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Article

Impact of Ethiopia's productive safety net program on household food security and child nutrition: A marginal structural modeling approach

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ABSTRACT

Safety nets are expanding in African countries as a policy instrument to alleviate poverty and food insecurity. Whether safety nets have improved household food security and child diet and nutrition in sub-Saharan Africa has not been well documented. This paper takes the case of Ethiopia's Productive Safety Net Program (PSNP) and provides evidence of the impact of safety nets on household food security and child nutritional outcomes. Prior studies provide inconclusive evidence as to whether PSNP has improved household food security and child nutrition. These studies used analytical approaches that correct for selection bias but have overlooked the effect of time-varying confounders that might have resulted in biased estimation. Given that household food security status is both the criteria for participation and one of the desirable outcomes of the program, estimating the causal impact of PSNP on household food security and child nutrition is prone to endogeneity due to selection bias and time-varying confounders. Therefore, the objectives of this paper are (1) to examine the impacts of PSNP on household food security, child meal frequency, child diet diversity, and child anthropometry using marginal structural modeling approach that takes into account both selection bias and time-varying confounders and (2) to shed some light on policy and programmatic implications. Results show that PSNP has not improved household food insecurity, child dietary diversity, and child anthropometry despite its positive impact on child meal frequency. Household participation in PSNP brought a 0.308 unit gain on child meal frequency. Given the consequence of food insecurity and child undernutrition on physical and mental development, intergenerational cycle of poverty, and human capital formation, the program would benefit if it is tailored to nutrition-specific and nutrition-sensitive interventions.

Introduction

The past two decades have seen a rapid increase of social protection programs in African countries to alleviate poverty, food insecurity, and vulnerability of poor households (World World Bank, 2012). Ethiopia's Productive Safety Net Program (PSNP) is one of the largest social protection schemes in sub-Saharan Africa and has been implemented since 2005. It has broader development objectives beyond fulfilling income shortfalls: smoothing *household consumption*, facilitating investment in human capital and other productive assets, *protecting household assets*, and strengthening the agency of those in poverty to overcome their predicament (MOA, 2009, 2014). However, evidence on its effectiveness in improving food insecurity, health, and nutrition outcomes has not been thoroughly documented. Thus far, available evidence shows that safety nets have improved food security, livestock ownership, healthcare service utilization, dietary diversity, health care expenditure, nutritional status, and resilience to shocks (Alderman, 2014; de Groot, Palermo, Handa, Ragno, & Peterman, 2017; Hidrobo, Hoddinott, Kumar, & Olivier, 2018).

Studies from Ethiopia also revealed that participation in PSNP is associated with increased months of adequate food provisioning (Berhane, Gilligan, Hoddinott, Kumar, Taffesse, 2014; Gilligan, Hoddinott, & Taffesse, 2009; Sabates-Wheeler & Devereux, 2010), increased number of child meal per day (Berhane, Hoddinott, Kumar, & Taffess, 2011), household asset formation (Berhane, Gilligan, Hoddinott, Kumar, & Taffesse, 2014; Debela & Hollden, 2014; Gilligan et al., 2009; Hoddinott,

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Berhane, Gilligan, Kumar, & Seyoum Taffesse, 2012), increased resilience to shocks (Knippenberg & Hoddinott, 2017), human capital accumulation (John Hoddinott, Gilligan, & Taffesse, 2009), breaking the intergenerational cycle of poverty (John Hoddinott et al., 2009), increased agricultural productivity and technology adoption (Gilligan et al., 2009; John Hoddinott et al., 2012), and reduced worrisome on availability of food in the household (Porter & Goyal, 2016). In contrast, few studies reported no impact of PSNP on the number of child meals per day (Gilligan et al., 2009), household dietary diversity, and consumption expenditure per capita (Gebrehiwot & Castilla, 2018; Tafere & Woldehanna, 2012). Evidence on the impact of PSNP on child nutrition is mixed. Some studies reported positive (Debela, Shively, & Holden, 2015; Porter & Goyal, 2016) whereas others found no impact (Berhane, Hoddinott, & Kumar, 2017; Gebrehiwot & Castilla, 2018) (Table 1). This might be due the different types of study design, sample populations, measurements, and/or analytical approaches used by the studies. Moreover, previous studies have also tried to address the issue of selection bias and confounders using conventional regression models (Baye, Retta, & Abuye, 2014), propensity score matching (Gilligan et al., 2009), inverse-probability-weighted regression-adjustment (Berhane et al., 2014), difference in difference (Gilligan et al., 2009), and exogenous switching regression methods (Debela and Hollden, 2014; Debela, Shively, & Holden, 2015). However, these studies did not take into account the effect of time-varying confounders and hence, might have resulted in biased estimation (Pega, Blakely, Glymour, Carter, & Kawachi, 2016). For instance, while estimating time-varying impact of PSNP on food insecurity, neglecting to control for prior PSNP participation increases the risk of confounding, and statistically controlling for it may also introduce bias because of the intermediary relationship between PSNP and food insecurity status (Pega et al., 2016), which makes it difficult to comprehend a causal relationship. PSNP by design was not random–it was administered to chronically food-insecure households on asset-based criteria and is prone to selection bias. Moreover, food insecurity was one of the desired outcomes of the program. Participation in PSNP is not only expected to improve household food security status but may also predict future PSNP participation by altering households' food insecurity status thereby confounding the association between households PSNP participation and food security status. Hence, by considering this complexity, we evaluated the magnitude of the association of PSNP with household food security and child nutrition outcomes using marginal structural model (MSM). Findings of this study have an important policy implications to make social protection nutrition-sensitive (Alderman, 2014; Ruel & Alderman, 2013).

Methods

A brief description of PSNP

PSNP is part of Ethiopia's National Food Security Program along with the Other Food Security Program (OFSP), the now Livelihoods Program, and the Resettlement Program. It offers predictable transfers to chronically food insecure households to ensure food security and prevent asset depletion while creating community assets and stimulating markets (MOA, 2009, 2014; Sharp, Brown, & Teshome, 2006). PSNP has two components: public works (PW) and direct support (DS). The PW component offers employment opportunities for households with able-bodied members to work on labor-intensive community asset building projects and earn a wage either in cash or in-kind (food). The DS is administered to households whose breadwinners are the elderly or disabled and hence could not take part in labor-intensive activities.

PSNP is the second largest social protection scheme in sub-Saharan Africa. During the first and second phases, from 2005 to 2009, the program reached up to 5 million people in four major regions of Ethiopia: Amhara, Oromia, Southern Nations, Nationalities, and Peoples' Region (SNNPR), and Tigray (Sharp et al., 2006). In the third phase, from 2010 to 2014, the program expanded to the pastoral regions of Afar and Somali, reaching 8.3 million people (MOA, 2009). In the ongoing fourth phase, which began in 2015, all regions of Ethiopia, except Gambella and Benishangul Gumz, are covered by the program and the number of beneficiaries has increased to around 8 million people (MOA, 2014).

PSNP uses a mix of geographic and community targeting criteria to choose vulnerable households. Beneficiaries are households that have experienced food shortage for at least three months during the past three years before enrollment, received food assistance prior to the program's commencement, experienced severe asset loss and are unable to support themselves, and/or have no other sources of social protection such as family support (PIM Section 1.4 as cited in (Sharp et al., 2006, MOA, 2009, 2014). Households are expected to graduate from the program once they can feed themselves for 12 months without the program's support and are able to withstand modest shocks based on the asset-based indicators (Sharp et al., 2006).

Data

We used the Young Lives (YL) cohort study dataset. YL is a longitudinal cohort study of 1000 "older" (initially 7.5–8.5 years of age) and ~2000 "younger" (initially 6–18 months of age) children in Ethiopia, India, Peru, and Vietnam. This study uses the Ethiopia data on younger cohorts. In Ethiopia, the first round of data collection started in 2002 and the second, third, fourth, and fifth rounds of surveys were conducted in 2006–2007, 2009–2010, 2012–2013, and 2016–2017, respectively (Woldemedihin, 2014). YL collected data in four major regions—Amhara, Oromia, Southern Nations Nationalities and People and Tigray— and one administrative city—Addis Ababa. The survey comprises modules on child health and anthropometry, household food security, caregiver characteristics, educational status, PSNP participation, socioeconomic characteristics, and household composition.[1] Although PSNP started in 2005, households' participation was measured starting from the third round of the YL survey (2009/10) onwards. Moreover, measurement on household food security was consistently available only for the younger cohort which restricted our analysis to the rural sample of the younger cohort in the four regions gathered during the third, fourth and fifth rounds of the survey (n = 1200). YL obtained ethical clearance from the University of Oxford Ethics Committee and Ethiopian Public Health and Nutrition Research Institute's review board. A parent or guardian of the children gave consent before the data collection.

Measurement

In this study, PSNP participation is considered as a treatment and is measured as a dichotomous variable that takes a value of "1" if a household has participated in PSNP and "0" otherwise. We evaluate the impact of PSNP participation on a wide range of outcomes on food security and child nutrition: household food insecurity, child dietary diversity, child meal frequency and child anthropometry. Food insecurity (a time-varying confounder) was measured using the Household Food Insecurity Access Scale (HFIAS). Following Coates, Swindale, and Bilinsky (2007), the HFIAS score was computed and households were classified as severely food insecure, moderately food secure, mildly food insecure, and food secure (Coates et al., 2007). Households were further categorized food insecure coded as "1" if households were severely and moderately food insecure and "0" otherwise. Child meal frequency was computed as the number of meals a child consumed in the past 24 h prior to the survey. Child dietary diversity was measured using a 24-h dietary recall questionnaire. A child's consumption of one or more different foods was aggregated into 9 food groups according to the Food and

[1] Details on the sampling methodology can be accessed at http://www.younglives.org.uk.

Table 1
Review of studies investigating the impact of PSNP on food security and nutritional outcomes.

Authors (year)	Dataset	Modeling approach	Study population	Outcome	Sample size	Coverage	Summary of results
Gilligan et al. (2009)	Food security program survey	PSM[a] DID[b]	Household level	Caloric acquisition, months of adequate household food provisioning, number of child meals per day	3700	Amhara, Oromia, SNNP[i] and Tigray	No impact[1]Reduced likelihood of having very low caloric intake[2], increase in daily per capita caloric acquisition in the past 7 days by 230[(1+2)], increased months of adequate household food provisioning by 0.369[(1+2)], and decrease in the change in the square of food gap by 3.25[(1+2)]
Sabates-Wheeler and Devereux (2010)	Longitudinal survey in 2006 and 2008	OLS[c] (log-linear model)	Household level	Months of adequate household food provisioning	8 93–960	Amhara, Oromia, SNNP[i] and Tigray	Food and mixed recipients experienced 1.24 months of lower food shortage compared with non-beneficiaries[7]
Tafere and Woldehanna (2012)	Young Lives	PSM[a] DID[b]	11.5–15.5 years old	Monthly per capita consumption expenditure	569	Amhara, Oromia, SNNP[i] and Tigray	Decreased per capita consumption expenditure[¥5]
Berhane et al. (2014)	Food security program survey	DID[b] PSM[a] Dose-response model	Household level	Months of adequate household food provisioning, caloric acquisition		Amhara, Oromia, SNNP[i] and Tigray	Increase in months of adequate household food provisioning by 1.28[14] and 1.5[15] months No effect on household caloric availability
Debela, Shively, & Holden (2015)	Data from northern Ethiopia, collected in 2006 and 2010	Exogenous switching regression model ATT[c]	<5 years old	WHZ[e]	400–519	Tigray	Increased mean WHZ mediated by female labor engagement in PSNP[12]
Motbainor, Worku, & Kumie (2015)	Cross-sectional data from northern Ethiopia	Logistic regression	Mothers with children < 5 years old	BMI[f]	4110	Amhara	Mothers with no authority in the HH had 4.13 times higher odds of becoming undernourished; for no PSNP mothers, the authority had no significant effect on maternal undernutrition[4]
Porter and Goyal (2016)	Young Lives	DID[b] PSM[a] ATT[c]	3-5, 5–8, and 12–15 years old	HAZ[g]	406-1605	Oromia, SNNP[i] and Tigray	Improved HAZ[8,9,10,11]; siblings at the age of 5 had a significantly higher HAZ than the pre-PSNP conditions[11] compared with those who did not receive PSNP or received PSNP in 2006 and 2009
Berhane et al. (2017)	Food security program survey	IPWAR[d]	<5 years	HAZ[g], WAZ[e], stunting, and wasting	1133–1728	Oromia, SNNP[i] and Tigray	No significant impact on HAZ, WAZ, stunting, and wasting[12]
Gebrehiwot & Castilla (2019)	Ethiopian Socioeconomic Survey (ESS) in 2012 and 2014	2SLS[h], reduced form IV, and generalized propensity score matching	Household, 0–56 months old children	Dietary diversity score; consumption of calories, protein, and iron; and HAZ[g]	3797 households and 688 children	Tigray, Amhara, Oromia, SNNP,Afar, Somali, Dire Dawa, and Harare	PSNP did not improve household dietary diversity, calorie, iron or protein intake nor did it reduce child stunting

Note: a = propensity score matching, b = difference in difference, c = ordinary least square, d = inversed probability weights adjusted regression, e = weight-for-height z-score, f = body mass index, g = height-for-age z-score, h = two stage least square, i = Southern, Nations, Nationalities and People, 1 = any payment from PSNP, 2 = food/cash worth 90 birr, 3 = Other Food Security Program, 4 = households living in areas where PSNP operates 5 = children from households who participated in both Round 2 and 3 compared with those who participated only in Round 3 (195 + 30), 7 = non-PSNP beneficiary versus only food, only, cash and mixed (cash and food) beneficiaries, 8 = matched sample, 9 = shortlisted for PSNP, 10 = participated only in 2006, 11 = participated only in 2009, 12 = participated in the public work component of PSNP vs. non-PSNP households, 13 = membership in PSNP, 14 = 1 year of participation in public work, and 15 = 5 years of participation in public work +3, 16 = change in Keble's PSNP budget received between 2012 and 2014. £ = significant only in the difference-in-difference regression on the matched sample but not in the propensity score kernel matching and average treatment effect on the treated – difference-in-difference kernel matching models.

Agriculture Organization (FAO) individual dietary diversity score guidelines (FAO, 2013), and food groups were summed up to generate a child dietary diversity score (DDS). To measure child anthropometry, height and weight of each child was measured using the World Health Organization's (WHO) standardized procedures (WHO, 2008). Height was measured using length board and stadiometer to the nearest 1 mm. Weight was measured using a calibrated digital balance (Soehnle 7831, Germany) to the nearest 0.1 kg. Sex- and age-adjusted HAZ and BMI were computed using the latest WHO child growth standard (de Onis, Garza, Lartey, & Reference, 2006; de Onis et al., 2007). Observations with implausible values of HAZ (below −6 or above +6) or BMI (below −5 or above +5) (WHO, 2008) and missing values of height or weight in all rounds of the survey were excluded from the analysis. A child is considered stunted or underweight if their height is less than two standard deviations below the median height or BMI for their age in a reference population (i.e., a child was classified as stunted/underweight (coded as "1") if they have a HAZ/BMIZ value < -2 and "0" if otherwise.

Other covariates

We chose covariates that are *a priori* associated with participation in PSNP and household food security and child nutrition. Variables used in our treatment model include previous PSNP participation, food security status, education level of the household head, age of the household head, sex of the household head, interaction of household sex and previous PSNP participation, household wealth status, exposure to drought, dependency ratio, land ownership, livestock ownership, access to credit and real annual total expenditure per adult. Sex of the household head was measured as a dummy variable where "1" indicates male and "0" indicates female. Dependency ratio was computed as the ratio of non-working-age (0–12 years and >60 years) and working-age (13–60 years) members of the household multiplied by 100. Exposure to drought was measured as a dichotomous variable where "1" indicates the household had experienced such an event in the past 12 months. Household land ownership was measured as a dummy variable that takes a value of 1 if a household owns a land and zero otherwise. Access to credit was measured as a dichotomous variable that takes a value of "1" if a household had access to credit in the 12 months before the survey and "0" if otherwise. In our estimation of the impact of PSNP participation on household food security, we included the variables in the treatment model and also interacted exposure to drought and head sex with PSNP participation. For nutritional outcomes, we added child characteristics (child's nutritional status during the first 1,000 days, dietary diversity score, sex, age, and general health status), and household- and community-level characteristics (household food security status, maternal age, and maternal education). Maternal education was measured as a categorical variable that takes a value of 0, 1, and 2, if the mother had no education, some education, and primary and above level of education respectively. Principal component analysis was used to compute a wealth index based on household ownership of items such as a bicycle, motorcycle, mobile phone, landline phone, radio, television, chair, sofa, and bedstead; the number of rooms per household member; the quality of the household's drinking water, cooking material, toilet, floor, roof, and walls; and household access to electricity. Items were standardized into "yes" or "no" responses. The weight of principal components was obtained using a covariance matrix. Bartlett's and KMO tests of homogeneity of variance across samples were done ($p = 0.000$ and KMO>0.8) (Cerny & Kaiser, 1977). Item correlation, internal consistency, and reliability were checked. A recommended value of Cronbach's alpha (>0.7) was obtained (Tavakol & Dennick, 2011). Items with low correlation with the rest of the items were excluded. Using the computed wealth index, households were classified into wealth tertiles of low (1), medium (2), and high (3).

Statistical analysis

We used MSM to estimate the causal association of time-dependent treatment (PSNP) in the presence of a time-dependent covariate (food security status) that is simultaneously a confounder and an intermediate variable (Robins, Hernán, & Brumback, 2000). The hypothesized temporal ordering and impact pathway of PSNP on household food insecurity and child nutritional outcomes is presented in Fig. 1. Accordingly, $PSNP_1$ (PSNP participation at round 3 of the YL survey), might be associated with FS_1 (food security status measured at round 3 of the YL survey), and time-invariant covariates (V). In turn, this affects both participation in $PSNP_2$ (PSNP participation at round 4 of the YL survey) and FS_2 (food insecurity status measured at round four of the YL survey). Similarly, $PSNP_2$ (PSNP participation at round 4 of the YL survey), might be associated with FS_2 (food security status measured at round 4 of the YL survey), and baseline covariates (V). In turn, this affects both participation in $PSNP_3$ (PSNP participation at round 5 of the YL survey) and FS_3 (food insecurity status measured at round five of the YL survey).

To put in another way, participation of households in the subsequent PSNP ($PSNP_2$) is affected not only by previous food security status at (FS_1) but also by prior PSNP enrolment ($PSNP_1$). Previous food security status at (FS_1), could affect future food security status (FS_2 and FS_3) directly or indirectly by predicting future participation in PSNP ($PSNP_2$ and $PSNP_3$). That means, food security status, FS_1 and FS_2, are both a confounder (i.e., a time-variant confounder of the association of $PSNP_1$ and FS_2 and $PSNP_2$ and FS_2, respectively) and an intermediary variable (between two treatment conditions, $PSNP_1$ and $PSNP_2$ and $PSNP_2$ and $PNSP_3$, respectively). Besides, covariates associated with $PSNP_1$ and $PSNP_2$ may also be associated with FS_1 and FS_2, respectively so that observed response differences cannot be attributed directly to exposure to $PSNP_1$ and $PSNP_2$. While neglecting to control for prior treatment status might increase the risk of confounding and statistically controlling for it (by just including the regression model) may also introduce bias because of the intermediary relationship between PSNP and FS (Kawachi, Carter, Glymour, Blakely, & Pega, 2016),not adjusting for prior food security status might lead to an invalid comparison of treatments. Statistically controlling for PSNP would also not allow for disentangling the causes and effects of PSNP households with different treatment statuses. Hence, following (Robins et al., 2000), we fitted MSM to allow for unbiased impact estimation in the presence of time-varying confounders. MSMs are a class of models that allows robust estimation of the causal effect of a time-dependent exposure in the presence of time-dependent confounders that may be simultaneously confounders and intermediate variables (Hernán & Robins, 2019). MSM estimation controls for time-varying confounders and loss to follow-up

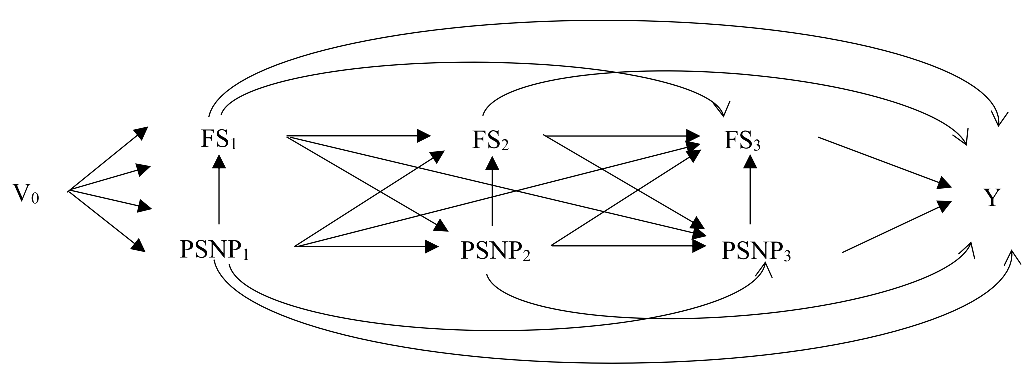

Fig. 1. Diagrammatic representation of the causal association of participation in PSNP and household food security status, child dietary diversity, child meal frequency, and child anthropometry.
Note: V represents time-invariant covariates, $PSNP_1$, $PSNP_2$ and $PSNP_3$ represent participation in the third, fourth, and fifth waves of the YL survey, respectively, FS_1, FI_2, and FS_3 stand for household food security status at the second, third and fourth waves of the YL survey, respectively, Y denotes outcomes at wave 5 (child anthropometry, dietary diversity and number of meal), FS_1 is a confounder and intermediate variable in the association of $PSNP_2$ and FS_2, and FS_2 is a confounder and intermediate variable in the association of $PSNP_3$ and FS_3. Similar hypothesis holds for the causal impact of PSNP on other outcomes (Y).
Source: authors

through inverse probability treatment weights (IPTWs) and inverse probability censoring weights, respectively. MSM estimation can be computed in two stages. In the first stage, IPTWs are calculated, and in the second stage, the outcome model is fit, including sensitivity analyses that take into account weight distributions (Williamson & Ravani, 2017).

Treatment model: Inverse Probability of Treatment Weights

Treatment weights are calculated as the inverse of each individual's probability of receiving the treatment (propensity score) conditional on pre-treatment covariate values. Propensity scores were computed using logistic regression as the probability of participating in PSNP as a function of pretreatment characteristics as shown below:

$$\begin{aligned} logit\Pr[PSNP_k = 1|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1 \dots FS_{K-1}] \\ = \beta_o + \beta_1 PSNP_1 + \dots + \beta_{k-1} PSNP_{k-1} + \beta_4 FS_{1\dots k} + \beta_5 V_0 \\ logit\Pr[PSNP_k = 1|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1 \dots FS_{K-1}] = \beta_o + \beta_1 PSNP_1 \\ + \dots + \beta_{k-1} PSNP_{k-1} + \beta_4 FS_{1\dots k} + \beta_5 V_0 \end{aligned} \tag{1}$$

Where $PSNP_K$ denotes participation in PSNP at time K, V_0 denotes baseline covariates from time 1 to K, and $FS_{1\dots k}$ stands for food security status from time 1 to K.

After computing propensity scores (PSs), IPTWs were created by taking the inverse of the PSs as shown below:

$$\begin{aligned} W(t) = \prod_{k=0}^{t} \frac{1}{f\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1 \dots FS_{K-1}\}} \\ W(t) = \prod_{k=0}^{t} \frac{1}{f\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1 \dots FS_{K-1}\}} \end{aligned} \tag{2}$$

where W(t) is the IPTW at time t. Those who have received the treatment are assigned a weight of *1/P(Z=1/V)*, and those in the control group receive a weight of *1/(1 - P(Z=1/V))* where *P* is the PS, and *V* is a set of baseline covariates (Hernán & Robins, 2019). Such weights are referred to as "unstabilized weights" and are prone to a higher variation. That is, observations with a lower propensity of receiving the treatment based on covariate values but have received the treatment will have a very larger weight and hence the analysis will be heavily dependent on those observations (Hernán & Robins, 2019). To correct for this, we used stabilized weights as shown below (Robins et al., 2000):

$$\begin{aligned} SW(t) = \prod_{k=0}^{t} \frac{p\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0\}}{p\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1, \dots, FS_{K-1}\}} \\ SW(t) = \prod_{k=0}^{t} \frac{p\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0\}}{p\{PSNP_K|PSNP_1, \dots, PSNP_{K-1}, V_0, FS_1, \dots, FS_{K-1}\}} \end{aligned} \tag{3}$$

where SW(t) is stabilized weight at time t. While computing stabilized weights, the baseline probability of receiving a treatment estimated from a model without covariates is divided by the probability of receiving a treatment given covariate values (see equation (3)). Thus, those who received the treatment are given a weight of *P(Z=1)/P(Z=1/V)* and those who are not treated receive a weight of *1 - P(Z=1)/(1 - P(Z=1/V))*.

Stabilized weights give estimates that have a small variance and a higher precision and hence are always preferred over the unstabilized weights (Hernán & Robins, 2019). The distribution of both stabilized and unstabilized weights are available in (see Supplementary Table 1). Once IPTWs are computed, they can be used in any desired outcome model to estimate treatment effects (Hernán & Robins, 2019).

Outcome model: Marginal Structural Model

We evaluated the effect of PSNP on household food insecurity and child dietary diversity, child meal frequency, and child anthropometry if households were exposed to PSNP, compared with having no PSNP. The MSM was fitted by regressing the outcomes on the predictors in the MSM and weighting the contribution of each subject by the stabilized weights in equation (3). We used mixed effects logistic and linear mixed effects for dichotomous and continuous outcomes, respectively. The model takes the form:

$$E[Y_{PSNP}|V = v] = \beta_0 + \beta_1 a_t + \beta_2 a_{t-1} + \gamma \beta_1$$

where Y denotes outcomes household food insecurity, child dietary diversity, child meal frequency and anthropometry, V stands for covariates, β_0 is the intercept, β_1 is coefficient estimate for PSNP participation, and β_2 is the regression coefficient for other covariates. We clustered variance estimates at child level to account for non-independence of observations within-subject.

Results

Socioeconomic and demographic characteristics

Table 2 presents the socioeconomic and demographic characteristics of respondents by their PSNP enrollment at round 3, 4, and 5, respectively. During round 3, children in PSNP households had a lower dietary diversity score ($p < 0.001$), higher meal frequency ($p < 0.001$), were more likely to be underweight ($p < 0.01$), have a poor health condition ($p < 0.005$), and have less educated ($p < 0.001$) and older ($p < 0.05$) mothers, compared to children in non-PSNP households. There was no significant difference in child sex, child age, HAZ score, BMI z-score, stunting, underweight and general health status of children by PSNP participation. Considering household characteristics, PSNP household owned fewer household durables ($p < 0.001$), spent less on food and non-food items ($p < 0.001$), are headed by female ($p < 0.001$), have more dependent members ($p < 0.01$), are more likely to experience drought ($p < 0.001$), are more likely to own livestock and borrow on credit ($p < 0.05$), and and are less likely to own land ($p < 0.05$) compared to non-PNSP households. There was no significant difference in household food security by PSNP participation.

During round 4, compared to children in non-PSNP households, children in PSNP households are younger ($p < 0.005$) and have a higher BMI z-score ($p < 0.005$). There was no significant difference in child sex, child age, child dietary diversity score, meal frequency, HAZ score, stunting, underweight, and child health status. With regard to household characteristics, PSNP households owned fewer household durables ($p < 0.001$), spent less on food and non-food items ($p < 0.001$), are more likely to be headed by female ($p < 0.001$), are more likely to be food insecure ($p < 0.001$), live in households with more dependent members ($p < 0.005$), are more likely to experience drought ($p < 0.01$), and more likely to borrow on credit ($p < 0.001$) as compared to non-PSNP households. There was no significant difference in maternal education, maternal age, and livestock and land ownership.

In round 5, children in PSNP households eat a less diversified diet ($p < 0.001$), have lower meal frequency ($p < 0.005$), and have less educated mothers ($p < 0.01$) compared to children in non-PSNP households. There was no significant difference in child age, child sex, HAZ score, BMI z-score, stunting, underweight, and child health status. PSNP households owned fewer durable assets ($p < 0.001$), spent less on food and non-food items ($p < 0.001$), are more likely to be headed by female ($p < 0.001$), have more dependent members ($p < 0.005$), and less likely to own land ($p < 0.005$) compared to non-PSNP households. No significant difference was observed in maternal age, livestock ownership, and borrowing on credit.

Table 2
Characteristics of study participants by program participation, YL cohort study, Ethiopia, 2009–2016.

	Round 3			Round 4			Round 5		
	Non-PSNP 740 (61%)	PSNP 482 (39%)	*P*-value	Non-PSNP 796 (67%)	PSNP 391 (33%)	*P*-value	Non-PSNP 882 (76%)	PSNP 275 (24%)	*P*-value
Child sex,[b]	52.7 (0.5)	53.3 (0.5)	0.83	54.5 (0.5)	49.6 (0.5)	0.11	53.3 (0.5)	52.7 (0.5)	0.87
Child dietary diversity score[a]	3.4 (1.3)	2.9 (1.2)	<0.001	4.4 (1.3)	4.4 (1.2)	0.92	4.7 (1.4)	4.2 (1.4)	<0.001
Child's age (in months)[a]	97.5 (3.9)	97.2 (4.6)	0.15	145.6 (3.9)	144.9 (4.0)	0.003	181.0 (3.8)	180.7 (3.7)	0.32
HAZ score at round[a]	−1.5 (1.9)	−1.3 (2.1)	0.14	−1.4 (1.9)	−1.5 (2.0)	0.75	−1.4 (2.0)	−1.3 (1.9)	0.52
Child meal frequency[a]	3.8 (0.7)	4.0 (0.7)	<0.001	4.7 (1.3)	4.7 (1.5)	0.84	4.5 (1.3)	4.3 (1.3)	0.047
HAZ score[a]	−1.4 (1.1)	−1.4 (1.1)	0.94	−1.6 (1.0)	−1.6 (0.9)	0.36	−1.5 (1.1)	−1.5 (1.1)	0.38
BMI z-score[a]	−1.4 (1.1)	'-1.4 (1.0)	0.39	−2.0 (1.0)	−1.9 (0.9)	0.048	−1.8 (1.2)	−1.8 (1.1)	0.91
Stunting[b]	26.8 (0.4)	30.3 (0.5)	0.18	28.6 (0.5)	29.4 (0.5)	0.78	30.5 (0.5)	29.5 (0.5)	0.74
Underweight[b]	20.7 (0.4)	24.9 (0.4)	0.083	45.6 (0.5)	41.2 (0.5)	0.15	41.2 (0.5)	39.6 (0.5)	0.65
Child has good health[b]	76.6 (0.4)	71.4 (0.5)	0.039	84.8 (0.4)	82.6 (0.4)	0.34	84.8 (0.4)	81.3 (0.4)	0.17
Wealth quantile									
Poor	40.7 (0.5)	64.2 (0.5)	<0.001	45.3 (0.5)	60.6 (0.5)	<0.001	44.8 (0.5)	63.6 (0.5)	<0.001
Medium	42.9 (0.5)	26.9 (0.4)		43.1 (0.5)	34.3 (0.5)		42.6 (0.5)	33.1 (0.5)	
Rich	16.4 (0.4)	9.0 (0.3)		11.6 (0.3)	5.1 (0.2)		12.6 (0.3)	3.3 (0.2)	
(log) total expenditure ¥[a]	4.7 (0.5)	4.6 (0.5)	<0.001	4.7 (0.5)	4.6 (0.5)	<0.001	4.7 (0.5)	4.6 (0.4)	<0.001
Maternal education[b]									
None	52.7 (0.5)	64.8 (0.5)	<0.001	49.9 (0.5)	50.7 (0.5)	0.81	48.3 (0.5)	55.4 (0.5)	0.085
Primary	12.4 (0.3)	9.9 (0.3)		15.6 (%)	16.6 (0.4)		17.7 (0.4)	13.1 (0.3)	
Above primary	34.9 (0.5)	25.3 (0.4)		34.5 (0.5)	32.7 (0.5)		34.0 (0.5)	31.5 (0.5)	
Household head's sex (male)[b]	90.9 (0.3)	82.2 (0.4)	<0.001	83.5 (0.4)	73.7 (0.4)	<0.001	87.1 (0.3)	65.5 (0.5)	<0.001
Food insecurity status[b]									
Food secure	12.1 (0.3)	8.7 (0.3)	0.12	24.5 (0.4)	11.3 (0.3)	<0.001	15.1 (0.4)	9.5 (0.3)	0.003
Mildly food insecure	8.8 (0.3)	11.6 (0.3)		15.3 (0.4)	8.4 (0.3)		26.9 (0.4)	21.1 (0.4)	
Moderately food insecure	64.9 (0.5)	66.8 (0.5)		54.4 (0.5)	68.5 (0.5)		51.5 (0.5)	64.0 (0.5)	
Severely food insecure	14.2 (0.3)	12.9 (0.3)		5.8 (0.2)	11.8 (0.3)		6.5 (0.2)	5.5 (0.2)	
Maternal age[a]	34.3 (6.3)	35.0 (6.6)	0.046	38.6 (6.2)	38.9 (6.8)	0.48	41.7 (6.4)	41.2 (6.4)	0.29
Dependency ratio[a]	0.8 (0.6)	0.8 (0.6)	0.068	0.7 (0.6)	0.8 (0.7)	0.069	0.8 (0.7)	1.0 (0.9)	0.005
Drought past 12 months[b]	44.7 (0.5)	57.3 (0.5)	<0.001	17.6 (0.4)	22.0 (0.4)	0.069	27.7 (0.4)	39.3 (0.4)	<0.001
Owned livestock past 12 months[b]	91.1 (0.3)	93.8 (0.2)	0.087	91.1 (0.3)	92.8 (0.2)	0.30	92.5 (0.3)	90.5 (0.3)	0.29
Owned land past 12 months[b]	94.5 (0.2)	91.2 (0.3)	0.026	93.1 (0.3)	92.1 (0.3)	0.53	96.3 (0.2)	93.0 (0.3)	0.025
Obtained credit since the previous round[b]	74.9 (0.4)	80.5 (0.4)	0.022	74.0 (0.4)	83.1 (0.4)	<0.001	69.1 (0.5)	65.8 (0.5)	0.30

[a] = mean (standard deviation).
[b] Percentage (standard deviation), and ¥ = real per adult, in real 2006 birr.

Impact of PSNP on food insecurity and nutrition outcomes

Tables 3 and 4 present the MSM results of the causal association of participation in PSNP and household food insecurity and child nutrition outcomes. Estimates show no difference in household food security status (β = 0.494, SE = 0.2427) and child dietary diversity score (β = −0.183, SE = 0.117) by household PSNP participation. However, PSNP participation is associated with increased child meal frequency (β = 0.308, SE = 0.121) (Table 3).

Similarly, PSNP had no effect on child linear growth (β = −0.032, SE = 0.091), BMI z-score (β = −0.032, SE = 0.114), stunting (β = 0.017, SE = 0.354) and underweight (β = 0.103, SE = 0.371)(Table 4).

Table 3
Association of PSNP, household food security, child dietary diversity and child meal frequency, YL, Ethiopia, 2009–2016.

	Household is food insecure	Child meal frequency	Child dietarydiversity score
PSNP	0.022	0.308**	−0.183
	[-0.493 - 0.536]	[0.070–0.545]	[-0.413 - 0.047]
	(0.262)	(0.121)	(0.117)
N	3305	3292	3295

Note: Results are estimates of marginal structural models. Confidence intervals are given in square brackets and robust standard errors are given in parenthesis. Mixed effects logistic regression model is used for dichotomous outcomes and linear mixed effects model is used for continuous. Models are adjusted for household durable asset quantile, dependency ratio, maternal education, maternal age, log of total expenditure real per adult, access to credit, ownership of livestock and land, head sex and its interaction with PSNP participation, and exposure to drought and its interaction with PSNP participation. The model for child meal frequency per day and child dietary diversity include child age, sex, and health status in addition to the covariates for food insecurity.

Table 4
Association of PSNP and child anthropometry, YL, Ethiopia, 2009–2016.

	Height-for-age z-score	Stunting	BMI z-score	Underweight
PSNP	−0.032	0.017	−0.032	0.103
	[-0.210 - 0.147]	[-0.676 - 0.711]	[-0.256 - 0.193]	[-0.624 - 0.82]
	(0.091)	(0.354)	(0.114)	(0.371)
N	3231	3285	3227	3292

Note: Results are estimates of marginal structural models. Confidence intervals are given in square brackets and robust standard errors are given in parenthesis. Mixed effects logistic regression model is used for dichotomous outcomes and linear mixed effects model is used for continuous. Models are adjusted for household durable asset quantile, dependency ratio, maternal education, maternal age, log of total expenditure real per adult, access to credit, ownership of livestock and land, head sex and its interaction with PSNP participation, exposure to drought and its interaction with PSNP participation, and age, sex, dietary diversity, and general health of the child.

For all outcomes considered, we observed similar patterns of relationship in terms of direction and significance with a slight change in the magnitude of estimates when comparing results of Inverse Probability Weighted Regression Adjustment, mixed effects logistic regression, and linear mixed-effects model with MSM (see Supplementary File 3).

Discussion

Evidence linking investment in child health and nutrition and economic growth is well established (McGovern, Krishna, Aguayo, & Subramanian, 2017; Vasquez & Daher, 2019). However, child nutrition remains one of the pressing challenges in low-and middle-income countries and is exacerbated by poverty, shocks, and household vulnerability. To address this challenges governments have designed and implemented social protection programs (World Bank, 2012). Social protection is recognized as an important strategy to accelerate progress in improving maternal and child nutrition (Ruel & Alderman, 2013; Manley et al., 2012). However, the potential role of safety nets on child health and nutrition remains largely untapped (Alderman, 2014). In this study, we estimated the causal impact of PSNPfood insecurity and nutrition outcomes. In so doing, we not only provide additional evidence as to whether safety nets could improve household food security and child malnutrition but also address the methodological challenges of impact estimation in the presence of time-varying confounders and intermediary variables. Contrary to our expectations, we found no impact of PSNP on household food security, child dietary diversity, child antropometrdespite its positive impact in increasing child meal frequency.

Studies conceptualized that social protection programs could improve child nutrition through increased resource for food security, health and or health care (Leroy, Ruel, & Verhofstadt, 2009). Safety nts could improve access to quality food, food production, productive assets ownershiop, and access to sanitation and health care. In turn, in combination with appropriate feeding, and good health status, food security and diet diversity could improve child nutrition. In this analysis, we found no impact of PSNP on child undernutrition. Evidence from previous studies are mixed. Berhane et al. (2017) and Gebrehiwot and Castilla (2019) did not find a significant impact of PSNP participation on child linear growth, BMI z-score or the likelihood of being stunted and underweight (Berhane et al., 2017; Gebrehiwot & Castilla, 2018). The recent systematic review also shows no statistically significant association between social protection programs and child antropometry (Manley, Gitter, & Slavchevska, 2013). On the contrary, a study by Porter and Goyal (2016) provides evidence of improvements in nutritional outcomes due to PSNP (Porter & Goyal, 2016). Debela et al. (2014) also reported that children living in PSNP households have a higher WHZ score than their non-PSNP counterparts (Debela, Shively, & Holden, 2015). Difference in these studies could be due to several factors. Chronic undernutrition is highly dependent on nutritional status during the 1000 days window (Victora et al., 2008). Even though we attempted to control for nutritional status during the 1000 days, our sample children were over eight years of age, an age group for whom improvement in long-term nutritional status may not be easily realized (Georgiadis et al., 2016). Moreover, PSNP is targeted to households with a history of chronic food insecurity in which children have a lower likelihood of having a good nutritional status. The absence of impact on child undernutrition in our study could also be due to other covariates that affect child health and nutrition. For instance, in this study, households receiving PSNP are different from those households that are not enrolled in PSNP (Table 2). They have lower dietary diversity, lower maternal education, lower expenditure, fewer durable assets, and high food insecurity. Although dietary diversity was generally low among the sample children, it was significantly lower among PSNP participants. However, studies show that child undernutrition is sensitive to dietary quality (Dewey & Begum, 2011) which, in turn, is associated with better child nutrition and nutrient adequacy (Ruel, 2003). Lower education level of mothers and the availability of public health facilities among households participating in PSNP (see Table 2) may have also contributed to poor child feeding practices, dietary quality and child health. Along the same line, Berhane et al. (2017) also reported the lack of good child feeding practices and contact with health extension workers among PSNP beneficiary mothers. Woldehana (2010) also reports the role of intra-household dynamics for child nutritional status (Woldehanna, 2010). Porter and Goyal (2016) points out that PSNP has produced both intended and unintended outcomes for children, in particular with regard to their time use (Porter & Goyal, 2016).

The High Level Panel of Experts on Food Security and Nutrition (HLPE) note that the impact of social protection on food security and nutrition could be leveraged by linking such programs with other sectoral programs related to, for example, access to clean water and sanitation, health services, agriculture, employment creation, investment in infrastructure, and appropriate training and information on food utilization (HLPE, 2012). This is also evident from previous impact evaluation studies of PSNP where access to both the PW and OFSP component had a 16.28 and 153.85 percent higher impact on the number of months of adequate food provisioning and livestock holding, respectively, than the PW program alone (Berhane et al., 2014). However, except for the OFSP, from which only a few benefited, such activities were not well integrated into PSNP in the period during which our data was collected and may have contributed to the lack of impact. Moreover, the duration and size of transfer matters for programs to have an impact on nutrition. As indicated in Leroy et al. (2009) higher amounts and a longer duration of the transfer are likely to produce greater impact (Leroy et al., 2009). If the size of transfers exceeds the minimum amount required for consumption and encourage investment, it will likely generate future income that could be spent on food security and nutrition-promoting activities. However, studies show that PSNP mainly operates for six months of the year (January through June) and beneficiaries receive less than half of the intended transfer, which is too small to cover a consumption need let alone encouraging investment in assets (Gilligan et al., 2009; Berhane et al., 2014). Moreover, there were payment delays (Gilligan et al., 2009). Given such implementation failures, the lack of functioning credit markets in Ethiopia, and the low stock of assets of beneficiary households, whether the program could result in improvement in household food security and child nutrition is questionable.

Previous studies report that PSNP improves household food security (Gilligan et al., 2009; Berhane et al., 2014; Porter & Goyal, 2016). Gilligan et al. (2009) examine the effect of PSNP on the food gap (number of months the household reports having difficulty meeting food needs), calorie intake, and child meal frequency in the hungry season. Similarly, Berhane et al. (2011) show statistically significant impacts of the PSNP on household food security and consumption status, and Berhane et al. (2014) find a significant impact of PSNP on food security as years of participation increase. On the contrary, our study shows no evidence to this claim. Similarly, Gebrehiwot and Castilla (2019) find no impact of PSNP on household food security status. While we cannot rule out all the possible reasons, the difference between these results could be due to several factors, one being the use of different statistical modeling and measurements of food insecurity, which makes comparisons more difficult. While this study used MSM, others (Gilligan et al., 2009; Berhane et al., 2014; Porter & Goyal, 2016) use propensity score matching, difference in difference, and dose-response models. To measure food insecurity we use HFIAS, whereas Gilligan et al. (2009) and Berhane et al. (2014) use the months of adequate household food provision, Porter and Goyal (2016) use only the first question of the HFIAS measurement questions, and Gebrehiwot and Castilla (2019) use intake of calorie, iron, and protein, an (Gilligan et al., 2009; Gebrehiwot & Castilla, 2018; Berhane et al., 2014) use a dietary diversity score. Moreover, the study sample used by these studies is different. While our evaluation is based on the younger cohorts of the YL cohort study dataset, the evaluations by Gilligan et al. (2009) and Berhane et al. (2014) are based on a survey undertaken in areas where PSNP operates, Gebrehiwot and Castilla (2019) use a nationally representative household survey, and Porter and Goyal (2016) use both the younger and older cohorts of the YL cohort study dataset. Moreover, the impact of external shocks such as the 2007/8 and 2011/12 food price spike and drought at the time of the survey may also have hindered the PSNP from achieving its intended objective of improving household food security. Such events might have caused transitory food insecurity, which is beyond the mainstream PSNP objectives to address. Hence, the income or substitution effects of food price shocks among households that received PSNP cannot be ruled out in this study. External shocks, such as food price spikes, might have affected PSNP households' food consumption by increasing food prices and substantially increasing their risk of undernutrition (Green et al., 2013). Error in the measurement of food security could also have introduced bias in the results. Berhane et al. (2014) and Gilligan et al. (2009) note that households' responses to the food gap survey questions are sensitive to whether or not households have received payment in the month prior to the survey whereby payment received close to the survey period trigger positive answers to the food security questions (Gilligan et al., 2009; Berhane et al., 2014). Hence, such inconclusive results warrant further investigation.

Studies show that child undernutrition is sensitive to dietary quality (Dewey & Begum, 2011) which in turn, is associated with better child nutrition and nutrient adequacy (Ruel, 2003). However, empirical evidence on the impact of PSNP on child dietary diversity is limited. Only few studies have addressed the impact of a social protection on children's nutritional intake, as opposed to household level diet diversity. Evidence from Kenya, Malawi, South Africa and Malawi show that social protection program have improved households diet diversity (de Groot, Palermo, Handa, Ragno, & Peterman, 2017). In Ethiopia, Berhane et al. (2014) find no impact of PSNP on dietary diversity (Berhane et al., 2014). Similarly, we found no impact of PSNP on child dietary diversity. In our sample, dietary diversity was generally low but significantly lower among children in PSNP households.

In this study, PSNP participation by households leads to a 0.302 increase in child meal frequency. Similarly Berhane et al., (2011) reported that PSNP has increased the number of child meals per day by 0.15 unit while Gilligan et al. (2009) has found no impact of PSNP on number of meal per day during the hungry season (Berhane, Hoddinott, Kumar, & Taffess, 2011; Gilligan, Hoddinott, & Taffesse, 2009). As studies show, PSNP has increased borrowing for productive purposes, the use of improved agricultural technologies, and agricultural productivity, consumption expenditure and has decreased the number of months of food shortage (Gilligan et al., 2009; Berhane et al., 2014; John Hoddinott et al., 2012), all of which are correlated with better child nutrition. However, whether the immediate gain in consumption translates to long-term improvement in child nutrition requires further study.

Our results have implications for the design of health and nutrition improving safety nets in Ethiopia. Unless PSNP is combined with nutrition sensitive programs, addressing the problem of undernutrition among social protection recipients is very difficult. The High Level Panel of Experts on Food Security and Nutrition (HLPE) note that the impact of social protection on food security and nutrition (HLPE, 2012). The safety net program could be leveraged by linking such programs to other sectoral programs related to, for example, access to clean water and sanitation, health services, agriculture, employment creation, investment in infrastructure, and appropriate training and information on food utilization. Therefore, integrating PSNP with other nutrition programs, such as nutrition education and access to health services, may not only solve the problem of undernutrition but also reduce the risk of nutrition-related chronic diseases. The nutrition sensitive interventions should also consider implementation costs.

This study has both strengths and weakness. Large sample size, the use of repeated measurements, and the analytical method are among the strengths. Assuming a correctly specified model and no violation of the underlying model assumptions, the MSMs gives accurate estimate the effect of PSNP on household food security and nutrition outcomes as compared with the conventional modeling approaches. MSMs do not suffer from collider stratification bias because of weighting, as opposed to conditioning, is used to control for time-varying confounders affected by previous treatment status. Moreover, this study has also attempted to check the necessary assumptions required for using MSMs. Among these, conditional exchangeability, the absence of unmeasured confounding inducing correlation between treatment (exposure) and residuals, was assumed by the inclusion of all measured covariates sufficient to adjust for both confounding and selection bias. Sensitivity analyses for unmeasured confounding were also undertaken, and results show that substantial residual unmeasured confounding was needed to explain away the observed significant associations of the treatment (PSNP) with the outcome of interests (see Supplementary File 2). Positivity requires that the probability of treatment is neither zero nor one for each combination of covariates. Put in another way, the distribution of treatment must vary across every unique covariate combination (i.e., the confounders cannot determine the treatment or non-treatment status perfectly). Hence, positivity was likely to hold based on descriptive statistics (see Table 1). Additional assumption of the correct model specification was likely to hold, given that stabilized weights has a mean of ~1. However, this study may not fulfill the consistency assumption, which requires that the outcome observed for each individual is precisely the causal outcome under their observed treatment history. This is difficult to verify and is not straightforward in our case due to the possibility of misclassification bias and compliance related to the PSNP program. A given household could use PSNP or other smoothing mechanisms through different programs, such as other formal and informal supports, which could have implications on our outcomes of interests. The exchangeability assumption is not verifiable since we rely only on known factors. Moreover, it is important to emphasize, given the nature of the data, we only adjusted for one of many time-varying confounding variables, food insecurity, but there are other possible time-varying confounders (e.g., assets/wealth). Therefore, controlling for only food insecurity did not alter the effect estimate in our MSM so that similar estimates were reported compared with multivariate logistic regression, linear mixed effect, and IPTWRA methods.

Conclusion

Both food insecurity and child undernutrition remain public health challenges in Ethiopia. In this study, we found no evidence that PSNP has improved household food insecurity and child undernutrition despite its positive impact on child meal frequency. Given the consequence of food insecurity and child undernutrition on individuals' physical and mental development, the intergenerational cycle of poverty and undernutrition, costs to the health care system, and human capital formation, the program would benefit by being integrated with other sectoral programs that are nutrition-specific and nutrition-sensitive. Some proven interventions include but are not limited to, the promotion of access to clean water and sanitation, access to health services, women's empowerment, nutrition education, and agricultural technology adoption. Further longitudinal research is required to corroborate our findings.

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Ethical statement

Young Lives obtained ethical clearance from the University of Oxford Ethics Committee and the Ethiopian Public Health and Nutrition Research Institute's institutional review board. A parent or guardian of the children gave consent before the data collection.

Author statement

Bezawit Adugna Bahru: Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing - original draft. Mulusew Gerbaba Jebena: Conceptualization, Data curation, Writing - review & editing, Methodology. Regina Birner: Writing - review & editing, Supervision. Manfred Zeller: Conceptualization, Methodology, Writing - review & editing, Validation, Supervision.

Declaration of competing interest

BAB, MJG, RB, and MZ have no conflict of interest. Young Lives had no role in analyses, or interpretation of the data or the writing of the manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2020.100660.

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