may cause streams from nonfarm enterprise operation to be highly cyclical and correlated with agriculture (Haggblade *et al.*, 2010), making them an insufficient means by which to smooth consumption.

Furthermore, if NFE income is strongly dependent on agricultural activity, NFEs may not provide an effective means of risk mitigation in the face of aggregate shocks to agriculture. There are two reasons for this, one being a supply-side problem and the other being a demand-side problem. First, in the absence of efficient credit markets, if agricultural income is insufficient, households may not have the capital necessary to invest in starting or growing an NFE (Reardon *et al.*, 1994). Second, operating an NFE in an agricultural economy may be heavily dependent on the demand for nonfarm products and services, which is generated by earnings from agricultural production (Rijkers *et al.*, 2008). Therefore, the effectiveness of using NFEs as insurance against risks remains uncertain and context-dependent. For example, if starting an NFE is highly dependent on an initial injection of agriculture income, or vice versa, then one could argue that operating a farm and an NFE are not necessarily diversifying; a threat to one activity is also a threat to the other.

1.2 NFEs in Ethiopia

There is some evidence from Ethiopia suggesting households might use NFEs to complement farming income during the agricultural off seasons. Loening *et al.* (2008) find NFE activity to be seasonal but countercyclical with agriculture, providing an alternative source of household income during times of low agricultural activity. However, the magnitude of additional income provided is called into question by the authors, who point to the small size as well as low productivity of NFEs. Conversely, risk diversification effects of NFEs are found to be low by Rijkers and Söderbom (2013) using the same RICS-Amhara data as Ali and Peerlings (2012),

matched with precipitation-based measures of risk. They show that the likelihood of operating an NFE and the returns to NFE operation are highly correlated with agricultural productivity shocks, thus providing only limited opportunities to smooth income across agricultural fluctuations. They infer that a good harvest is favorable to NFE activity through increasing local demand, but that NFE operation is not effective in mitigating weather risk. They also find that *ex-ante*, there is no strong link between vulnerability to shocks and NFE ownership.

Overall, the existing theoretical literature on the nonfarm sector, as well as the empirical findings on NFEs in Ethiopia display mixed findings on the role that they play in mitigating risk and smoothing consumption. In addition, evidence has been collected largely based on data with incomplete coverage of Ethiopia as a whole. Past research on NFEs and the nonfarm sector in Ethiopia has focused on Amhara (Ali and Peerlings, 2012; Rijkers and Söderbom, 2013) or Tigray (Woldenhanna and Oskam, 2001), or on a sample that otherwise covers less of the entire rural population (Loening *et al.*, 2008; Bezu *et al.*, 2012). The wider coverage of the survey data we use allows us to make very careful inferences about the situation of NFEs in rural Ethiopia. Moreover, since we use survey data from 2011-2012, our analysis reflects recent information on NFEs in rural Ethiopia, which carries great relevance for current policy.

Therefore, the aim of our analysis is to update and expand insight into the role of NFEs in Ethiopia. Using nationally representative data we are able to provide a clearer and more comprehensive picture of nonfarm enterprises in rural Ethiopia and the households that operate them. The analysis of NFEs presented hereafter broadly yields two main findings. Firstly, nonfarm enterprises are largely pro-cyclical with agriculture; the highest months of NFE activity coincide with the harvest season and the sale of crops. Further analysis suggests this dependency is driven by both supply and demand side links to agricultural income; though evidence implies demand-driven factors may more fully explain this pro-cyclicality. Secondly, we find income from NFEs does not temporally complement agricultural income or help households to generate steady streams of income throughout the year. We

find no evidence that households operating NFEs are better off in the face of shocks or food insecurity, reinforcing the notion that NFEs do not significantly contribute to risk mitigation or consumption smoothing.
The remainder of this report is structured as follows. Section 2 outlines the data used in this study. Section 3 presents descriptive statistics on NFEs, their temporal operation, and supply vs. demand driven seasonality. Section 4 presents results on the risk-mitigating potential of NFEs. Finally, section 5 concludes.

2. Data

This paper uses data from the first wave of the Ethiopian Socioeconomic Survey (ESS1), which is part of an ongoing collaborative project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study – Integrated Surveys of Agriculture (LSMS-ISA) team.[9] The survey contains detailed individual, household, and community-level data, ranging from information on household and agricultural activities to human capital, access to services, and food security. The ESS1 was implemented in 290 rural and 43 small town enumeration areas (EAs), which cover all regional states apart from Addis Ababa and are nationally representative of all rural and small town areas in Ethiopia[10]. Small towns are defined as those with a population estimate of less than 10,000 according to the 2007 population census.

The sampling followed a two-stage design, stratified at the regional level.[11] The first stage of sampling selected primary sampling units from the sample of CSA EAs, which had been selected based on probability proportional to

[9] The ESS1 survey was conducted in three rounds. The first round containing the post-planting agriculture questionnaire was conducted in September to October of 2011; the second round containing the livestock questionnaire was conducted in November to December of 2011; and the third round containing post-harvest agriculture, household, and community questionnaires was conducted from January to March 2012.
[10] Excluding three zones in the Afar region and six zones in the Somali region
[11] For more detailed information on the sampling design and survey set-up the reader is advised to consult the ESS1 survey documentation, available on the website of the World Bank's LSMS-Ethiopia.

size of the total EAs in each region. The second stage selected 12 households to be interviewed in each EA. In rural areas, ten of these households were randomly selected from the sample of 30 Annual Agricultural Sample Survey (AgSS) households, and were thus involved in farming or livestock activities. In addition, two households were randomly selected from all other households in the rural EA which were not involved in agriculture or livestock. In small towns these households were randomly selected without stratification based on household activities. Households were selected without replacement and the interview response rate amounted to 99.3%, yielding 3,969 household observations, all of which are weighted to represent the national-level population of rural and small town households of Ethiopia. The data is representative of five domains of analysis (DOA), which include the regions of Amhara, Oromiya, SNNP, and Tigray. The sample is insufficient to support region-specific estimates for the smaller regions of Afar, Benishangul, Gumuz, Dire Dawa, Gambella, Harari and Somalie, which are all combined to represent "Other".

A final note concerns the definition of NFEs as used in the ESS household survey question identifying ownership of NFEs. This definition closely matches the definition set out in the introduction of this paper, and defines NFE ownership as the operation of a nonfarm enterprise involved in the provision of non-agricultural services such as carpentry, the processing and sale of agricultural by-products such as flour, trade, professional services, transportation services, and food services. This operationalization of the definition of NFE ownership is similar to that of Rijkers and Söderbom (2013), and consistent with the broader literature, allowing for comparability of results. A household was considered to operate an NFE in the survey if it reported to have operated one or more of these types of enterprises in the twelve months prior to the survey, including those ventures that had been shut down permanently or temporarily during that time.

2. NFEs and seasonality

Descriptive statistics on NFE characteristics can be found in Appendix Table S1. The ESS1 data indicate that 20% of households in rural and small town Ethiopia own at least one NFE.[12]NFE participation rates are significantly higher in small towns than in rural areas, with 54.8% of small town households operating at least one NFE, compared to 19.9% of households in rural areas.[13] While there is no difference in real consumption per capita for individuals from households that do and do not operate NFEs, we do observe a slight increase in NFE participation for households in higher welfare quintiles.[14] However, these results may be partially driven by the fact that NFEs are more prevalent in small towns, where the average household consumes significantly more than its rural counterpart.

Table 1 provides an overview of household characteristics among NFE and non-NFE households, for the overall sample as well as rural and small town areas. Overall, the average household head from an NFE household is significantly younger (45 vs. 41 years old) and has more education (2.4 vs. 1.7 years) than a head whose household does not operate an NFE. However, we find that this pattern is reversed when restricting the analysis to small towns; there, household heads from NFE-operating households have approximately half the years of schooling reported by non-NFE household heads (4.2 vs. 7.5 years). NFE and non-NFE households are equally likely

[12] This figure is slightly lower than the NFE participation rate of 25% estimated by Loening *et al.* (2008) for the four largest regions of Oromiya, Tigray, SNNP and Amhara.[12] It also varies from Woldenhanna and Oskam (2001) who estimate that 28% of households. These discrepancies may be a result of the ESS1' wider regional coverage, the data's lack of urban coverage, variation in NFE activity across different years, or general time trends.

[13] The primary income-generating activities in rural and small town areas are agricultural activities and wage employment, respectively.

[14] The annual consumption aggregate used is the publicly available aggregate released by the LSMS team at the time of the analysis. Annual consumption expenditures include annualized measures of food consumption over the past 7 days, non-food expenditures, and educational expenditures, indexed for regional spatial price. Welfare quintiles are derived from adult equivalent annual consumption expenditures.

to have female heads in rural areas, but NFE households in small towns are more likely to have a female head than are non-NFE households (38 vs. 29 percent, respectively). Not surprisingly, households engaged in the NFE sector own fewer sheep and cattle than households without an NFE. Real annual expenditure per adult equivalent is higher among NFE households, as compared to non-NFE households, in rural areas, but is higher in non-NFE households in small towns, though neither difference is statistically significant.[15]

[15] The overall annual mean difference is 289 Birr, which is approximately US $17 if converted at the average market exchange rate for 2011, or US $53.5 if converted using 2011 purchasing power parity factors. Rijker and Söderbom's (2012) find similar results in their study of Amhara in which households that run an NFE are not found to have higher per adult annual expenditures than those households not engaged in Nativity.

Table 1: Socioeconomic characteristics of households by NFE ownership

	Overall			Small Town			Rural		
	NFE	**No NFE**	**Diff.**	**NFE**	**No NFE**	**Diff.**	**NFE**	**No NFE**	**Diff.**
	(1)	**(2)**	**(1)-(2)**	**(3)**	**(4)**	**(3)-(4)**	**(5)**	**(6)**	**(5)-(6)**
Household characteristics									
Size of HH	5.291	5.070	0.221	4.469	3.259	1.210***	5.315	5.081	0.234
	(0.127)	(0.062)		(0.151)	(0.195)		(0.130)	(0.062)	
Cattle per household	2.509	3.609	-1.100***	0.777	1.027	-0.250	2.560	3.625	-1.065***
	(0.193)	(0.180)		(0.329)	(0.517)		(0.199)	(0.181)	
Sheep per household	1.164	1.576	-0.412*	0.208	0.279	-0.071	1.192	1.584	-0.392**
	(0.183)	(0.144)		(0.060)	(0.096)		(0.189)	(0.145)	
Annual per adult equivalent	1,108.3	819.6	288.7	1,571.8	1,819.1	-247.3	1,097.2	816.8	280.4
expenditures (mean)	(220.2)	(48.6)		(135.6)	(232.0)		(225.2)	(48.8)	
Household head characteristics									
Age	40.703	45.394	-4.691***	42.998	37.388	5.610***	40.632	45.441	-4.809***
	(0.708)	(0.444)		(1.047)	(1.560)		(0.728)	(0.447)	
Female	0.188	0.205	0.017	0.383	0.293	0.090*	0.182	0.204	0.022
	(0.019)	(0.012)		(0.033)	(0.037)		(0.019)	(0.012)	
Years of schooling	2.347	1.672	0.675***	4.171	7.459	-3.288***	2.344	1.899	0.445**
	(0.172)	(0.122)		(0.274)	(0.663)		(0.147)	(0.101)	
Literate (%)	0.500	0.402	0.098**	0.626	0.705	-0.079	0.497	0.400	0.097**
	(0.032)	(0.019)		(0.037)	(0.052)		(0.033)	(0.019)	
Ever attended school (%)	0.467	0.338	0.129***	0.590	0.705	-0.115*	0.463	0.335	0.128***
	(0.028)	(0.020)		(0.031)	(0.053)		(0.029)	(0.020)	
Number of obs.	3,969			503			3,466		

Note: Standard errors in parentheses adjusted for EA clustering and stratification. Differences significant at *p<0.1, **p<0.05, and ***p<0.01.

3.1 NFE seasonality

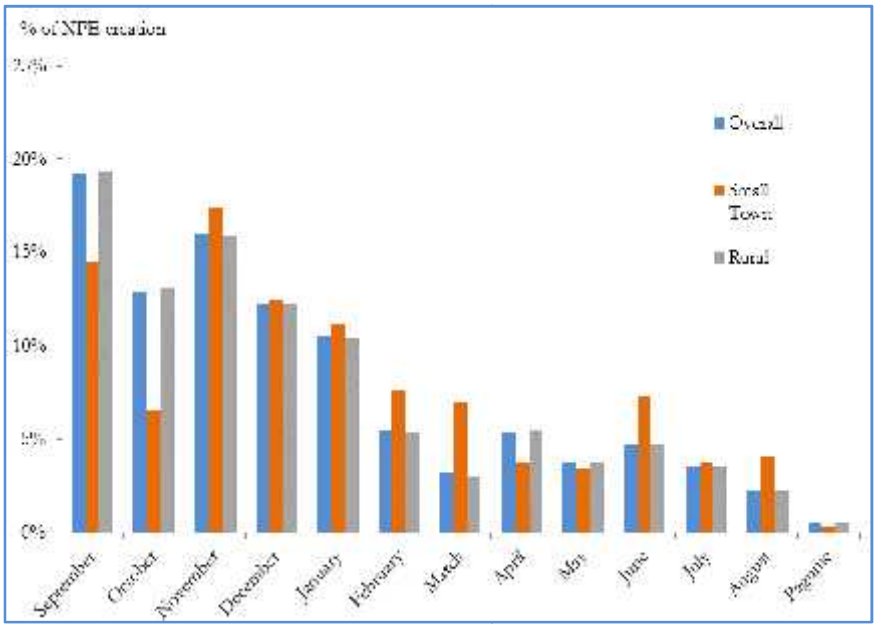
Overall, 53.4% of NFE-operating households reported that their NFEs operate seasonally. Reported seasonality differs significantly by subpopulation, with 33% of small town NFEs reporting to be seasonal compared to 54% of rural NFEs. Rural NFEs may plausibly experience one of two forms of seasonality. First, and perhaps most widely seen in the literature, households may channel excess labor supply into NFE activities during the agricultural off-season in order to generate alternative income streams throughout the year (Ellis, 2000). Employing the complementary seasonality of the two activities serves as an income diversification technique that can help smooth consumption across the year (Haggblade *et al.*, 2010). In this case we would expect to find NFE activity to be counter-cyclical with agricultural seasons. Second, households may be best able to generate income from NFEs during times when market demand for their goods is high, which is likely during and after the agricultural harvest when farmers are able to generate substantial income to expend (Reardon *et al.*, 1994).

We look further into the seasonality of NFEs and compare the timeline of NFE activity with the agricultural seasons. The main harvest period in Ethiopia, or the Meher season, typically occursfrom September to February. If NFE activity begins or peaks during the lean season, and thus is counter-cyclical with agriculture, we would have some *primafacie* evidence that NFEs aid households in smoothing consumption throughout the year. However, we observe the opposite temporal relationship between NFE and agricultural activities, with the timing of NFE activities strongly corresponding to the Meher season.

The ESS1 prompts respondents to report the month and year in which their NFE began operation; we find the month of inception largely coincides with the timing of the Meher season. As displayed in Figure 1, we observe that approximately 80% of NFEs first began operating between the months of September and January. NFE start-up rates gradually fall after November and remain lowest between the months of February and Pagume, which is

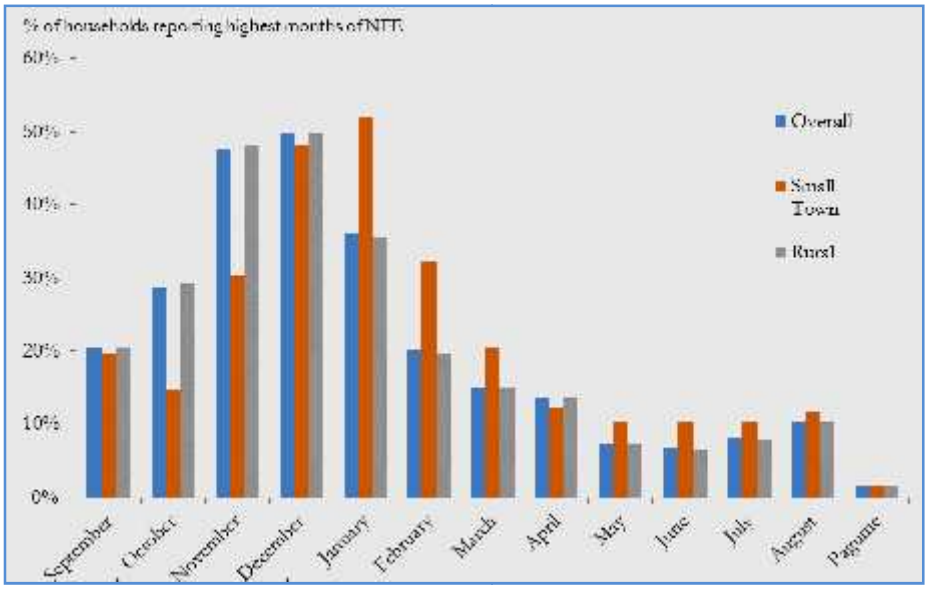
also the lean season. The variability in timing of NFE start-ups is slightly less pronounced in small towns than in rural areas, a finding that we would expect given that small town NFEs report less overall seasonality and are less strongly tied to agriculture.

Figure 1: Month in which NFE began operation



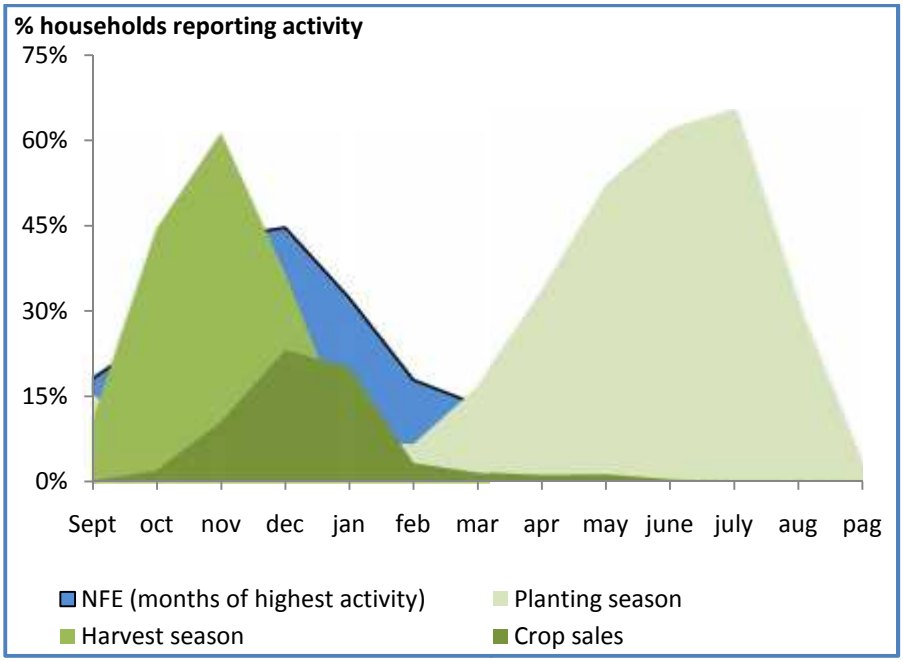
Second, we look at the results of a survey question that asked households in which months of the last year enterprise activity was highest. These findings are consistent with those on the timing of NFE start-ups, as the highest months of NFE activity largely correspond to the months with the highest NFE start-up rates, with a minor lag. Nonfarm enterprises tend to be most active during the months of November, December, and January, with 42.7%, 44.5%, and 32.2% of NFEs listing these as one of their three most important months of activity, respectively (see Figure 2). Conversely, NFE activity appears to be significantly lower from April to Pagume.

Figure 2: Highest months of NFE operation 2



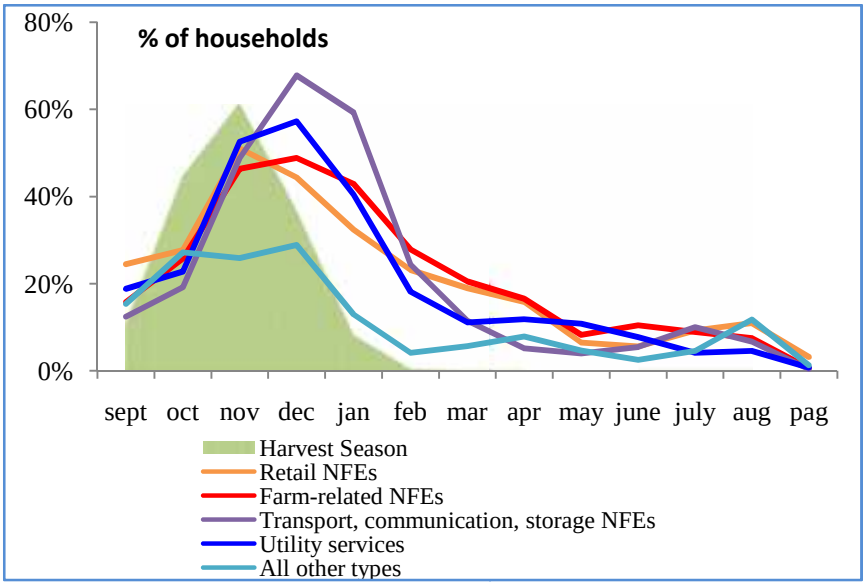
Despite minor differences in peak NFE activity between rural and small town populations, we find that the overall trends are the same and, further, that the timing of NFE activity strongly corresponds to the Meher harvest season (see Figure 3). The peak months for NFE activity line up with the harvest and crop sale seasons, peaking immediately after the harvest and almost simultaneously with the sale of crops. Furthermore, very few enterprises report high NFE activity during the months when planting season takes place.

Figure 3: NFE operation and agricultural seasons



These findings provide further evidence that NFE activity is pro-cyclical with agriculture. Rather than using NFEs to supplement periods of low agricultural income, households generate a disproportionately high influx of income from the months of October to January. Furthermore, this trend is observed across different NFE sectors. Even NFEs that do not rely on agricultural products as NFE inputs, such as retail and utility service enterprises, enjoy higher months of activity during and immediately after the Meher harvest (see Figure 4).

Figure 4: Harvest season and NFE operation, by type NFE sector



3.2 NFE seasonality and supply vs. demand

Expanding on the result that most NFEs are pro-cyclical with agriculture, and therefore not necessarily helping to generate an even stream of income throughout the year, we investigate the mechanisms through which NFE operation is linked to agricultural income. Agricultural income may encourage NFE activity through both supply-side and demand-side links. For example, NFEs may rely on agricultural income as a source of start-up funds or, alternatively, agricultural income might increase cash flow in the community, thus increasing the market demand for NFE goods.

On the supply-side, we find that most households rely on agricultural income to fund the creation of NFEs. Overall, agricultural income is reported as either the primary or secondary source of start-up capital for 64% of NFEs (see Table 2). The second most reported source of start-up capital is nonfarm self-employment income, noted as a primary or secondary source of funds by 18% of households. This result can be explained by the fact that some households operate multiple NFEs and may thus use the income from one NFE to start another. Our findings for agricultural start-up funds are

consistent with those of Loening et al. (2008), who found that agricultural income represented 60% of start-up capital for NFEs.[99]

Table 1: Source of start-up funds for NFEs

	Overall (1)	Small Town (2)	Rural (3)	Difference (2)-(3)
Agricultural income	0.642	0.137	0.657	0.520***
	(.030)	(.020)	(.031)	
NFE self-employment	0.175	0.369	0.169	0.200***
	(.024)	(.049)	(.025)	
Family/friends	0.116	0.312	0.111	0.201***
	(.018)	(.040)	(.018)	
Money Lender	0.076	0.095	0.076	0.019
	(.017)	(.027)	(.018)	
Microfinance	0.029	0.045	0.028	0.017
Institution	(.009)	(.013)	(.009)	
	0.016	0.088	0.014	0.074***
Wage employment	(.004)	(.020)	(.004)	
	0.003	0.005	0.003	0.002
Remittances	(.002)	(.003)	(.002)	
	0.009	0.011	0.009	0.002
Sale of assets	(.004)	(.006)	(.004)	
	0.006	0.014	0.006	0.008
Bank loan	(.003)	(.009)	(.003)	
	0.055	0.101	0.054	0.047
Other	(.011)	(.026)	(.011)	
N	1,315	345	970	

Note: Standard errors corrected for EA clustering and stratification in parentheses. Differences are significant at * $p< 0.10$, ** $p< 0.05$, *** $p< 0.01$. Columns do not sum to one as numbers account for the proportion of NFEs reporting each source as either a primary or secondary source of start-up capital.

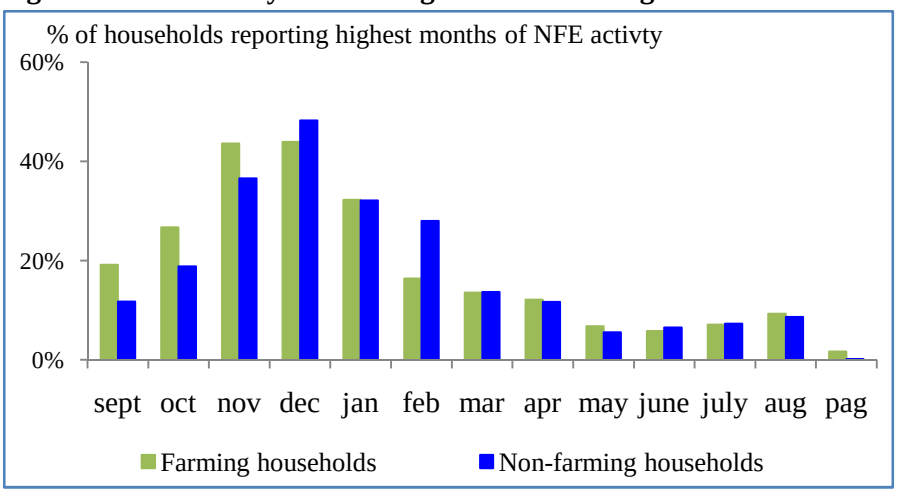
Rural NFEs, as compared to those in small town areas, tend to rely more heavily on agricultural income for start-up capital, with 65.7% of rural households citing agricultural income as a main source of funds for NFEs, as opposed to only 13.7% of small town households. Households in small

[99] However, they also find NFE self-employment to be of less importance and funding from family and friends to be more significant.

towns reported nonfarm self-employment income as the main source of start-up funds for NFEs, with 36.9% of NFE-operating households citing it as a main source, compared with only 16.9% in rural areas. The finding that small town NFEs rely less on agricultural start-up funds and display less seasonality suggests that the seasonality of NFE activity bears some relation to the supply-side effects of agricultural seasonality.

However, further exploration suggests that agricultural income's contribution to starting an NFE only partially explains the cyclical relationship between NFE and agriculture activity. Figure 5 demonstrates the temporal nature of NFEs for both farming and non-farming households. Although there is a statistically significant difference in the proportion of households reporting September, October, and November as a high month for NFE activity, there is no significant difference in the overall *trend* throughout the year for farming and non-farming households. Despite the fact that non-farm households don't rely on agricultural income to fund the operation of their NFEs, they still exhibit increased NFE activity from November to February.

Figure 5: NFE activity for farming and non-farming households



Therefore, we investigate the extent to which demand-side factors may be driving the seasonality of NFE activity by looking at the location and

customer base for these NFEs, as well as self-reported demand-side constraints to NFE growth. We find that NFEs tend to operate locally, selling to local customers, and are thus constrained by the limits of local market demand, which fluctuates with seasonally driven agricultural income. Approximately 30.4% of NFEs operate from inside the household residence, compared to only 7.9% that operate outside. The fact that over one-third of NFEs operate from home suggests that the market they serve is mainly local. These results do not differ significantly by rural and small town subpopulations, implying that differences identified in the seasonality of NFEs by subpopulation are driven to a large extent by differences in the nature of local demand, rather than fundamental variations in the nature of NFE operation. Furthermore, the customer base of for NFEs appears to comprise mainly of the market, local consumers or passers-by, and traders, further indicative of the local nature of the markets they serve.

The data also show that NFEs perceive low demand and a lack of access to better markets as the primary operational barriers. While almost 40% of NFEs identified access to markets as one of three main obstacles, another 21.0% and 16.9% viewed low demand and difficulty to obtain market information, respectively, as key constraints; the top three constraints identified, out of more than 30 categories, were all related to markets. This further affirms that local market demand, which is mainly driven by seasonal agriculture, is often insufficient to generate sizeable NFE income throughout the year.

4. NFEs and risk mitigation

The previous section casts doubt on NFEs' ability to smooth households' consumption, or at the very least to temper seasonal changes in income. This section explores whether there is any evidence suggesting that, despite these findings, NFEs still enable households to protect against shocks and avoid seasonal food insecurity. Due to the strong interdependence between agriculture and NFE activity, particularly in rural areas, we might conjecture that aggregate shocks affecting agricultural production would also dampen the success of NFEs. However, other studies suggest that NFEs may still be a useful tool for insuring households against idiosyncratic shocks and, if

employed as an income diversification tactic, may stave off food insecurity and other threats to well-being.

Using ESS1 data, we find no significant evidence that NFE households are better able to mitigate shocks, or that greater exposure to risk is associated with a higher likelihood of owning an NFE. Owning an NFE is not associated with the ability to better cope in the face of a shock. In the event of any negative shock in the previous 12 months, NFE and non-NFE households report statistically similar incidence of decreases in income (89 and 87 percent),assets (67 and 71 percent), and food purchases (58 and 54 percent).

We further assess the ability of NFEs to mitigate risk by looking specifically at the relationship between NFE ownership and food insecurity. We ask the following question based on the ESS1 survey: "Conditional on having been faced with severe shocks in the past 12 months, were NFE-owning households more or less likely to report experiencing food insecurity over this same period?". To answer this question, we estimate the following regression specification:

$$Pr(Fi)_h = \beta_0 + \beta_1 S_h + \beta_2 NFE_h + \beta_3 S_h \times NFE_h + \beta_4 Rural_h + \beta_5 Rural_h \times NFE_h + \beta_6 HHsize_h + \beta_7 Landsize_h$$

$Pr(Fi)_h$ is the probability that a household h has reported not having enough food to feed their family in the past 12 months; S_h indicates whether in the past 12 months the household has experienced a shock which it classified as one of the most severe of the year; NFE_h indicates whether the household operates a NFE; $Rural_h$ is a dummy variable equal to 1 if the household resides in a rural area, and 0 if the household resides in a small town; $HHsize_h$ controls for the size of the household, and $Landsize_h$controls for household landholdings, which are a proxy for asset wealth and agricultural production potential. We focus on the impact of shocks on food insecurity rather than household consumption because food insecurity is a widespread and persistent phenomenon in Ethiopia. Even in a year with enough rainfall, it is estimated that approximately 4-5 million Ethiopians depend on food aid

(Devereux 2006). As such, in Ethiopia, food security is perhaps a far more salient indicator of welfare than consumption.[100]

Table 3 reports the average marginal effects estimated using the above specification, which paints an interesting picture. According to Model 1, being exposed to a shock of any kind is associated with a 31 percentage point increase in the likelihood of being food insecure, implying that mean reported food insecurity increases to 63.3% in the presence of shocks. Model 2 breaks down the shock variable to capture only the most commonly experienced and severe shocks, a categorization which is almost identical to that in Dercon (2005). Model 2 suggests that the relationship between shocks and food insecurity is mostly driven by the incidence of weather shocks, price shocks, and crop damage. Idiosyncratic shocks are also significantly and positively correlated with food insecurity.

These findings are consistent with previous studies demonstrating that weather variation significantly affects food security (Rosenzweig *et al.* 1995; Demeke and Zeller 2009). They are also consistent with Dercon's (2005) study of the effect of shocks in the past five years on present consumption. Similar to our results, his study shows that weather shocks and personal idiosyncratic shocks have high and significant negative effects on household consumption. Moreover, Models 1 and 2 highlight that weather may not be solely responsible for food insecurity in Ethiopia. While the correlation between the different shock types may be high (as suggested by a general

[100]Whilst our measure of food insecurity is self-reported and endogenous, and as such certainly does not capture all facets of a complex concept, it does have advantages. Unlike measures of food supply, it also encompasses a household's access to food, bowing to Sen's distinction between supply and availability (Sen, 1981). We thus rely on respondents' statements to tell us whether food was not *enough* at any point in the last 12 months, with the advantage that information they provide is measured against personal and cultural norms and may better indicate respondents' sense of deprivation (Webb, 2006).We chose not to complement our subjective measure of food insecurity with an objective measure because of the nature of those objective indicators available in the data. The indicators of calorie consumption and food purchases in our data refer to the seven days prior to the survey (and thus do not account for seasonal variation). Additionally, information on the average number of meals per day is not directly linked to the nutritional value of those meals.

shock variable which is lower than the sum of the individual coefficients), the findings call for an investigation into what is causing food insecurity in Ethiopia other than weather shocks.

In light of the framework outlined above, we find no significant indication that NFE ownership is associated with a lower likelihood of reporting being food insecure conditional on receiving a shock. We obtain this finding as we interact the variable for having received a shock (aggregated and disaggregated in models 1 and 2 respectively) with the dummy variable for NFE ownership. This allows us to estimate the difference between the conditional relationship linking shocks and food insecurity for those households that do and do not own a NFE. Whilst all the coefficients on these interactions have the expected negative sign, which would be predicted if NFEs enabled households to insure themselves against shocks, the coefficients are extremely small in magnitude and not statistically significant at conventional levels. It would appear that our data offers no support to the hypothesized role of NFE ownership as an insurance mechanism, as we fail to reject the null hypothesis that NFE ownership offers no protection against food insecurity when facing a shock. Moreover, the insignificant coefficient on NFE ownership can be interpreted to provide additional evidence that NFEs do not help smooth consumption, as NFE households do not appear to be significantly less likely to be food insecure even in the absence of shocks. This is most likely related, at least to some extent, to the failure of households to smooth consumption across the year.

We find that the insignificant association between NFE ownership and resilience to shocks is not specifically driven by NFEs that display stronger links with agriculture, such as those involved in the sale of agricultural by-products. This is found when we investigate whether specific types of NFEs are more likely to be associated with households reporting lower food insecurity. We thus explore the interactions between different NFE types and the general shock variable to both isolate and look beyond the resiliency of households operating NFEs that are more strongly tied to agriculture.[101] The results are presented in Model 3, and show an insignificant relationship

[101] For a description of the construction of the NFE type variable, please see Appendix Figure S1.

between different NFE types and food insecurity in the face of shocks. Not only does it appear that NFEs are unimportant in helping households cope with shocks, but these results do not seem to be driven by agricultural NFEs that may be particularly sensitive to weather shocks.[102] Across the different types, NFEs seem uncorrelated with food insecurity in the face of shocks.[103]

[102]An implicit assumption we are making in interpreting the results is that NFE ownership affects food insecurity, and not vice-versa. There are, however, theoretical reasons to believe that food insecurity affects NFE ownership. Fafchamps (1999) and Sen (1981), for instance, suggest that concerns about insufficient food supplies could reduce farmers' willingness to invest in crops and more productive nonfarm activities, while reducing the local demand for nonfarm products. As such, we might expect food insecurity to have a negative effect on NFE ownership, introducing a downward bias in our coefficients. On the other hand, risky environments such as those prone to frequent food insecurity may encourage diversification through nonfarm enterprises as a response to shocks, making our coefficients upward biased. Disentangling these potential sources of bias would require developing an identification strategy that would produce less biased estimates, as for example, using instrumental variable estimation.

[103] This finding is robust to different model specifications, such as interacting different types of NFEs with weather shocks specifically. We chose not to report all robustness checks to preserve the clarity of our output in the table.

Table 3: NFE ownership and reported food insecurity

	Model 1	Model 2	Model 3
Shock	0.306***		
	(0.035)		
Weather shock		0.251***	
		(0.043)	
Price shock		0.171***	
		(0.045)	
Idiosyncratic personal shock		0.101***	
		(0.032)	
Crop damage		0.174*	
		(0.090)	
Livestock loss		0.024	
		(0.056)	
Other type of shock		0.136**	
		(0.055)	
NFE owner	-0.094	-0.069	
Agribusiness owner	(0.096)	(0.087)	-0.057
			(0.083)
Non-agricultural business owner			-0.135
Shock * NFE owner	-0.035		(0.084)
	(0.066)		
Shock * Agribusiness owner			-0.011
			(0.132)
Shock * Non-agricultural business owner			-0.030
Weather shock * NFE owner		-0.023	(0.124)
		(0.077)	
Idiosyncratic shock * NFE owner		-0.004	
		(0.056)	
Crop damage * NFE owner		-0.016	
		(0.157)	
Livestock loss * NFE owner		-0.002	
		(0.105)	
Price shock * NFE owner		-0.016	
		(0.079)	
Other type of shock * NFE owner		-0.013	
		(0.096)	
Rural	0.021	0.021	0.156**
	(0.084)	(0.075)	(0.061)
Rural * NFE owner	-0.002	-0.002	
	(0.145)	(0.129)	
Household size	0.009	0.008	0.037***
	(0.006)	(0.006)	(0.010)
Size of land owned by household	-0.009*	-0.008*	-0.010*
	(0.004)	(0.004)	(0.005)
Observations	3,079	3,079	767

Note: All regressions report average marginal effects and are significant at * $p<$ 0.10, $^{**}p<$ 0.05, $^{***}p<$ 0.01. Coefficients in models (1) and (2) are estimated using the full sample involved in agricultural activities. Coefficients in model (3) are estimated using the sample of NFE owners. The mean probability of reported food insecurity in the full sample is 32.7%. The mean of food insecurity among NFE owners is 37.3%.Standard errors adjusted for EA clustering and stratification in parentheses.

While we find that NFE-operating households are not less likely to report at least one incident of food insecurity, we look deeper to determine if NFEs might at least temper the timing or severity of food insecurity. For this, we utilize a survey question in which households are asked to identify specific months from the previous year during which they experienced food insecurity. Unsurprisingly, the most food-secure period takes place from November to March; this period coincides with both the Meher harvest as well as increased NFE activity (see Appendix Figure S2). However, during periods of increased food insecurity, April to October, NFE households do not report lower rates of food insecurity than their non-NFE counterparts.

We use a negative binomial regression model to estimate the effect of NFE income on food insecurity spells, as measured by the number of months a household was food insecure in the past year. The negative binomial distribution is an unbiased count estimator and is particularly useful for count data with an unbounded positive range when the sample variance is greater than the mean. We look at two separate specifications. In model 1, we regress months of food insecurity on consumption quintiles and income coming from four primary sources: farm, NFE, wage, and other. We might reasonably expect two households, at the same *level* of consumption, to exhibit different *patterns* of consumption throughout the year. Therefore, if we hypothesized that NFEs were helping households to buffer against food insecurity, we would expect each additional 1,000 Birr of NFE income to have a negative impact on months of food insecurity in our model. However, holding all other factors included in the model constant, we find that an additional 1,000 Birr of NFE income has no statistically significant bearing on months of food insecurity (see Table 4). In Model 2, we regress months of food insecurity on consumption quintiles, number of income sources, and

whether one of these income sources is an NFE. Once again, we find no correlation between operating an NFE and facing fewer spells of food insecurity.

These results fail to support the notion that income diversification as a risk reduction strategy mitigates the incidence of food insecurity. Holding all other factors in the model constant, a household with three income sources, for example, does not face fewer months of food insecurity than a household with two income sources. Traditionally, expanding the income portfolio can help mitigate the risks associated with agricultural productivity and cultivate a more consistent, reliable stream of income (Davis & Bezemer 2001). In fact, the key motivation for diversifying one's income portfolio as a risk prevention strategy is to ensure that the elements of the portfolio have very few, if any, overlapping risks (Ellis 2000). Given our earlier finding of the pro-cyclicality of NFE and agricultural activities, it is clear that these two income sources are in fact strongly linked.

Table 4: Months of food insecurity and income sources

NFE income (1,000 Birr)	-0.017	
	(.017)	
Farm income (1,000 Birr)	-0.020***	
	(.007)	
Wage income (1,000 Birr)	-0.001	
	(.010)	
Other income (1,000 Birr)	-0.123**	
	(.054)	0.127
NFE operation		(.104)
		-0.025
Number of income sources		(.056)
		0.127
Consumption quintiles		
2nd	-0.192	-0.271
	(.159)	(.172)
3rd	-0.311**	-0.396**
	(.151)	(.165)
4th	-0.420***	-0.508***
	(.156)	(.174)
5th (richest)	-0.480***	-0.569***
	(.155)	(.172)
Observations	3,494	3,657

Note: Standard errors adjusted for clustering and stratification in parentheses. The regression reports average marginal effects, which are significant at * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The number of observations included in each model reflect the number of observations which are not missing any information on the covariates included; thus coefficients for models 1 and 2 are estimated using 3,494 and 3,657 households, respectively. The mean number of months facing food insecurity in this subsample is 0.87 months.

5. Conclusion

Overall, our findings show that NFE activity is seasonal and pro-cyclical with agriculture. NFEs both begin and exhibit they're highest operational activity during the main harvest period. Further exploratory analysis suggests this pro-cyclical seasonality is the result of two key factors; first, enterprise owners receive an influx of investment capital for their NFEs

through harvest sales and, second, they react to an increase in local demand generated by agricultural income and seasonal purchasing power in the community. Furthermore, this interdependency between NFE operation and agricultural activity appears to matter across NFE sector, rural and small town households, and farm and nonfarm households, implying the pro-cyclical relationship is primarily demand-driven.

Our analysis also reveals that NFEs are unlikely to present households with effective consumption smoothing and risk mitigating opportunities. NFE income is not associated with a decreased likelihood of experiencing food insecurity nor with a shorter duration of food insecurity over the past 12 months, regardless of exposure to negative shocks over the same period. When interpreted in light of our findings on the strong links between NFEs and agricultural production, as well as the local nature of NFE markets, the result that NFEs do not significantly reduce household vulnerability to shocks is somewhat unsurprising. Dependency on seasonal local markets, which are highly susceptible to weather shocks, renders NFE households likewise exposed to risk. This further reduces the insurance potential of operating an NFE.

While the capacity of NFEs to generate income and provide a source of livelihood for rural and small town households is undisputed, our findings cast doubt on the temporal and consumption smoothing benefits of NFEs often presented in the literal. At least in the context of rural and small town Ethiopia, our results suggest that, in their current state, NFEs do not offer the buffer from food insecurity one might expect. Policies addressing food insecurity and other forms of vulnerability would be wise to not exclusively target the growth of non-farm enterprises as a means of protecting households from seasonal vulnerability.

References

Abebe, G. (2007). "Review of country poverty eradication/reduction strategies with particular reference to the progress in achievement of the MDGs". *United Nations*, Discussion Note.

African Development Bank (2014). "Open Data for Ethiopia". Retrieved 28 February 2014 from http://ethiopia.opendataforafrica.org/btkqfmd/ethiopia-gdp-per-capita.

Ali M., Peerlings, J. (2012). "Farm households and nonfarm activities in Ethiopia: Does clustering influence entry and exit?", *Agricultural Economics*, Vol. 43, No. 3, pp. 253-266.

Barrett, C. B., Reardon, T., and Webb R. (2001). "Nonfarm Income Diversification and Household Livelihood Strategies in Rural Africa: Concepts, Dynamics and Policy Implications", *Food Policy*. Vol. 26 (4), pp. 315-331.

Bezu, S., Barrett, C., and Stein, H. (2012). "Does nonfarm economy offer pathways for upward mobility? Evidence from a panel data study in Ethiopia," *Cornell University Working Paper*.

Chenery, H. and Syrquin, M. (1975). "*Patterns of Development, 1950-1970.*" London: Oxford University Press.

Davis, B., Winters, P., Carletto, G., Covarrubias, K., Quinones, E., Zezza, A., Stamoulis, K., Azzarri, C., and Digiuseppe, S. (2010). "A Cross-Country Comparison of Rural Income Generating Activities", *World Development*, Vol. 38, No. 1, pp. 48-63

Demeke, A. B., and Zeller, M. (2009). "Weather Risk and Household Participation in Off-farm Activities in Rural Ethiopia," *Quarterly Journal of International Agriculture*, No. 1/12.

Dercon, S., Hoddinott, J., and Woldehanna, T. (2005). "Shocks and consumption in 15 Ethiopian Villages, 1999-2004," *Journal of African Economies*, 14 (4), pp. 559 - 585.

Devereux, S. (2006). "Distinguishing between chronic and transitory food insecurity in emergency needs assessments". *World Food Program*, Emergency Needs Assessment Branch.

Ellis, F. (2000). "The determinants of rural livelihood diversification in developing countries", *Journal of Agricultural Economics*, Vol, 51, No. 2, pp. 289-302.

Fafchamps, M. (1999). "Rural poverty, risk, and development", *FAO*, Economic and social development paper, No. 144.

FAO (1998). "The State of Food and Agriculture 1998", *FAO Agriculture Series No. 31*.

Fox, L. & Sohnesen, T. (2012), "Household enterprises in sub-Saharan Africa: Why they matter for growth, jobs, and livelihoods", *Policy Research Working Paper*, No. 6184, World Bank.

Haggblade, S., Hazell, P., and Brown J. (1989). "Farm-nonfarm linkages in rural Sub-Saharan Africa", *World Development*, Vol. 17, no. 8, (1989), pp. 1173-1201.

Haggblade S., Hazell P. and Reardon T. (2010). "The Rural Nonfarm Economy: Prospects for Growth and Poverty Reduction", *World Development*, Vol. 38, No. 10, pp. 1429–1441.

Lanjouw, J., and Lanjouw, P. (2001). "The rural nonfarm sector: Issues and evidence from developing countries", *Agricultural Economics*, No. 26, pp. 1–23.

Loening, J. and Laketch, M. I. (2009): "Ethiopia: Diversifying the Rural Economy. An Assessment of the Investment Climate for Small and Informal Enterprises, "Washington, DC: World Bank. Retrieved on April 1, 2017 from: http://documents.worldbank.org/curated/en/867321468339667665/Ethiopia-Diversifying-the-rural-economy-an-assessment-of-the-investment-climate-for-small-and-informal-enterprises

Loening, J., Rijkers, B., and Söderbom, M. (2008). "Nonfarm micro enterprise performance and the investment climate: Evidence from rural Ethiopia," *Policy Research Working Paper Series*, no. 4577. The World Bank. Retrieved on April 1, 2017 from:http://documents.worldbank.org/curated/en/243931468037784690/pdf/wps4577.pdf

Ministry of Finance and Economic Development (MoFED). (2010). "Growth and Transformation Plan (GTP) 2010/11-20114/15", Retrieved 28

February 28 from http://www.vliruos.be/media/1829405/growth_and_transformation_plan.pdf.

Owusu, V., Abdulaib A., Abdul-Rahmana, S. (2010). "Nonfarm work and food security among farm households in Northern Ghana", *Food Policy*, Vol. 36, pp. 108-118

Reardon, T. (1997). "Using Evidence of Household Income Diversification to Inform Study of the Rural Nonfarm Labor Market in Africa", *World Development*, Vol. 25, No. 5, pp. 735-747

Reardon, T., Crawford, E., Kelly, V. (1994). "Links between Nonfarm Income and Farm Investment in African Households: Adding the Capital Market Perspective", *American Journal of Agricultural Economics*, Vol. 76, No. 5, pp. 1172-1176

Reardon, T., Berdegué, J., Barrett, C., and Stamoulis, K. (2006). "Household Income Diversification into Rural Nonfarm Activities". In Haggblade *et al.* (Ed.) Transforming the rural nonfarm economy: opportunities and threats in the developing world (Chapter 8). Baltimore*: Johns Hopkins University Press.*

Rijkers, B. and Costa, R. (2012). "Gender and rural nonfarm entrepreneurship", *Policy Research Working Paper Series*, no. 6066, The World Bank.doi: 10.1596/1813-9450-6066

Rijkers, B., and Söderbom M. (2013). "The Effects of Risk and Shocks on Nonfarm Enterprise Development in Rural Ethiopia, "*World Development*, Volume 45, May 2013, pp. 119-136.

Rijkers, B., Söderbom, M., and Teal, F. (2008). "Rural Nonfarm Enterprises in Ethiopia: Challenges and Prospects," *Briefing note prepared for the DFID funded study* "Understanding the constraints to continued rapid growth in Ethiopia: the role of agriculture."

Rosenzweig, C., Parry, M, L., and Fischer, G. (1995). "World food supply," In Strzepek, K. M. And Smith, J. B., (eds.), *As Climate Changes: International Impacts and Implications*, Cambridge University Press, New York, pp. 27–56.

Sen, A. (1981). "*Poverty and famines*", Clarendon Press, Oxford.

Webb, P., Coates, J., Frongillo, E. A., Rogers, B. L., Swindale A. and Bilinsky P. (2006). "Measuring household food insecurity: why it's

so important and yet so difficult to do." *The Journal of Nutrition* 136.5: 1404S-1408S.

Woldenhanna, T. and Oskam, A. (2001). "Income diversification and entry barriers: evidence from the Tigray region of northern Ethiopia", Food Policy. Vol. 26, pp. 351-365.

World Bank. (2009). "Ethiopia - Diversifying the Rural Economy: An Assessment of the Investment Climate for Small and Informal Enterprises", *World Bank*.

World Bank. (2014). "Data: Ethiopia". Retrieved on February 28, 2014 from http://data.worldbank.org/country/ethiopia.

Appendix

Table S: Characteristics of NFEs 2

	Overall (1)	Small Town (2)	Rural (3)	Difference (2)-(3)
Age (Mean)	5.652	8.302	5.573	3.271***
	(.419)	(.668)	(.430)	
Age (Median)	2.153	4.153	2.153	
Number of HH workers	1.250	1.463	1.244	0.219***
	(.028)	(.065)	(.028)	
Number of hired workers	0.274	0.353	0.272	0.081
	(.059)	(.069)	(.0617)	
conditional on any hired workers	2.611	2.107	2.635	-0.528
	(.354)	(.333)	(.370)	
Total number of workers	1.537	1.857	1.528	0.329**
	(.060)	(.110)	(.062)	
Proportion of NFEs with a formal license	0.089	0.298	0.083	0.215***
	(.015)	(.046)	(.015)	
Gross entry rate	0.323	0.175	0.328	-0.153***
	(.028)	(.025)	(.029)	
Annual income per NFE (Mean)	2,552.2	1,524.6	2,582.3	-1,057.7
	(1,133.1)	(1,769.2)	(1,164.9)	
Annual income per NFE (Median)	700	1600	650	
N	1,337	352	985	

Standard errors corrected for clustering and stratification in parentheses. Standard errors are not reported for medians as we were unable to bootstrap in order to obtain them. This is due to the fact that there is little literature at the intersection of variance estimation in the presence of complex sample design and bootstrapping. We have attempted to use replicate weights, but median estimation using them was not possible.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure S1: Broader categories of NFE types

Processing and sale of agricultural by-products	(2)	Processing/sale of agricultural by-products (e.g. flour, excluding livestock by-products and fish)
Non-agricultural business	(1)	Non-agricultural services from home/ house-hold-owned shop (e.g. mechanic, tailor, barber)
	(4)	Sale of products/services offered on a street/in a market (e.g. firewood, mats, bricks)
	(5)	Professional office, professional services from home (e.g. doctor, translator, midwife)
	(6)	Transportation or moving services (e.g. driving a household-owned taxi or pick-up truck)
	(7)	Bar/restaurant ownership
Other	(3)	Trading business on a street/market
	(8)	Other non-agricultural business from home/on a street

Figure S2: Seasonality of Food Insecurity