The role of social protection and agriculture for improved nutrition in Ethiopia

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University of Hohenheim

By:
Bezawit Adugna Bahru
Born in Addis Ababa,
Ethiopia

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Examination committee:

Prof. Dr. Andrea Knierim, head of examination committee

Prof. Dr. Manfred Zeller, supervisor

Prof. Dr. Meike Wollni, co-reviewer

Prof. Dr. Regina Birner, additional examiner

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Executive Summary

Nearly all nations embarked on a commitment to free the world from hunger and poverty by 2030 as part of the Sustainable Development Goals (SDGs). Considerable progress has been made in reducing poverty and hunger. Yet, a significant proportion of people in the global south, especially those living in rural areas, still live in poverty, go hungry, and suffer from malnutrition. Social protection and nutrition-sensitive agriculture are among the strategies implemented by several countries to alleviate poverty, food insecurity, and malnutrition. While consensus exists on the impact of safety nets on poverty, evidence on their impact on agriculture, food security, and nutrition is not definitive. Moreover, the impact of nutrition-sensitive agricultural interventions, particularly the role of production diversification, in improving smallholders' diet is not thoroughly examined.

Ethiopia presents an interesting case study to investigate the role of social protection and nutrition-sensitive agriculture on household welfare. Ethiopia has one the largest social protection program in Africa called the Productive Safety Net Program (PSNP). More recently, Ethiopia has also made several efforts to make agriculture and social protection interventions nutrition-sensitive. Moreover, the country is not only one of the fastest-growing economies in the world, but has high rates of poverty, food insecurity, and malnutrition. Thus, using Ethiopia as a case study, this dissertation provides a rigorous assessment of the impact of PSNP on agricultural, food security and nutrition outcomes, and the impact of agricultural diversification on household and child nutrition. To this end, it uses two longitudinal data sets from Ethiopia—the Living Standard Measurement Study - Integrated Surveys on Agriculture and the Young Lives cohort study.

This dissertation is organized into six chapters. Chapter 1 presents the conceptual framework, highlighting linkages between social protection, agriculture, and nutrition. Chapter 2 provides information about the data sources and the identification strategies used in the following three chapters. Chapter 3 evaluates the impact of a social protection intervention on a range of agricultural outcomes. Chapter 4 analyzes the role of agricultural diversification on household and child nutrition. Chapter 5 estimates the impact of social protection on household food security and child nutrition. Chapter 6 concludes the dissertation by provides policy and methodological implications, and outlines recommendations for future research.

Since 2005, Ethiopia has shifted its social protection strategy from relief types of interventions of mainly an ad hoc distribution of food/cash following droughts into a development-oriented program called the Productive Safety Net Program (PSNP). The PSNP provides cash and in-kind transfers for labor contributions in public work projects such as roads, irrigation, schools, hospitals, and training centers for farmers. The program is complemented by asset building programs that transfer assets with the aim to improve livelihoods. Hence, household participation in the PSNP

could improve agricultural outcomes by alleviating liquidity and credit constraints, improving certainty, acting as insurance against risks, improving access to inputs and agricultural markets, and building community agricultural assets.

Chapter 3 evaluates the impact of PSNP on productive asset ownership, improved seed and fertilizer adoption, crop and livestock diversity, advisory services, and women's control over resources by applying targeted maximum likelihood estimation. Doing so it contributes to the literature by considering a range of outcomes along the causal pathway and employing a novel method that uses machine learning algorithms and hence provides estimates that are less prone to model misspecification and outliers. Results show that PSNP participation increased ownership of agricultural tools, the value of livestock sales, the share of household income from non-farm sources, time spent on agricultural work, and access to credit at the household level. Moreover, PSNP participation improves community access to irrigation water and advisory services on natural resource management, as well as household credit access, crop production, and livestock production. However, PSNP participation has no impact on technology adoption, women's control over income, crop and livestock counts, and access to extension services at the household level. Results also show that PSNP participants have a lower endowment of durable assets, human capital, and land, which might hinder improved community access to inputs and advisory services to improve agricultural outcomes. These results underscore the need to integrate household-level interventions that could lift household endowments to create an asset threshold that would allow the productive use of created community assets. One avenue to achieve this could be complementing cash/in-kind transfers with a well-designed productive asset transfer. Other studies have shown delays and underpayment of entitled public work transfers. Hence improving the timeliness and size of cash/in-kind payments are also critical to achieve impact on agriculture. Doing so may elevate the impact of the PSNP beyond improving community access to inputs and may promote agricultural development, ultimately improving rural livelihoods.

Agriculture as a source of food and livelihood for the hungry and malnourished has an important role in alleviating malnutrition and its associated welfare consequences. Especially in a context where subsistence agriculture constitutes a large share of agricultural production and market participation is hindered by market failure, own production plays a crucial role in household food security and nutritional outcomes. Evidence as to whether production diversity improves nutritional outcomes is not definitive. It largely draws on studies that did not address the endogenous relationship between production and consumption decisions.

To fill this research gap, Chapter 4 analyzes the impact of production diversity on household diet and child undernutrition. It uses instrumental variable approach to account for endogeniety in production and consumption decision among smallholders. Results show that production diversity is associated with improvements

in household diet, but not child chronic undernutrition. Positive effects could come through three possible pathways: consumption, improved agroecology due to production diversification, and improved risk-bearing capacity. We find higher consumption of more nutritious foods (egg, fish, fruits, legumes/nuts/seeds, meat, roots, tubers, milk, milk products, and vegetables) among households with higher levels of production diversity. Nevertheless, production diversification above 7.5 and 7 food groups, for household with access to community market and those with no access respectively, is negatively associated with household nutrition. This could be due to foregone income benefits from specialization. As far as the role of markets is concerned, we found that market access improves household dietary diversity even when production diversity is high. Our analysis of the role of market participation shows a positive impact of market participation on household diets, but finds no impact on child nutrition. Given that an average farmer in our sample produces about six groups of foods, promoting more production diversity is likely to result in negative effect on household diets. Hence, policies that aim to improve smallholders' nutrition should focus on improving conditions for market participation over increasing the diversity of production.

While there is ample evidence on the impact of safety nets on poverty, their role in addressing the root causes and manifestations of poverty, such as child malnutrition, is not well documented. Moreover, the available evidence on the impact of safety nets on household food security and child nutrition emanates from programs in Latin American countries that were implemented under different institutional capacity and implementation modalities. Moreover, evidence as to whether safety nets impact child nutrition is not conclusive. In addition, in Ethiopia, the very few studies examining the impact of safety nets on child nutrition and household food security provided mixed evidence. These studies used methods that are prone to bias due to time-variant confounders that are pertinent to the program design and implementation. In Chapter 5, we address this gap by evaluating the impact of the PSNP on household food security and child nutrition outcomes. We did this by applying marginal structural models that adjust not only for timein-variant, but also time-variant confounders. We find that although PSNP participation increases child meal frequency, it has no impact on household food security and child dietary diversity, height-for-age z-scores, body-mass-index, the likelihood of stunting, and the likelihood of being underweight. We also find important predictors of child nutrition, such as maternal education, child dietary diversity, household food security, durable assets, expenditures, and nutritional status during the 1,000 days window to be lower among children in PSNP participant households. Moreover, while experts note that integrating safety nets with other sectoral programs is critical to result in impacts on nutrition, such integrations are lacking in the PSNP's implementation. Therefore, we recommend integrating PSNP 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.

To summarize, using Ethiopia as a case study, this dissertation contributes to the growing body of literature on impact evaluation of programs aimed at achieving the SDG targets. It does so by applying novel techniques in impact evaluation using observational studies including those that integrate learning algorithms. It shows that a higher production diversity negatively affects household nutrition while market access and participation improve household diets. Hence, improving conditions for market participation and increased participation in markets might be one of the pathways through which agriculture improves nutrition, especially in contexts where production is already diversified enough. It also shows that despite the potential of safety nets to address the root cause of poverty by improving household livelihoods and breaking the inter-generational cycle of poverty, these impacts are mostly nonexistent in one of Africa's largest social protection program. To alleviate these constraints and elevate the contribution of PSNP beyond the limited impact on nutrition and agriculture, we recommend integrating nutrition-sensitive interventions and well-designed asset transfer programs.

Zussamenfassung

Nahezu alle Nationen haben sich im Rahmen der Sustainable Development Goals (SDGs) verpflichtet, die Welt bis 2030 von Hunger und Armut zu befreien. Bei der Reduzierung von Armut und Hunger wurden erhebliche Fortschritte erzielt. Dennoch lebt ein erheblicher Teil der Menschen im globalen Süden, vor allem in ländlichen Gebieten, immer noch in Armut, hungert und leidet unter Mangelernährung. Sozialer Schutz und eine ernährungssensitive Landwirtschaft gehören zu den Strategien, die von mehreren Ländern umgesetzt werden, um Armut, Ernährungsunsicherheit und Mangelernährung zu lindern. Während es einen Konsens über die Auswirkungen von sozialen Sicherungssystemen auf Armut gibt, sind die Erkenntnisse über ihre Auswirkungen auf Landwirtschaft, Ernährungssicherheit und Ernährung nicht eindeutig. Darüber hinaus ist die Wirkung von ernährungssensitiven landwirtschaftlichen Interventionen, insbesondere die Rolle der Produktionsdiversifizierung, auf die Verbesserung der Ernährung von Kleinbauern nicht gründlich untersucht.

Äthiopien stellt eine interessante Fallstudie dar, um die Rolle von Sozialschutz und ernährungssensitiver Landwirtschaft auf das Wohlergehen von Haushalten zu untersuchen. Äthiopien hat eines der größten Sozialschutzprogramme in Afrika, das Productive Safety Net Program (PSNP). In jüngster Zeit hat Äthiopien auch mehrere Anstrengungen unternommen, um die Landwirtschaft und Maßnahmen zur sozialen Sicherung ernährungssensitiv zu gestalten. Darüber hinaus ist das Land nicht nur eine der am schnellsten wachsenden Volkswirtschaften der Welt, sondern weist auch hohe Raten an Armut, Ernährungsunsicherheit und Unterernährung auf. Am Beispiel Äthiopiens werden in dieser Dissertation die Auswirkungen des PSNP auf die Landwirtschaft, die Ernährungssicherheit und die Ernährung sowie die Auswirkungen der landwirtschaftlichen Diversifizierung auf die Ernährung von Haushalten und Kindern untersucht. Zu diesem Zweck werden zwei Längsschnittdatensätze aus Äthiopien verwendet - die Living Standard Measurement Study - Integrated Surveys on Agriculture und die Young Lives Kohortenstudie.

Diese Arbeit ist in sechs Kapitel gegliedert. Kapitel 1 stellt den konzeptionellen Rahmen vor und hebt die Zusammenhänge zwischen Sozialschutz, Landwirtschaft und Ernährung hervor. Kapitel 2 informiert über die Datenquellen und die in den folgenden drei Kapiteln verwendeten Identifikationsstrategien. Kapitel 3 evaluiert die Auswirkungen einer Sozialschutzmaßnahme auf eine Reihe von landwirtschaftlichen Ergebnissen. Kapitel 4 analysiert die Rolle von landwirtschaftlicher Diversifizierung auf die Ernährungssituation von Haushalten und Kindern. Kapitel 5 schätzt die Auswirkungen des PSNP auf die Ernährungssicherheit der Haushalte und die Ernährung der Kinder. Kapitel 6 schließt mit politischen und methodischen Implikationen und skizziert Empfehlungen für zukünftige Forschung.

Seit 2005 hat Äthiopien seine Sozialschutzstrategie von Hilfsmaßnahmen, die hauptsächlich aus einer Ad-hoc-Verteilung von Nahrungsmitteln/Bargeld nach Dürren

bestehen, auf ein entwicklungsorientiertes Sozialschutzprogramm namens Productive Safety Net (PSNP) umgestellt. PSNP bietet Geld- und Sachmitteltransfers für Arbeitsleistungen in öffentlichen Arbeitsprojekten wie Straßen, Bewässerung, Schulen, Krankenhäuser und Ausbildungszentren für Bauern. Ergänzt wird das Programm durch Vermögensaufbau, die das Ziel haben, den Lebensunterhalt der beteiligten Haushalte zu verbessern. Daher könnte die Teilnahme der Haushalte am PSNP die landwirtschaftliche Produktion zu verbessern, indem Liquiditäts- und Kreditbeschränkungen gemildert werden, Sicherheiten erhöht werden, eine Versicherung gegen Risiken besteht, der Zugang zu Betriebsmitteln und Agrarmärkten verbessert wird und gemeinschaftliche landwirtschaftliche Vermögen aufgebaut werden.

Kapitel 3 bewertet die Auswirkungen des PSNP auf den Besitz von Produktionsmitteln, die Einführung von verbessertem Saatgut und Düngemitteln, die Vielfalt von Nutzpflanzen und Viehbeständen, Beratungsdienste und die Kontrolle von Frauen über Ressourcen durch die Anwendung einer gezielten Maximum-Likelihood-Schätzung. Der Artikel trägt zur Literatur bei, indem er eine Reihe von Ergebnissen entlang der kausalen Zusammenhänge berücksichtigt und eine Methode einsetzt, die Algorithmen des maschinellen Lernens verwendet. Das Modell liefert Schätzungen, die weniger anfällig für Fehlspezifikationen und Ausreißer sind. Die Ergebnisse zeigen, dass die PSNP-Teilnahme den Besitz von landwirtschaftlichen Werkzeugen, den Wert von Viehverkäufen, den Anteil des Haushaltseinkommens aus außerlandwirtschaftlichen Quellen, die für landwirtschaftliche Arbeiten aufgewendete Zeit und den Zugang zu Krediten auf Haushaltsebene erhöht. Darüber hinaus verbessert die PSNP-Teilnahme den Zugang der Gemeinschaft zu Bewässerung und Beratungsleistungen zum Management natürlicher Ressourcen sowie den Zugang der Haushalte zu Krediten, die Ernteproduktion und die Viehzucht. Die PSNP-Teilnahme hat jedoch keinen Einfluss auf die Nutzung von Technologien, die Kontrolle der Frauen über das Einkommen, die Ernte und den Viehbestand sowie den Zugang zu Beratungsdiensten auf Haushaltsebene. Die Ergebnisse zeigen auch, dass PSNP-Teilnehmer eine geringere Ausstattung mit langlebigen Vermögenswerten, Humankapital und Land haben, was einen verbesserten Zugang der Gemeinschaft zu Betriebsmitteln und Beratungsdiensten zur Verbesserung der landwirtschaftlichen Ergebnisse behindern könnte. Diese Ergebnisse unterstreichen die Notwendigkeit, Interventionen auf Haushaltsebene zu integrieren, die die Ausstattung der Haushalte anheben könnten, um eine Vermögensschwelle zu schaffen, die die produktive Nutzung des geschaffenen Gemeinschaftsvermögens ermöglicht. Eine Möglichkeit, dies zu erreichen, könnte darin bestehen, Bargeld-/Sachmitteltransfers durch einen gut konzipierten Vermögenstransfer zu ergänzen. Andere Studien haben Verzögerungen und Unterbezahlung von berechtigten öffentlichen Arbeitstransfers gezeigt. Daher ist die Verbesserung der Pünktlichkeit und des Umfangs von Geld-/Sachleistungen ebenfalls entscheidend, um Auswirkungen auf die Landwirtschaft zu erzielen. Dadurch kann die Wirkung des PSNP über die Verbesserung des Zugangs der Gemeinden zu Betriebsmitteln hinausgehen und die landwirtschaftliche Entwicklung fördern, was

letztlich die Lebensbedingungen im ländlichen Raum verbessert.

Die Landwirtschaft als Quelle von Nahrung und Lebensunterhalt für Hungernde und Unterernährte spielt eine wichtige Rolle bei der Linderung von Unterernährung und den damit verbundenen Folgen für das Wohlergehen. Insbesondere in einem Kontext, in dem die Subsistenzlandwirtschaft einen großen Teil der landwirtschaftlichen Produktion ausmacht und in dem die Marktteilnahme durch Marktversagen behindert wird, spielt die Eigenproduktion eine entscheidende Rolle für die Ernährungssicherheit der Haushalte und die Ernährungsergebnisse. Die Beweise dafür, ob die Produktionsvielfalt die Ernährung verbessert, sind nicht eindeutig. Sie stützen sich größtenteils auf Studien, die sich nicht mit der endogenen Beziehung zwischen Produktions- und Konsumentscheidungen befasst haben.

Um diese Forschungslücke zu schließen, analysiert Kapitel 4 die Auswirkungen der Produktionsvielfalt auf die Ernährung der Haushalte und die Unterernährung von Kindern. Um die Endogenität dieser Auswirkungen zu berücksichtigen, wird ein Instrumentalvariablenansatz gewählt Die Ergebnisse zeigen, dass die Produktionsvielfalt mit Verbesserungen in der Ernährung der Haushalte verbunden ist, nicht aber mit chronischer Unterernährung von Kindern. Die positiven Effekte könnten über drei mögliche Wege zustande kommen: Konsum, verbesserte Agrarökologie aufgrund der Produktionsdiversifizierung und verbesserte Risikotragfähigkeit. Der Artikel findet einen höheren Konsum von nährstoffreicheren Lebensmitteln (Eier, Fisch, Früchte, Hülsenfrüchte/Nüsse/Samen, Fleisch, Wurzeln, Knollen, Milch, Milchprodukte und Gemüse) in Haushalten mit höherer Produktionsvielfalt. Dennoch ist die Produktionsdiversifizierung über sieben Lebensmittelgruppen hinaus negativ mit der Ernährung der Haushalte verbunden. Dies könnte auf entgangene Einkommensvorteile durch Spezialisierung zurückzuführen sein. Was die Rolle der Märkte betrifft, so wurde gezeigt, dass der Marktzugang die Ernährungsvielfalt der Haushalte verbessert, selbst wenn die Produktionsvielfalt hoch ist. Unsere Analyse der Rolle der Marktteilnahme zeigt einen positiven Einfluss der Marktteilnahme auf die Ernährung der Haushalte, findet aber keinen Einfluss auf die Ernährung der Kinder. Angesichts der Tatsache, dass ein durchschnittlicher Landwirt in unserer Stichprobe etwa sechs Gruppen von Nahrungsmitteln produziert, dürfte die Förderung einer größeren Produktionsvielfalt negative Auswirkungen auf die Ernährung der Haushalte haben. Daher sollten sich politische Maßnahmen zur Verbesserung der Ernährung von Kleinbauern darauf konzentrieren, die Bedingungen für die Marktteilnahme zu verbessern, anstatt die Produktionsvielfalt zu erhöhen.

Während es zahlreiche Belege für die Auswirkungen von Maßnahmen zur sozialen Sicherung auf die Armut gibt, ist ihre Rolle bei der Bekämpfung der eigentlichen Ursachen und Erscheinungsformen von Armut, wie z. B. der Unterernährung von Kindern, nicht gut dokumentiert. Dazu stammen die verfügbaren Erkenntnisse über

die Auswirkungen von Maßnahmen zur sozialen Sicherung auf die Ernährungssicherheit von Haushalten und die Ernährung von Kindern aus Programmen in lateinamerikanischen Ländern, die mit unterschiedlichen institutionellen Kapazitäten und Umsetzungsmodalitäten durchgeführt wurden. Darüber hinaus ist die Evidenz, ob Maßnahmen zur sozialen Sicherung die Kinderernährung beeinflussen, nicht schlüssig. Auch in Äthiopien lieferten die wenigen Studien, die die Auswirkungen von Maßnahmen zur sozialen Sicherung auf die Ernährung von Kindern und die Ernährungssicherheit von Haushalten untersuchten, gemischte Erkenntnisse. In diesen Studien wurden Methoden verwendet, die anfällig für Verzerrungen durch zeitvariable Störfaktoren sind, die mit dem Programmdesign und der Implementierung zusammenhängen. In Kapitel 5 wird diese verbleibende Lücke geschlossen, indem die Auswirkungen des PSNP auf die Ernährungssicherheit von Haushalten und die Ernährung von Kindern untersucht wird. Dazu werden marginale Strukturmodelle angewandt, die nicht nur für zeitvariante, sondern auch für zeitinvariante Einflussfaktoren adjustieren. Die Studie stellt fest, dass die Teilnahme am PSNP zwar die Häufigkeit der Mahlzeiten für Kinder erhöht, aber keinen Einfluss auf die Ernährungssicherheit der Haushalte und die Ernährungsvielfalt der Kinder, die z-Scores für die Körpergröße, den Body-Mass-Index, und die Wahrscheinlichkeit von Wachstumshemmung und Untergewicht hat. Es wird außerdem festgestellt, dass wichtige Determinanten für die Kinderernährung, wie z.B. die Bildung der Mutter, die Ernährungsvielfalt des Kindes, die Ernährungssicherheit des Haushalts, das langfristige Vermögen, die Ausgaben und der Ernährungszustand während des 1.000-Tage-Fensters bei den Kindern in den Haushalten der PSNP-Teilnehmer niedriger sind. Darüber hinaus weisen Experten darauf hin, dass die Integration von Maßnahmen zur sozialen Sicherung mit anderen sektoralen Programmen entscheidend ist, um Auswirkungen auf die Ernährung zu erzielen. Solche Integrationen fehlen bei der Umsetzung des PSNP. Es wird daher empfohlen, das PSNP mit anderen sektoralen Programmen zu integrieren, die ernährungsspezifisch und ernährungssensitiv sind. Zu den bewährten Interventionen gehören unter anderem die Förderung des Zugangs zu sauberem Wasser und sanitären Einrichtungen, der Zugang zu Gesundheitsdiensten, die Stärkung der Rolle der Frau, Ernährungserziehung und die Einführung landwirtschaftlicher Technologien.

Zusammenfassend lässt sich sagen, dass diese Arbeit am Beispiel Äthiopiens einen Beitrag zur wachsenden Literatur über die Wirkungsevaluierung von Programmen zur Erreichung der Nachhaltigen Entwicklungsziele bis 2030 leistet. Dies wird durch die Anwendung neuer Techniken in der Wirkungsevaluation mit beobachtenden Studien erreicht, einschließlich solcher Techniken, die integrierte Lernalgorithmen verwenden. Sie zeigt, dass sich eine höhere Produktionsvielfalt negativ auf die Ernährung der Haushalte auswirkt, während Marktzugang und -teilnahme die Ernährung der Haushalte verbessern. Daher könnte die Verbesserung der Bedingungen für die Marktteilnahme und die verstärkte Teilnahme an Märkten einer der Wege sein, über

den die Landwirtschaft die Ernährung verbessert, insbesondere in Kontexten, in denen die Produktion bereits ausreichend diversifiziert ist. Die Studie zeigt auch, dass trotz des Potenzials von Maßnahmen zur sozialen Sicherung, die Ursache von Armut zu bekämpfen, indem sie die Lebensgrundlage von Haushalten verbessern und den generationenübergreifenden Kreislauf der Armut durchbrechen, diese Auswirkungen in einem der größten Sozialschutzprogramme Afrikas weitgehend ausbleiben. Um diese Einschränkungen zu beheben und den Beitrag des PSNP über die begrenzten Auswirkungen auf Ernährung und Landwirtschaft hinaus zu erhöhen, wird die Integration von ernährungssensitiven Interventionen und gut konzipierten Vermögenstransferprogrammen empfohlen.

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AGP	**A**griculture **G**rowth **P**rogramme
AIPW	**A**ugmented **I**nverse **P**ropensity **W**eighted
ATE	**A**verage **T**reatment **E**ffect
BCC	**B**ehaviour **C**hange **C**ommunication
BMI	**B**ody Mass **I**ndex
CCI	**C**omplimentary **C**ommunity **I**nvestment
CFW	**C**ash **f**or **W**ork
CSA	**C**entral **S**tatistical **A**gency
CT	**C**ash **T**ransfer
DDS	**D**ietary **D**iversity **S**core
DR	**D**oubly **R**obust
DS	**D**irect **S**upport
EA	**E**numeration **A**rea
ECA	**E**conomic **C**ommission for **A**frica
EM-DAT	**T**he **E**mergency **E**vents **D**atabase
EPHI	**E**thiopia **P**ublic **H**ealth **I**nstitute
ETB	**E**thiopian **B**irr
FAO	**F**ood and **A**griculture **O**rganization
FDRE	**F**ederal **D**emocratic **R**epublic of **E**thiopia
FFW	**F**ood **F**or **W**ork
FS	**F**ood **S**ecure
GDP	**G**ross **D**omestic **P**roduct
HABP	**H**ousehold **A**sset **B**uilding **P**rogramme
HAZ	**H**eight-for-**A**ge **Z**-score
HDDS	**H**ousehold **D**ietary **D**iversity **S**cores
HFIAS	**H**ousehold **F**ood **I**nsecurity **A**ccess **S**cale
HH	**H**ousehold
HLPE	**H**igh **L**evel **P**anel of **E**xperts
ICF	**I**ncident **C**ommand **F**acility
IPTW	**I**nverse **P**robability of **T**reatment **W**eighting
IPTWRA	**I**nverse **P**robability **W**eighted **R**egression **A**djustment
IPWRA	**I**nverse **P**robability **W**eighted **R**egression **A**djustment
IV	**I**nstrumental **V**ariable
IV-GMM	**I**nstrumental **V**ariable **G**eneralized **M**ethod of **M**oments
KG	**K**ilogram
KMO	**K**aiser **M**eyer **O**lkin
LCS	**L**iving **C**ondition **S**urvey **LH**
Livelihoods	
LMICs	**L**ow and **M**iddle **I**ncome **C**ountries
LSMS-ISA	**L**iving **S**tandard **M**easurement **S**tudy - **I**ntegrated **S**urveys on **A**griculture
ML	**M**achine **L**earning
MoA	**M**inistry of **A**griculture

MoANR	**M**inistry of **A**griculture and **N**atural **R**esource
MoLAF	**M**inistry of **L**ivestock and **F**isheries
MoLF	**M**inistry of **L**ivestock and **F**isheries
MSM	**M**arginal **S**tructural **M**odel
NASA	**N**ational **A**eronautics and **S**pace **A**dministration's
NOAA	**N**ational **O**ceanic and **A**tmospheric **A**dministration's
NPC	**N**ational **P**lanning **C**ommission
NPS	**N**ational **P**anel **S**urvery
OC	**O**lder **C**ohort
OFSP	**O**ther **F**ood **S**ecurity **P**rogramme
PCA	**P**rincipal **C**omponent **A**nalysis
PS	**P**ropensity **S**core
PSM	**P**ropensity **S**core **M**atching
PSNP	**P**roductive **S**afety **N**et **P**rogram
PW	**P**ublic **W**ork
RA	**R**egression **A**djustment
SE	**S**tandard **E**rror
SNNP	**S**outhern **N**ation **N**ationalities and **P**eople
SUTVA	**S**table **U**nit **T**reatment **V**alue **A**ssumption
SW	**S**tabilized **W**eight
TLU	**T**ropical **L**ivestock **U**nit
TMLE	**T**argeted **M**aximum **L**ikelihood **E**stimation
UN	**U**nited **N**ations
UNICEF	**U**nited **N**ations **C**hildren's **F**und
WB	**W**orld **B**ank
WFP	**W**orld **F**ood **P**rogramme
WHO	**W**orld **H**ealth **O**rganization
YC	**Y**ounger **C**ohort
YL	**Y**oung **L**ives

Chapter 1

Introduction

1.1 General Introduction

Ethiopia has one of the fastest-growing economies in the world and has recorded considerable progress in improving living conditions. In the past decade, Ethiopia has recorded over 8% GDP growth every year (World Bank, 2020). Poverty rate has declined from 56% in 2000 to 23.5% in 2016 (Figure 1.1). The proportion of households who experienced food shortage decreased from 29% in 2005 to 10% in 2016 (Hill and Tsehaye, 2014; World Bank, 2020). The prevalence of stunting, wasting, and underweight among children below five years of age declined from 51.5%, 10.5%, and 47.2% in 2000, respectively, to 37%, 7%, and 21% percent in 2019, respectively (CSA, 2001; ICF and EPHI, 2019). The achieved progress in living conditions is largely driven by improvements in urban than rural areas (Figure 1.1).

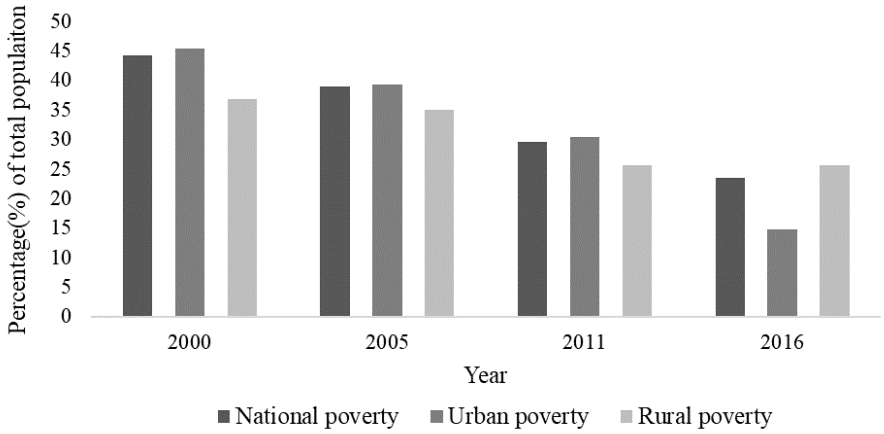

FIGURE 1.1 Poverty headcount rate based on the national poverty line, 2000-2016
Source: Authors compilation from Hill and Tsehaye, 2014; World Bank, 2020

Nonetheless, food insecurity and undernutrition remain intolerably high and are a challenge to achieving Ethiopia's vision to become a lower-middle-income country

by 2025 (Figure 1.2). For instance, in 2009 alone Ethiopia lost ETB 55.5, equivalent to 16.5% of GDP, due to child undernourishment (ECA & WFP, 2013). Food insecurity and undernutrition are dominantly a rural phenomenon where agriculture is the dominant source of livelihoods (CSA, 2001; Hill and Tsehaye, 2014; ICF and EPHI, 2019; World Bank, 2020). The causes of undernourishment in Ethiopia are complex and multifactorial. Drought, poverty, food insecurity, lack of access to healthcare, household environment, and lack of appropriate child care and feeding practices are among the major contributing factors (Tasic et al., 2020).

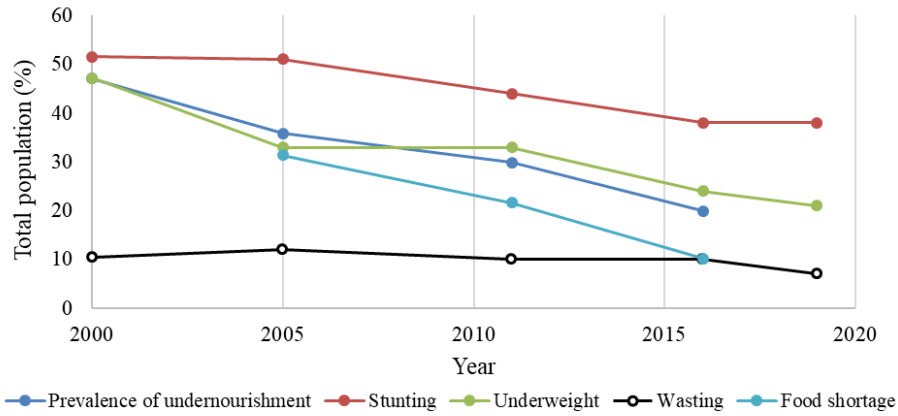

FIGURE 1.2 The prevalence of undernourishment, food shortage, underweight, stunting and wasting in Ethiopia
Source: Authors compilation from CSA, 2001; Hill and Tsehaye, 2014; ICF and EPHI, 2019; FAO, 2020

Agriculture has been the driving force for economic growth and poverty reduction in Ethiopia (Bachewe et al., 2018; World Bank, 2020; World Bank, 2014). Estimates shows that a 1% growth in agricultural output reduces poverty by 0.9% (Hill and Tsehaye, 2014). From 2011 to 2016, agriculture contributed two-thirds towards poverty reduction (World Bank, 2020). Agriculture (yield increase) was also the major driver of improvement in child nutrition, contributing 32–34% to the total reduction in undernourishment (Tasic et al., 2020). Given the sheer size of employment in agriculture (i.e., over 70% of the population), the sector remains crucial to achieve poverty reduction and inclusive economic growth in Ethiopia.

Agriculture has also been at the center of Ethiopia's development strategies. From the Imperial regime in 1968–1973 to the current home-grown economic reform, the country has put tremendous effort to transform agriculture into a productive and competitive sector, fueling growth in other sectors (Diriba, 2020; FDRE, 2019). This is reflected in Ethiopia's high public spending in agriculture, accounting for about 15% of total government spending (Hill and Tsehaye, 2014). Half of the investment in agriculture goes to a safety net program that aims to smooth consumption, reduce asset depletion, and build community assets (Hill and Tsehaye, 2014).

Yet, agriculture growth in Ethiopia is challenged by climate-related shocks, such as drought, which put the lives of millions of Ethiopians at the mercy of food aid (Caeyers and Dercon, 2012; Devereux and Guenther, 2009; Gebreselassie, 2006). Drought in Ethiopia is associated with yield reduction, household food insecurity, and poor child growth and development and has contributed to failed agricultural policies (Bahru et al., 2019; Demeke and Zeller, 2012; Dercon, Hodinnott, and Woldehanna, 2006; Nelson et al., 2009). This has also made the country one of the most food aid-dependents countries in the world (Caeyers and Dercon, 2012; Gebreselassie, 2006). Especially during the late 1990s and early 2000s, Ethiopia has experienced repeated droughts which led to near annual emergency appeal for food aid and humanitarian assistance (Gebreselassie, 2006). The scale of the affected population and development resources that went to finance food aid led to a shift in Ethiopia's food security strategy and the introduction of the Productive Safety Net Program (PSNP) (Devereux and Guenther, 2009).

PSNP is the largest food insecurity and poverty alleviation strategy and an important pillar of agricultural transformation. Before the introduction of the PSNP, food aid in Ethiopia has been addressed largely by an ad hoc distribution of food/cash transfer following shocks, mostly drought. While these interventions sustained millions of lives, they did not address the underlying causes of food insecurity nor did they assist rural development (Gilligan, Hoddinott, and Taffesse, 2009). Hence, in 2005, the Ethiopian government and consortium of donors introduced the PSNP with the objective to smooth household consumption, protect household assets, and promote household livelihoods (FDRE, 2004; MoA, 2009; MoA, 2014). Currently, the program operates in all regions of Ethiopia, except Gambella and Benishangul-Gumuz, and covers nearly 8 million people.

In recent years, Ethiopia has also tried to mainstream nutrition in its growth and poverty alleviation programs (Bossuyt, 2019). The PSNP has incorporated nutrition-sensitive provisions, including public work waivers for pregnant and lactating women for soft conditionalities, such as nutrition education, cooking demonstrations, and the promotion of frequent contact with healthcare providers (MoA, 2014). The Agricultural Growth Program (AGP), which previously emphasized increasing the production of staple crops, commercialization, and linkage to markets, has recently incorporated improving food consumption and dietary diversity as one of its objectives (World Bank, 2019). Ethiopia has also formulated a 5-year national nutrition-sensitive agriculture strategy (2017–2021). The strategy acknowledges the need to increase year-round availability, access, and consumption of diverse, safe, and nutritious foods via promoting improved fruit and vegetable production at the household and community level, especially in areas where access to markets is limited (MoANR and MoLF, 2016).

Social protection programs and nutrition-sensitive interventions are among the main interventions to eradicate hunger and poverty in the world (World Bank, 2018; Ruel

and Alderman, 2013; Bossuyt, 2019). Over the past two decades, LMICs implementing social protection has more than doubled (World Bank, 2018). Governments, donors, and development organizations commitment to support nutrition-sensitive agriculture has grown (Russell et al., 2018). While the knowledge base for the effectiveness of these interventions is growing, there remain gaps in our understanding of the role of these interventions in improving agricultural outcomes and nutrition. The available evidence is uneven across outcomes and regions/geographic areas (see Tables 3.1, 4.1, and 5.1). Moreover, the impact of social protection on nutrition has been less documented. Furthermore, although the coordination between agriculture and social protection, agriculture and nutrition, social protection and nutrition, and agricultural and nutrition policies is growing, the evidence base for this linkages is still limited.

This dissertation contributes to this growing body of knowledge by assessing the impact of: social protection on agricultural outcomes (Chapter 3); agricultural production diversity on household dietary quality and child nutrition (Chapter 4); and social protection on household food security and child nutritional outcomes (Chapter 5). To analyze these impacts, this dissertation draws on a conceptual framework of the linkages between social protection, agriculture, and nutrition, which are presented in Section 1.2. Specific objectives and the outline of the dissertation are in Section 1.4 and 1.5, respectively.

1.2 Background Information

1.2.1 Social Protection in Ethiopia

From 1995–2015, Ethiopia experienced 15 droughts which affected over 77 million people (Figure 1.3). This has made Ethiopia one of the largest recipients of food aid, ac-counting for about 10% of global food aid in the late 1990s and early 2000s (Caeyers and Dercon, 2012; Gebreselassie, 2006). Before PSNP came into play in 2005, food aid in Ethiopia was addressed via emergency food assistance following weather-related shocks, mostly drought (Sabates-Wheeler and Devereux, 2010). While food aid interventions have sustained the lives of millions, they neither addressed the un-derlying causes of food insecurity nor assisted the country's development objectives (Devereux and Guenther, 2009; Gilligan, Hoddinott, and Taffesse, 2009).

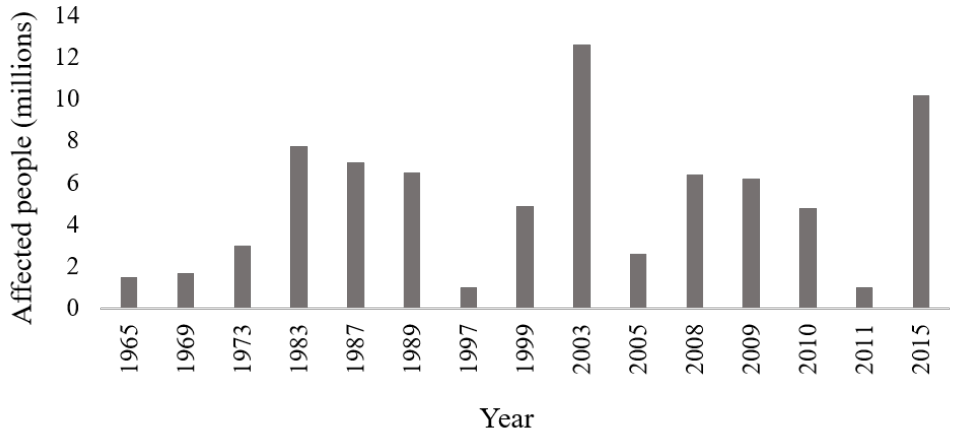

FIGURE 1.3 Drought affected population by the year of drought occurrence
Source: EM-DAT, 2020

In response, the government of Ethiopia and development partners launched the PSNP. The PSNP was introduced by Ethiopia's 'New Coalition for Food Security' in 2005 after the 2002 food crisis. It is part of Ethiopia's Food Security Program along with the Household Extension Package and Voluntary Resettlement Program. The introduction of the PSNP is motivated by the rationale of creating a relief program that addresses developmental needs. The program has three main objectives: smoothing food consumption of food-insecure households via food or cash transfers (protection); protecting household assets by reducing distress sales (prevention); and building community assets via public work programs (promotion) (Devereux and Guenther, 2009; FDRE, 2004; MoA, 2009; MoA, 2014). As summarized in Figure 1.3, the program has undergone four phases and has evolved in its modality and coverage (Figure 1.3). In what follows, we provide details about each phase of the program.

During all phases, i.e., from 2005 to 2020, the PSNP has two components. The first component is public work (PW), which is targeted to households with able-bodied members. The second component is direct support (DS), which is targeted to households whose breadwinners are the elderly or disabled. Under the PW component, beneficiaries engage in labor intensive community asset building projects, such as construction/rehabilitation of rural roads, water harvesting schemes, irrigation channels, clinics, and training centers for farmers in exchange for cash and/or in-kind transfers. During phase I and II, the PSNP's objective was to provide predictable transfers and prevent household asset depletion while creating community assets via PW (FDRE, 2004). During phase III, together with other programs, the PSNP aimed to contribute to food security of chronically and transitorily food-insecure households by ensuring food security, preventing asset depletion, stimulating acess to markets and other services, and rehabilitating and enhancing the natural environment (MoA, 2009). During phase IV, the goal of the PSNP was to enhance household's resilience to shocks, enhance livelihoods, and improve food

security and nutritional outcomes of households vulnerable to food insecurity (MoA, 2014). In terms of coverage, about five to eight million people in 192–382 Woredas/districts have benefited from the PSNP. Although coverage was higher in 2006, there is a general increasing trend in the number of beneficiary households and geographical areas covered (Figure 1.4).

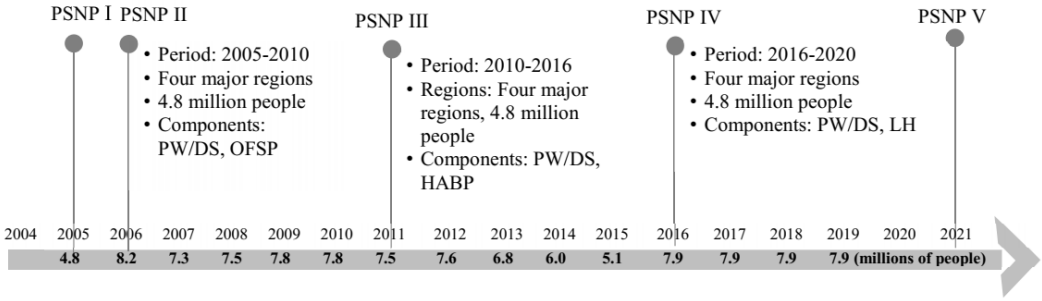

FIGURE 1.4 PSNP coverage and components
Source: Authors compilation based on MoA, 2009; MoA, 2014; Gilligan, Hoddinott, and Taffesse, 2009; Berhane et al., 2014; Berhane et al., 2020

Since its inception, the PSNP was complemented by asset-building programs that aim to bring sustained improvement in livelihoods. These complementary programs have evolved in their modality and coverage. During phase I and II, from 2005 to 2010, the PSNP was complemented by the Other Food Security Program (OFSP). The OFSP provided a suite of transfers or services including agricultural extension services, beekeeping, seed/fertilizer packages, and soil and water conservation activities (Hoddinott et al., 2012). The OFSP was not specifically targeted to PSNP beneficiaries and benefited only 32.7 percent of PW households.

During phase III, from 2011 to 2015, the Household Asset Building Program (HABP) replaced the OFSP. The HABP was aimed at diversifying sources of income and increasing productive asset endowments. During phase III, from 2011 to 2015, the Household Asset Building Program (HABP) replaced the OFSP. The HABP was aimed at diversifying sources of income and increasing productive asset endowments. Similar to the OFSP, the HABP was not exclusively targeted to PNSP households; however, PSNP households were given priority in resource/capacity constrained settings (Gilligan, Hoddinott, and Taffesse, 2009; MoA, 2014; MoA, 2009).

During phase IV, from 2016 to 2020, the livelihoods (LH) program complemented the PNSP. The LH was exclusively targeted to PSNP households, offering a tailored and sequenced package of support for clients in the on-farm, off-farm, and wage employment pathways with the objective to diversify income sources and aid asset accumulation (MoA, 2009; MoA, 2014). The support package in the LH includes financial literacy training, technical training tailored to the LH pathway chosen, assistance with business plan development, links to financial institutions, and follow-up

motoring and coaching. The LH also provided grants for the poorest households who were not creditworthy. Under the LH program, coverage improved and diversification into off-farm activities increased.

Although nutrition was neglected in previous phases of the PSNP, phase IV explicitly introduced nutrition-sensitive features to achieve nutrition and health behavior change among the PSNP PW clients (FDRE, 2004). These include monthly health and nutrition-related behavior change communication (BCC) sessions for PW clients that count toward their PW requirements (FDRE, 2004). Moreover, the program introduced a 12-month PW waiver for pregnant and lactating women for 'soft conditionalities'. These includes participation in community-based BCC sessions, antenatal care, post-partum health consultations, attendance in growth monitoring, uptake of routine immunization, a monthly checkup for children at the closest health facility, participation in community management of acute malnutrition, and targeted supplementary feeding as advised by health extension workers (FDRE, 2004).

1.2.2 Nutrition-sensitive Agriculture in Ethiopia

Unlike food security, which has always been a priority for Ethiopia's agricultural strategies, nutrition was neglected in Ethiopia's national agricultural strategies. The focus of agricultural policies in Ethiopia was improving the productivity of staple crops to ensure food security. Although nutrition-related indicators were included in earlier agricultural programs, such as the Agriculture Sector Policy and Investment Framework 2010–2020, the PSNP (2005–2010), and AGP I (2010–2015), actual implementation details and how to reach targets were not clearly stipulated (Bossuyt, 2019).

Later in 2015/2016, in parallel with the design of the National Nutrition Program II, discussion about a national nutrition-sensitive agriculture strategy began and opened the eyes of agricultural ministries to better understand the role of the agricultural sector in improving nutrition. The 5-year (2017–2021) National Nutrition-Sensitive Agriculture Strategy was launched. The strategy aims to harness the full potential of agriculture for nutrition via improving food production and productivity, agricultural income, and women's empowerment (MoANR and MoLF, 2016). The strategy highlights the importance of mothers and children in terms of their contribution to the overall objective of improving availability, access, and utilization of nutritious and safe food (MoANR and MoLF, 2016). The strategy also highlights the importance of promoting diversified production of improved fruits and vegetables for consumption, particularly in areas that have limited access to markets (MoANR and MoLF, 2016).

Currently, nutrition is mainstreamed in various sector and programs. Within the

agricultural sector, nutrition is mainstreamed in extension, horticulture, and post-harvest strategies (MoANR and MoLF, 2016). The PSNP has also included nutrition sensitive features, such as public work waivers for pregnant and lactating women, health and nutrition education, cooking demonstrations, and encouraging visits to health care facilities. The agriculture growth program, which was aimed only at increasing productivity and commercialization of smallholder farmers in its first phase, incorporated an objective to enhance the production of nutritious foods, household dietary diversity, and household food consumption (World Bank, 2019).

1.3 Conceptual Framework

This section provides the conceptual framework used to elaborate research questions addressed in this thesis. We first describe the linkages between social protection and agriculture. Then, we explain agriculture-nutrition linkages and the relationship between social protection and food security and nutrition.

1.3.1 Social Protection and Agriculture

Social protection has long been used to smooth consumption and ensure the minimum standard of living for survival. In the mid-1980s, the surge of emergencies absorbed aid resources, leaving few resources for development (Buchanan-Smith and Fabbri, 2005)). This led to the emergence of the thinking 'linking relief rehabilitation and development', i.e., development and relief has bidirectional relationship (Ross, Maxwell, and Buchanan-Smith, 1994). Proponents of this thinking argue that better 'development' has the potential to reduce the need for relief, better relief has the potential to bring in development, better 'relief' can contribute to development; and better 'rehabilitation' aids the transition from relief to development (Ross, Maxwell, and Buchanan-Smith, 1994). Motivated by this line of reasoning, safety nets have became a tool not only to smooth consumption (relief), but also to build resilience and bring a sustained exit from poverty (development). This has also led to the integration of agricultural development objectives into safety net programs. For instance, in Ethiopia, public works were used to construct/rehabilitate rural infrastructure, such as roads and irrigation cannels, to improve market integration and access to inputs for agricultural growth.

Figure 1.5 presents the conceptual framework of this dissertation. As shown, the relationship between agriculture and social protection in Ethiopia is complex. Social protection might have both a direct and indirect impact on agriculture. First, most social protection beneficiaries live in rural areas and engage in agriculture for their livelihoods. Second, although agriculture continues to be the major driver of poverty reduction and contribute a great deal to the reduction of food insecurity and

malnutrition (Hill and Tsehaye, 2014; World Bank, 2020; Tasic et al., 2020), its dependency on the mercy of weather conditions makes it a source of risk and vulnerability. Third, the non-separable nature of production and consumption decisions in Ethiopia means that households could use transfers from social protection to make agricultural investments.

As shown by Dorward, Guenther, and Wheeler, 2008, at the macro-level, investment in agriculture may increase available resources and budgetary requirement for social protection (see line a in Figure 1.5). However, agriculture and social protection policies might compete for government budget, especially when implemented by different agencies. At the micro-level, social protection may improve agricultural production by alleviating financial constraints (credit, liquidity, and saving), increasing certainty, and improving access to technology, knowledge, and factors of production (see line b) (Tirivayi et al., 2013). These, in turn, induce behavioral responses, such as changes in household spending, investment, and risk behavior, and a shift in resource allocation (see line c). In addition, these outcomes of social protections lead to changes in agricultural livelihoods, i.e., increasing investment in agricultural assets, altering input use, facilitating technology adoption, changing labor allocation decisions, and improving infrastructure, such as roads which increase access to markets, aid human capital accumulation, and stimulate off-farm investments (see line d).

Moreover, social protection may improve access to inputs and factors of production when they are tied to PW requirements, such as the construction of small-scale irrigation, micro-dams, schools, training centers for farmers, water harvesting schemes, and soil and water conservation practices (Dorward, Guenther, and Wheeler, 2008; Tirivayi et al., 2013). Other activities, such as the construction of social infrastructure (school classrooms and health posts) improve human capital outcomes, which, in the long-run, improve overall development outcomes, including agricultural productivity (Tirivayi et al., 2013). Improved agricultural livelihoods, in turn, improve the quantity and diversity of agricultural production, household income, and women's control over resources. Empirical evidence also shows that predictable transfers from social protection may alter risk behavior by acting as an insurance against shocks that may cause consumption shortfalls, increasing household agricultural asset endowments especially when coupled with asset-building programs, and changing household's coping strategies from less to more damaging ones (Alem and Broussard, 2018; Berhane et al., 2014; Coady, Grosh, and Hoddinott, 2004). Social protection may also have a multiplier effect on the local economy. For instance, transfers could be spent on purchasing goods and services in the local economy, which, in turn, stimulates the local economy by creating employment (see line e) (Dorward, Guenther, and Wheeler, 2008; Winters and Davis, 2009). Transfers also have a multiplier effect on the local economy such as increase in consumption, asset ownership, and demand for food. These multiplier effects has been shown to

to be beneficial for smallholder farmers more than larger farmers (Davies and Davey, 2008).

Several factors may mediate the relationships between social protection and agriculture (see line f) (Tirivayi et al., 2013). Some of these factors are seasonality, threshold, scale, complementarity, program sequence, as well as targeting, gender, and transfer size. For instance, the dominance of rainfed agriculture in Ethiopia means that rural livelihoods are characterized by seasonality. Thus, if not properly planned, social protection may negatively affect agriculture when PW overlaps with the agricultural season (Dorward, Guenther, and Wheeler, 2008).

There are also threshold and scale effects of programs (Dorward, Guenther, and Wheeler, 2008). Threshold effects exist in assets where certain combinations or levels of assets are necessary to engage in a productive livelihood activity (i.e., two oxen are needed for ploughing) (Carter and Barrett, 2007). Thresholds also exist in prices and market whereby increasing market players and volumes reduce transactions, which, in turn, result in thresholds below which investment is not profitable, triggering under-investment traps (Dorward et al., 2004; Dorward and Kydd, 2005). Scale effects exist when large numbers of people pursue similar activities affecting the environments in which they operate, causing undesired activities, such as natural resource depletion or price distortions (Dorward, Guenther, and Wheeler, 2008).

Another important factor for social protection to bring growth in agricultural production is policy complementarity and sequencing (Dorward, Guenther, and Wheeler, 2008). Selected policy instruments should complement each other at different stages of market development. In contexts where markets are less developed, market-based policies are not likely to bring in success. Hence, in such conditions, instruments will need to be largely non-market-based. However, when markets are well-developed, market-based instruments should be pursued.

Targeting plays a crucial role in the link between social protection and agriculture. Social protection targeted to the poorest of the poor has a marginal indirect effect on agriculture as these target groups do not have the necessary means to engage directly in agricultural production, yet benefit from participation as casual laborers. However, transfers targeted to the poorest might indirectly im-pact agriculture by increasing demand in the local food market (Dorward, Guenther, and Wheeler, 2008). Moreover, PW have been criticized for imposing heavy work requirements on the poor and alternatives, such as unconditional or conditional cash transfers, could have led to investments in agriculture or non-farm income-generating activities (Dorward, Guenther, and Wheeler, 2008). Such alternatives may help recipients of transfers access well-being enhancing services and aid hu-man capital formation, a potential pathway out of poverty (Dorward, Guenther, and Wheeler, 2008).

The role of gender in the relationship between social protection and agriculture is ambiguous. For instance, while efforts to ensure women's participation in PW increase women's control over resources, the labor-intensive nature of PW creates a high time burden for women in terms of managing reproductive tasks and meeting PW requirements (Sharp, Brown, and Teshome, 2006). Moreover, although there is no clear-cut relationship between transfer size and productivity impacts, transfers that elevate people across an asset threshold have a stronger productive impact than transfers that do not. Hence, the impact of the transfer size depends on the micro-poverty of individual beneficiaries and the transfer size in filling the gap between the beneficiary assets and the asset threshold.

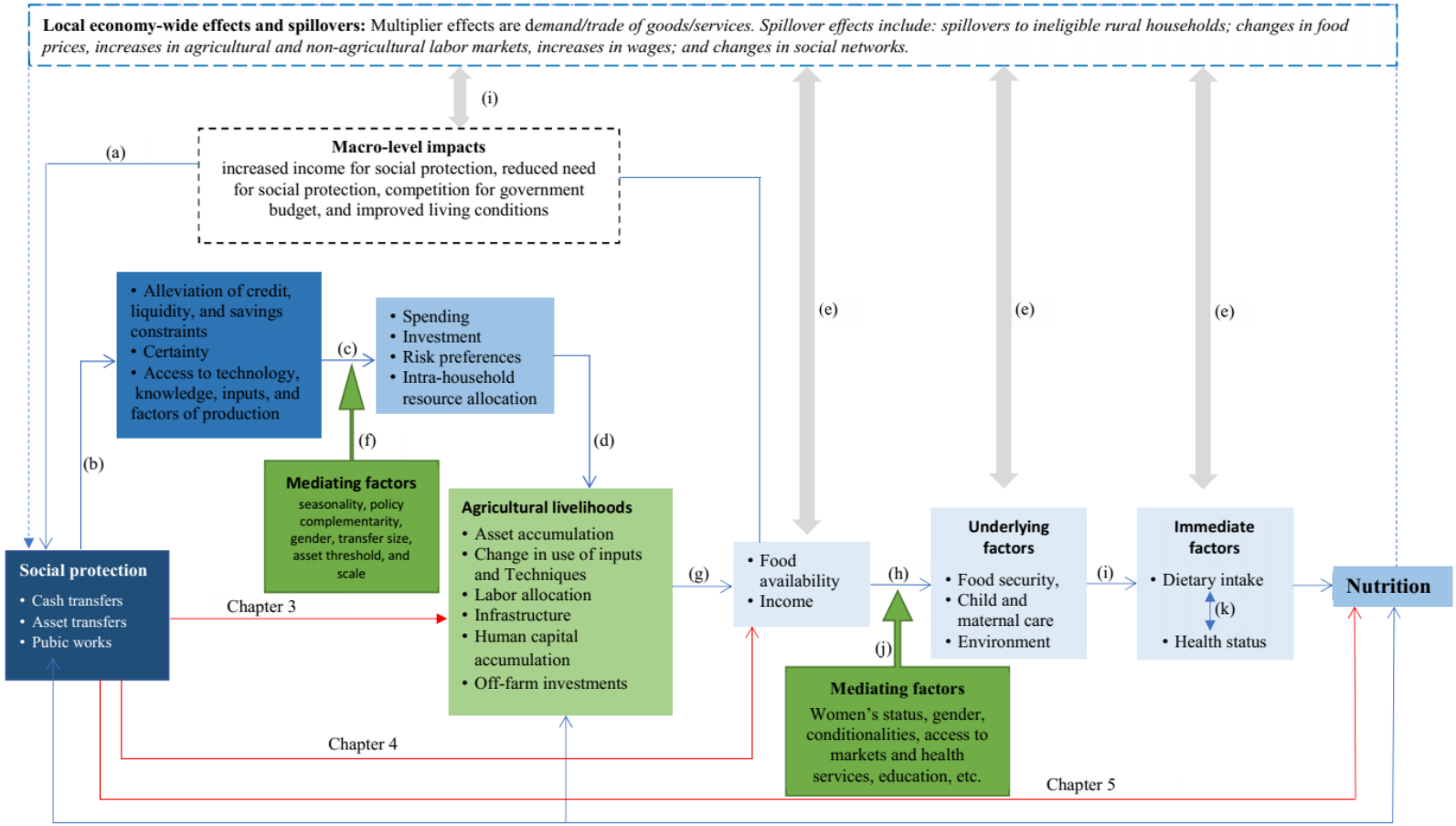

FIGURE 1.5: PSNP phases, coverage and components
Source: Authors compilation based on Gilligan, Hoddinott, and Taffesse, 2009; Berhane et al., 2014; Berhane et al., 2020

1.3.2 Agriculture and Nutrition

Globally, the need for agriculture to support better nutrition and health has been recognized (Ruel, Quisumbing, and Balagamwala, 2018). Several studies have demonstrated that nutrition-sensitive approaches to agriculture are key to achieving food security and good nutrition (Gillespie, Harris, and Kadiyala, 2012; Hawkes and Ruel, 2008; Herforth and Harris, 2013; Masset et al., 2012; Ruel and Alderman, 2013; Webb, 2013). These studies suggest several pathways through which agriculture improves nutrition: food consumed from own production; income from own agricultural production or employment in agriculture; policies that influence agricultural production and inputs, resulting in income and purchasing power changes; and women's access to and control over resources and assets, decision making in the intra-household allocation of resources (food, health, and childcare), time spent on productive and reproductive tasks and leisure, and health and nutritional status due to participation in agriculture (Gillespie, Harris, and Kadiyala, 2012; Hawkes and Ruel, 2008; Herforth and Harris, 2013; Masset et al., 2012; Ruel and Alderman, 2013; Webb, 2013). Food consumption from own production (agricultural diversification) and income from the sale of agricultural produce and working in agriculture are the most frequently suggested pathways that could lead to food security and better nutritional outcomes.

As shown in Figure 1.5, increased production at the household level improves food availability and food security (see line g) . Moreover, agriculture could improve nutrition by acting as a source of income from the sale of agricultural produce and/or employment in agriculture, which could be used to purchase food and other nutrition promoting goods and services (see line f). At the household level, improved food production and income could improve food security, care provided to children and mothers, and household environments, including access to water and sanitation (see line h). These, in turn, bring improvement in the immediate determinants of child nutrition, such as dietary intake and health (see line i). Dietary intake could be improved either only from the consumption of own production and/or the use of income from agriculture to purchase nutritious foods. If production is diversified enough by employing biofortified staple food crops and strengthening the production of food groups, such as fruit, vegetables, milk, milk products, eggs, fish, and meat, this then also increases dietary quality and the intake and adequacy of micronutrients, such as calcium, iron, vitamin A, and zinc (Bouis et al., 2011; Bouis and Saltzman, 2017; Ruel, 2003). Moreover, income from agriculture could be used to purchase healthcare services and ultimately improve the nutritional status of household members (see line i).

The linkage between agriculture and nutrition is mediated by several factors: women's status, market access, intra-household resource allocation, the caregiver's education level, and access to healthcare (see line j). Studies show that women are more likely to spend income on child nutrition promoting goods and services (Kennedy and

Peters, 1992). Hence, women's decision-making on agricultural production, control over income from agriculture, and access to resources is more likely to increase nutritional impact of agriculture. Considering market access, if market access is limited, households will be limited not only in terms of selling their produce, but also in terms of purchasing produce from others. Hence, the impact of agriculture on nutrition will be limited. In terms of intra-household resource allocation, if a member of a household, traditionally the adult male, receives favoritism in food distribution, the nutritional status of children and women is more likely to be jeopardized. As far as education is concerned, if knowledge of the caregiver about childcare and feeding is low, improved income and food availability are less likely to result in improved nutrition. Lastly, if access to health services is limited, infections and other diseases will hinder the assimilation of consumed food resulting in no improvement on nutrition (see line k)).

1.3.3 Social Protection and Nutrition

Social protection could lead to better nutritional outcomes through several pathways. Groot et al., 2017 suggested improved food security, health, and childcare as the three main pathways through which social protection improves the underlying determinants of child nutrition. Cash transfers from social protection programs could directly increase income, which could be invested to purchase nutrition and health-promoting goods and services (see line h). Social protection could also affect nutrition through indirect pathways. For instance, transfers from social protection could be invested in productive activities, such as food production for consumption or for sale, as well as the purchase of assets which improve household food security and dietary diversity (see line m). Income from these activities could be spent on food, health services, and improving sanitation facilities for households, such as housing condition improvements, curative/preventive health visits, medical supplies, and deworming tablets, which improves the health and food intake (see line h). Moreover, income from social protection programs may also alleviate poverty-related stress and improve the caregiver's physical and mental state. This, in turn, reduces household stress, positively impacts caregiving behavior, and improves the quality of child care and hence child health. Moreover, income from social protection programs may relieve incentives for pregnant women to engage in dangerous or rigorous work, which could have implications for birth outcomes. There are also synergetic effects of the above-described pathways. For instance, when food availability is coupled with good child care, feeding, and health-seeking behavior, the effect is likely to be stronger.

As indicated in Figure 1.5 (line j), factors such as program modality, availability of food, economic shocks, food prices, intra-household resource allocation, access to health services, gender, and child care and feeding practices mediate and/or moderate the relationship between safety nets and child nutrition (Groot et al., 2017).

Programs that have a behavioral component, such as health and nutrition education, may alter household preferences towards purchasing more nutritious goods and services. Programs that involve the construction of community assets, such as rural roads, irrigation schemes, training centers for farmers, schools, and clinics, also increase the impact of cash transfers on child nutrition. Moreover, conditionalities imposed in programs, such as regular visits to healthcare facilities and attendance in behavior change communication sessions, could increase utilization of health services, alter feeding and care behavior, and ultimately improve child nutrition.

External factors, such as as the availability of food and economic shocks also play important roles in how social protection improves nutrition. For instance, increases in food prices lower the purchasing power of transfers, which reduces the effect of transfers on food security and child nutrition. Household conditions, such as the intra-household distribution of resources, gender of the social protection recipient, and caregiver characteristics, also play a crucial role. For instance, if the intra-household allocation of food is child sensitive, programs are likely to have a strong impact on child nutrition. Moreover, proper feeding practices and a good health status are essential to ensure that nutrients contained in the food are absorbed. As far as gender is concerned, transfers given to women may improve women's control over resources, empowerment, and decision-making power, which are associated with positive impacts on child nutrition. However, if transfers involve labor contributions, such as in public work, this is likely to impose a time burden for women and compromise childcare.

1.4 Specific Objectives and Research Hypothesis

Ethiopia has tried to transform smallholder agriculture into a more productive and competitive sector using several interventions (Diriba, 2020). A safety net program that has protective, preventive, and promotive components and agriculture growth programs are included in these interventions. The country has also tried to mainstream nutrition in both safety net and agricultural programs. Despite these efforts, food security, undernutrition, and their associated welfare consequences remain a development challenge in Ethiopia. Nonetheless, evidence on the impact of these interventions is scant and inconclusive. Following the conceptual framework described in Section 1.3, this dissertation attempts to: estimate the impact of the PSNP on agricultural productivity, asset accumulation, and technology adoption (Chapter 3); examine the effect of agricultural production diversity on dietary diversity and child nutritional outcomes (Chapter 4); and estimate the impact of the PSNP on household food security and child nutritional outcomes (Chapter 5). Specific research questions and corresponding hypotheses formulated are listed below:

Research question 1: does participation in PSNP improve agricultural outcomes?

- Does participation in the PSNP improve productive asset ownership, improved seed and fertilizer adoption, increase the diversity of livestock and crop, improve access to advisory services, and improve women's control over resources?

Research hypothesis 1: we hypothesize that participation in the PSNP improves agricultural outcomes both directly and indirectly by increasing household income, altering investment and risk behaviour, changing intra-household resource allocation, stimulating the local economy, and improving access to advisory services, credit, and community infrastructure.
Research question 2: does higher production diversity lead to improved household and child nutrition?

- Does higher production diversity lead to improved household dietary diversity, child height-for-age z-score, and child stunting?

Research hypothesis 2: we hypothesize that higher production diversity improves household and child nutritional outcomes by improving the availability of diversified food; diversifying risk associated with the production of a single crop, thereby affecting household income to purchase food and other nutrition-promoting goods and services; and improving agricultural production through improved agroecology from diversified production in the long-run.
Research question 3: what is the impact of the PSNP on food insecurity and nutritional outcomes?

- Does PSNP participation improve household food security status, child dietary diversity, child meal frequency, and child anthropometry?

Research hypothesis 3: we hypothesize that participation in PSNP improves household food security and child nutrition by directly increasing income and the availability of food in the household; directly increasing investment in productive activities, such as food production for consumption or sale; directly increasing investment in nutrition-promoting goods and services; and indirectly alleviating poverty-related stress, thereby improving caregiver's physical and mental state.

1.5 Outline of the Dissertation

The remainder of this dissertation is organized as follows. Chapter 2 provides information about the data and identification strategies use. Chapter 3 presents an assessment of the linkages between PSNP and agricultural outcomes. Chapter 4 examines the role of agricultural diversification on household and child nutritional outcomes. Chapter 5 estimates the impact of the PSNP on child nutrition; Chapter 6 summarizes the main findings of this dissertation, provides the program, policy, and methodological contributions, and finishes by highlighting the limitations of the dissertation and recommendations for future research.

Chapter 2

Data and Method

In this section, we describe our data source, measurements of main variables, identification strategies, and methodological issues involved when estimating program impacts under non-randomization. We also provide a detailed description of the identification strategies used in Chapters 3-5.

2.1 Data

This dissertation used data from two longitudinal studies conducted in Ethiopia: The Young Lives (YL) cohort study and the Living Standard Measurement Study - Integrated Survey on Agriculture (LSMS-ISA). YL is a longitudinal study of children in Ethiopia, India, Peru, and Vietnam. YL follows two cohorts of children, younger cohorts (6-18 months) and older cohorts (7.5-8.5 years) in four LMICs—Ethiopia, India, Peru, and Vietnam. As shown in Figure 2.1, the first wave of data for Ethiopia was collected in 2002. Data for the second to fifth survey waves were gathered from 2006 to 2017 (Figure 2.1).

YL applied a multistage sampling procedure to gather data from around 3,000 children residing in 20 sentinel sites (clusters) (Woldemedihin, 2014; Young Lives, 2018). In the first stage, regional states (Amhara, Oromia, SNNP, and Tigray) and one administrative city (Addis Ababa) were purposively selected based on their representativeness of Ethiopia's diversity in terms of religion, culture, living conditions, infrastructure, and wellbeing (Woldemedihin, 2014; Young Lives, 2018). In the second stage, three to five Woredas (districts) that have a balanced proportion of people with respect to the level of poverty and city type (capital city, intermediate city, and district centers) were selected (Woldemedihin, 2014; Young Lives, 2018). YL oversampled Woredas experiencing food deficits as understanding child poverty was its main objective. In the third stage, at least one Kebele was selected from each Woreda that was selected in the second stage, followed by random selection of 100 Younger Cohort (YC) and 50 Older Cohort (OC) children from each kebele or sentinel site (Woldemedihin, 2014; Young Lives, 2018). To minimize bias due to dropouts, YL traced the sample children in subsequent waves of the survey. In the fifth wave, only 2.2% and 8.4% respectively of the YC and OC children were lost in follow ups.

Modules contained in the YL study include child health and anthropometry, caregiver characteristics, child and caregiver educational status, household food security, PSNP participation status, household composition, and other household socioeconomic characteristics[1] Due to inconsistency in food security measurements and operational areas of the PSNP, this dissertation is restricted to using only younger cohorts of children residing in rural areas[2].

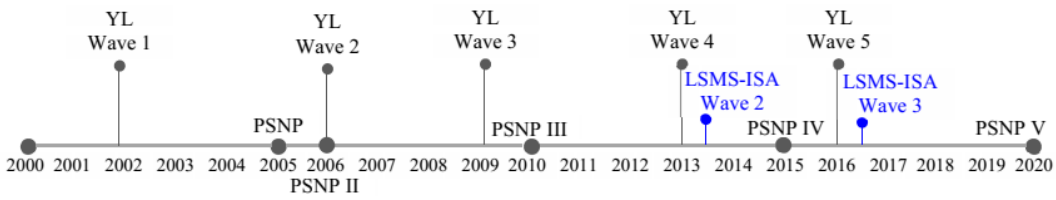

FIGURE 2.1 Summary of data sources used in this dissertation
Source: Authors compilation based on CSA & WB, 2017; CSA & WB, 2015; Woldemedihin, 2014; Young Lives, 2018

Our second data source is the LSMS-ISA, which is a collaborative project of the World Bank and national statistical offices of selected Sub-Saharan African countries. The LSMS-ISA is designed with a strong focus on agriculture and its linkages between household socioeconomic characteristics and non-farm activities. It is a nationally representative survey of households that gathers data on a wide range of topics via modules at household, plot, and community levels. The data is also regionally representative for the most populous regions (Amhara, Oromia, SNNP, and Tigray) and the Addis Ababa administrative city. Data collection for the first wave of the LSMS-ISA was conducted in 2011–2012 (Figure 2.1). Second and third waves of data collection were conducted in 2013–2014, and 2015–2016, respectively (Figure 2.1).

The surveys employed two-stage probability sampling. The first stage involves the selection of primary sampling units/enumeration areas (EAs) from each region based on the probability proportional to the size of the EAs (CSA & WB, 2015; CSA & WB, 2017). In the second stage, households from each EA were systematically sampled for an interview. For the rural sample, a total of 12 households were selected, of which 10 were randomly selected from 30 agriculture households and two were randomly drawn from nonagricultural households in each EA (CSA & WB, 2015; CSA & WB, 2017). For cases in which there was just one non-agricultural household in an EA, the quota for non-agricultural households was replaced by agricultural households and more agricultural and less non-agricultural households were surveyed.

[1]More details on the methodology employed for the sampling can be found at: http://www.younglives.org.uk.

[2]Household food security data are not available for the older cohort of the sample and during the second survey wave.

The second and third waves added large town areas (CSA & WB, 2015; CSA & WB, 2017).

The LSMS-ISA collects data on a wide array of agricultural, socio-economic, and child nutrition information. The household module was administered to all (farming and non-farming) households and the agricultural module was additionally administered to agricultural households. The household module collected data on a rich set of socio-economic variables, including wealth, consumption, child anthropometry, household had characteristics, program participation, and non-farm enterprises. The agricultural module contained detailed crop and plot level data, as well as livestock production. Since we intended to estimate the link between social protection and agriculture and production diversity and dietary diversity using the LSMS-ISA data, we focus only on agricultural households, namely households that own and/or engage in farming or livestock raising in the rural sample [3].

2.2 Identification Strategy

2.2.1 Overview of Causal Inference in Observational Studies

Estimating "impact" or the "treatment effect" of a program, policy change, or intervention is one of the goals of social science research. Such a task is difficult in experimental designs and more so in non-experimental designs, which are popular in the social science research. The conventional wisdom among scientists is that although experimental designs provide the most unbiased estimate, they are most often not feasible for reasons such as ethical, cost, and time considerations. Taking one of the treatment variables in this research, PSNP participation, from ethical point-of-view, one cannot exclude a poor household from participating in a poverty alleviation program because that household is not lucky enough to be randomly selected to be in the treatment group. Hence, observational studies remain relevant in our understanding of the behavior of economic agents and in identifying best policies and interventions to improve the human condition.

In this dissertation, the simplest method of estimating the impact of treatments, namely PSNP participation and production diversity, on agricultural outcomes, household food security, and nutrition is to compare mean outcomes of households who received the treatment with households who did not. However, due to selection bias and endogeneity, beneficiary households are likely to be systematically different from nonbeneficiary households in addition to their participation in the PSNP and level of production diversity.

Selection bias is likely to occur for three reasons (Laure, 2007). First, although our sample population is nationally representative, it is not representative of all PSNP beneficiaries. Second, participation in the PSNP is not based on random assignment,

[3] More details about the data can be found here: http://www.worldbank.org/lsms.

but instead is based on household food insecurity criteria. Thus, participation is correlated with household characteristics that vary across treatment regions. Third, household characteristics that are not randomly distributed between the treatment and control groups – and hence affect treatment – could also affect outcomes of interest.

Confounding bias occurs when a confounder, a variable that is associated with the treatment and outcome, distorts the true relationship between the treatment and outcome. Bias due to confounders may under- or overestimates the magnitude and/or changes the directions of relationships between the treatment and the outcome. Confounders could be time-variant and time-invariant. While the effect of time-invariant confounders is not influenced by prior participation in the treatment, the effect of time-variant confounders is influenced by prior participation in the treatment (Schuler and Rose, 2017). Moreover, given the non-separable nature of production and consumption decisions of farm households in LMIC, the decision to produce a diverse range of food group is likely to be endogenous to the consumption of diverse food groups and improved nutrition. For these reasons, attributing observed differences in unconditional means as "impact" would result in erroneous conclusions about treatment effects.

Hence, impact estimation is more complicated than measuring the difference between the treatment and control group with respect to the outcome of interest. Several methods are used to account for confounding biases. These include, but are not limited, to G computation, propensity score methods, doubly robust estimation techniques, and instrumental variable approaches. More recently, other approaches, such as data mining, have also been increasingly used to improve casual identification, particularly to reduce bias due to model misspecification. Although these methods are different in their statistical approaches, their theoretical underpinning can be explained by using the potential outcome framework developed by Newman and Rubin (Rubin, 1979).

Using the notation by Rubin, 1979 for a binary treatment variable, A (A=1 if in the treatment group and A= 0 if in the control group), and a binary outcome variable, Y (Y=1 if yes and Y= 0 if no), and a vector of pre-treatment confounders, W, the individual causal effect (which is the difference in the outcome of an individual (hereafter, i) under treatment condition, Y(1) and the outcome under no treatment condition, Y(0), is Yi(1) - Yi (0) (Rubin, 1979). However, we could only observe Y under only one of the treatment conditions i.e., Y(1) for those who are exposed and Y(0) for those who are not exposed, but not what would have happened had those exposed been unexposed, Y1, and those who were exposed were unexposed, Y0. Y1 and Y0 are often referred to as potential outcomes/counterfactual outcomes to emphasize the fact that both treatment and control conditions could be observed depending on the treatment condition and that they reflect a situation that is unlikely to be observed, which is counter to what is already observed. Hence, the average causal effect of the

population, the Average Treatment Effect (ATE) and Average Treatment Effect for the Treated (ATT), could be computed as E[Y(1) - Y(0)] and E[Y(1) - Y(0) | A=1], respectively by comparing a population of individuals whose outcomes are Y(1) and Y(0) under certain assumption (Abadie and Cattaneo, 2018; Robins, Hernán, and Brumback, 2000). Causal inference based on the Rubin potential outcome framework allows for the adjustment of confounders given that certain assumptions hold: conditional exchangeability, positivity, consistency, and correct model specification (Rubin, 1979).

2.2.2 Identifiability and Causal Assumptions

Ignorablility / no unmeasured confounders: This assumption claims that there are no unobserved confounders, i.e., that all confounders are measured. This assumption can be expressed as:

$$(Y_i(1), Y_i(0)) \perp A_i \mid W_i \tag{2.1}$$

However, this assumption is not testable since the effect of confounders that are not measured cannot be computed (Tylor and Ing, 2017).

Positivity: This entails that all observations should have a non-zero probability of being assigned to either of the treatment conditions, i.e., the predicted value of the propensity scores should be between 0 and 1. Mathematically, this is expressed as:

$$P(A = a \mid W) > 0 \; for \; all \; a, \; W \tag{2.2}$$

This can be observed when covariate values are roughly equally distributed between the treatment and control groups. Hence, participants in the treatment and control groups have comparable covariate combinations. Whether this assumption holds true can be checked from a descriptive table of variables by treatment status and observing whether observations in the treatment and control group contain different combination of covariate values.

Stable-Unit-Treatment-Value Assumption (SUTVA): This assumption is a combination of consistency, no interreference, and correct model specification assumptions (Angrist, Imbens, and Rubin, 1996). The consistency assumption states that there is only one version of the treatment. In other words, an individual with treatment status equal to a, has observed outcome Y which is equal to his/her counterfactual outcome Y(a). Mathematically, consistency can be expressed as::

$$Y(1) \; if \; A = 1 \; and \; Y(0) \; if \; A = 0 \tag{2.3}$$

The no interference or independently identically distributed assumption entails that assignment to the treatment to one unit does not affect the outcome of another unit.

Correct model specification: This assumption claims that the treatment model is correctly specified, i.e., it reflects the true relationship between the treatment/outcomes and confounders. Parametric models, such as logistic regression which are often used to estimate the counterfactual outcome rests on the linearity assumption. Hence, violation of the linearity assumption, such as via omission of non-linear and interactive terms, may lead to model misspecification. Hence, PSs estimated from such a model may not remove all confounding biases. To minimize model misspecification biases, smoothing techniques, data mining, and winsorizing extreme values of PSs are recommended. Recent advances also integrate machine learning (ML), such as targeting learning approaches, though in practice there is no way to prove whether a model is correctly specified.

There are several methods that rely on these assumptions to make causal inference using observational data. These approaches include regression adjustment, G-computation, endogenous/exogenous regression methods, propensity score methods, doubly robust estimation, and instrumental variable (IV) methods. Below, we describe some of the commonly used methods in observational studies, particularly when having a binary treatment measure, with emphasis on the methods used in this dissertation. One of the fundamental differences between this model is the approach used to adjust for confounding. Methods, such as regression adjustment and G-computation rely on modeling the relationship between a covariate and the outcome. Models such as propensity score methods rely on modeling the relationship between a covariate and the treatment. Other models such as doubly robust estimation model the relationship of a covariate both with the outcome and the treatment.

2.2.3 Causal Models and Estimation

Regression Adjustment

Regression adjustment (RA) tries to model the relationship between a covariate and the outcome variables. It entails including confounding variables in a multiple regression model of the treatment and the outcome variable with other covariates. Mathematically, RA can be expressed as:

$$E\left(Y|A\ ,\ W\right) = \ \alpha_0 + \alpha_1 A + \alpha_2 W_1 \ldots + \alpha_{n+1} W_n \tag{2.4}$$

where Y is the outcome, A is the exposure variable, and W represents a vector of confounders. Although this method is praised for its simplicity compared to other methods, it is criticized for the linear functional form assumed between the covariates and the outcomes and bias that might occur in case of non-linear association (Rubin, 1979). In case of violation of the non-linearity assumption, RA fails to remove confounding bias resulting in biased estimates of impact (Rubin, 1979). Moreover, in RA it is difficult to ensure covariate balance between the treated and control

groups and also to identify if the observed effect is due to the treatment or extrapolation (King and Zeng, 2006). Furthermore, in RA interaction effects of a covariate and the exposure variable cannot be estimated.

Propensity Score Methods

Propensity score-based methods try to control for confounding by modeling the relationship between observed covariates and treatment assignment (Ali, Groenwold, and Klungel, 2018; Austin, 2011; Rosenbaum and Rubin, 1983). In observational studies, the propensity score (PS) is unknown and is estimated using a logistic/probit regression model where participating in the treatment is predicted using baseline covariates (Rosenbaum and Rubin, 1983). Equation **??** below summarises the PS estimation.

$$E\left(A\right) = P(A = 1|W) \tag{2.5}$$

where A is treatment status and W is a vector of observed covariates. The estimated PS is used as a balancing score of baseline covariates – observed covariates are evenly distributed across treatment and control groups that have similar PSs (Thoemmes and Ong, 2016). There are various methods to adjust for confounding by using PSs– PS matching, stratification on the PS, Inverse Probability Treatment Weighting, and covariate adjustment using the PS (Austin, 2011; Rosenbaum and Rubin, 1983; Thoemmes and Ong, 2016).

Covariate adjustment using the propensity score: In this method, PSs are used in a chosen outcome regression along with the treatment variable as covariates (Thoemmes and Ong, 2016). The coefficient of the treatment variable is interpreted as the treatment effect. This method rests on the assumption that the relationship between the PS and the outcomes is modeled correctly.

Propensity score matching: This method involves creating a matched set of treatment and control observations that have closer PSs (how close depends on the type of matching algorithm used). Impact is then estimated as difference in the outcome of interest between those matches (Rosenbaum and Rubin, 1983).

There are several methods that could be used to create treatment and control matches in PS machining. The choose of method involves a decision whether to match with or without replacement (Rosenbaum, 2002). When matching without replacement, observations in the control group could be used to match with observations in the treatment group only once. Hence, one control group could be used to create only one match set. On the other hand, when using matching with replacement, observations from the control group could be used more than once to create matches. Hence, one observation in the control group could be used more than once to create matches and estimation of variance and standard error should take this fact into account. Greedy and optimal classification have to do with how matches are formed.

Greedy matching involves randomly selecting a treated observation and repeatedly choosing an untreated observation that has the closest PS to the randomly selected treated subject until all treated units are matched with untreated units. However, in optimal matching, matches are formed with the objective to reduce the total difference in PS within the paired units.

Stratification on the propensity score: When using this method for matching, observations are classified into mutually exclusive strata based on a pre-determined threshold of estimated PSs. There is no agreed upon threshold for stratifying observations; however, stratifying on the quintiles of the propensity score is shown to eliminate about 90% of measured confounding (Rosenbaum and Rubin, 1984). For a correctly specified PS model, PSs and hence measured baseline covariates of treated and control observations within the same stratum will be roughly similar. Hence, the overall treatment effect could be estimated by directly comparing outcomes of interest between treated and control observations in each stratum and pooling stratum specific estimates (Rosenbaum and Rubin, 1984).

Inverse probability of treatment weighting (IPTW): This method has its origin in survey sampling. Unlike matching and stratification techniques where PSs are used to match observations in the treatment group to those in the control group, the inverse of PSs is used as a survey weight in the outcome regression. this way, weighting creates a pseudo randomized sample where confounders are evenly distributed across treatment and control observations and confounding is eliminated. The IPTWs are computed as:

$$1/P(A=1|W)\ and\ 1\ /(1-(P\,(A=1|W)) \tag{2.6}$$

for observations in the treatment and control groups, respectively, where $P\,(A=1|A)$ is the estimated PS and Z are observed covariates. Such weights are referred to as unestablished weights. Unstabilized weights might result in biased estimation of impacts when there are observations that have a very high and very low PSs. This could occur if, for example, an observation that has a very low PS based on observed covariates (i.e., a low chance of being selected in the treatment) happens to be treated, which would result in a high variance of estimates (Thoemmes and Ong, 2016). Moreover, unstablized weights provide biased estimates when there are time-variant confounders. To avoid this ill effect, stabilized weights are often used (Thoemmes and Ong, 2016). Stabilized weights are computed in the same way as unstabilized weights. However, for treated observations, they have the conditional probability of being treated as estimates with no covariates in the numerator and one minus the probability of the control observation. This is given by:

$$P\,(A=1) = \ 1/P(A=1|W) and 1-P\,(A=1)\,/P(A=1|W) \tag{2.7}$$

for observations in the treatment and control groups, respectively, where $P\,(A=1|X)$

is the PS and W are observed covariates. Stabilized weights are also useful when confounders are time-variant. In this case, unlike cases in which all time invariant cofounders are included in the conditional probability estimation in the numerator, the model is estimated without covariates. Stabilized weights produce estimates that have less variance and are always preferred over unstabilized weight (Robins, Hernán, and Brumback, 2000). IPTW are used similarly to survey weights in a preferred outcome model and estimated coefficients for the treatment variable are interpreted as treatment effects. When used in this way, IPTW are considered part of Marginal Structural Models, described below.

Marginal structural models (MSMs): These models belong to a large part of causal models used to estimate the causal effect of a time-dependent treatment in the presence of time-dependent covariates that may simultaneously be confounders and intermediate variables. In MSMs, stabilized IPTW are first computed in a similar manner as stabilized IPTW (Robins, Hernán, and Brumback, 2000; Thoemmes and Ong, 2016)

G-computation

When using G-computation, counterfactual outcomes are considered as a missing data problem, which prevents estimation of the causal effect as the difference between the outcomes in both treatment conditions (Snowden, Rose, and Mortimer, 2011). Missing values are potential outcomes of observed outcomes. Implementation of G-computation involves three steps. First, a regression model of the outcome on the exposure and relevant covariates is estimated using the observed data set, $(E(Y|A,\ W)$. This model is comparable with what is used in regression adjustment and should be correctly specified to provide unbiased estimates. Second, using the model in the first step, counterfactual outcomes are predicted for each observation under each treatment condition by plugging $A = 1$ and $A = 0$ into the regression fit. Predicted outcomes are obtained under both treatment regimes, $Y^a = Y^0,\ Y^1$. This gives a full dataset with no confounding under causal assumptions and solves the missing data problem. Third, the predicted set of counterfactuals are regressed on the treatment, $E(Y^a)$ and the ATE is estimated as the difference in the potential outcome of interest.

Doubly Robust Estimation

Unlike models that rely on understanding only the exposure, such as matching, or outcomes, such as G-computation, doubly robust (DR) estimation combines both the exposure and outcome mechanism thereby give a second chance for the consistency assumption to hold (Funk et al., 2011; Hernán and Robins, 2019). DR estimation improves on IPTW as it involves augmenting the IPTW with predictive information about the outcome variable. When using DR estimation, regression models of

both the treatment and outcome are specified as a function of covariates (Funk et al., 2011). There are various types of doubly robust estimators. In what follows, we will discuss three types of DR estimation techniques: Inverse Probability Weighted Regression Adjustment (IPWRA), Augmented Inverse Probability Weighting (AIPW), and Targeted Maximum Likelihood Estimation (TMLE). All of these models are doubly robust and estimate both the treatment and outcome model to estimate unbiased effect of a given treatment. However, these methods differ in how they use information in the outcome model to minimize bias.

Augmented Inverse Probability Weighting (IPWRA): This model is basically a RA weighted by the inverse of the PS or IPW. This estimator removes bias if the treatment model is wrong and the outcome model is correctly specified, leaving the treatment model untouched if the outcome model is wrong (Funk et al., 2011). In this sense, for a correctly specified treatment model, IPW and IPWRA provide similar results, but for an incorrectly specified treatment model, IPWRA provides another chance of unbiased estimation of effect if the outcome model is correctly specified. Estimation of IPWRA involves three steps (Glynn and Quinn, 2010):
Step I - Estimation of the PS model: This step could be considered as a PS model for PS-based methods where the probability of being exposed is estimated conditional on observed covariates. In this step, PS are estimated as the predicted probability of participating in the treatment given observed covariates.
Step II - Estimation of the outcome model: This step can be considered as G-computation where parameter estimates of the regression model of the outcome and the covariates are used to predict potential outcomes, Y^0 (for A=1) and Y^0 (for A=0).
Step III – Estimation of the DR estimates under both treatment conditions and the DR causal estimates: In this step, the observed outcome, treatment condition, estimated potential outcomes, and PS are combined to make doubly robust estimates under treatment (DR_1) and control (DR_0) conditions as shown below:
For A=1

$$\mathrm{DR}_1 = \frac{Y\,(1)}{PS} - \frac{Y^1\,(A - PS)}{PS} \tag{2.8}$$

$$\mathrm{DR}_0 = \frac{Y\,(0) * (1 - A)}{1 - PS} - \frac{Y^0\,(A - PS)}{1 - PS} \tag{2.9}$$

For A=0

$$\mathrm{DR}_1 = \frac{Y\,(1)}{PS} - \frac{Y^1\,(1 - PS)}{PS} \tag{2.10}$$

$$\mathrm{DR}_1 = \frac{Y\,(1)}{PS} - \frac{Y^1\,(1-PS)}{PS} \tag{2.11}$$

where Y(1) and Y(0) are observed outcomes under exposure (A) condition A=1 and A=0, Y^0 and Y^1 are their respective potential outcomes predicted using the outcome model, and PS is the estimated likelihood of participation in the treatment given observed covariates.

As can be seen from equations 8 to 11, for treated observations DR_1 represents the predicted potential outcomes under the treatment condition given covariates that are weighted by the PSs. DR_0 is the predicted potential outcome had the observation not been treated and is based on the parameter estimates from the outcome regression for the untreated and covariates values of treated individuals. For the exposed group, DR_1 is computed as the observed outcome weighted by the estimated PS, but now the observed response DR_0 is computed by combining observed and predicted potential outcomes. Referring to the above equation, the augmentation terms (shown in red) are composed of bias terms from the PS and the outcome model. If either of treatment or outcome bias terms are zero, the augmentation term will also be zero. In other words, if either the outcome or treatment model are correctly specified, DR_1 is equivalent to E[Y(1)] and DR_0 is equivalent to E[Y(0)] (see Glynn and Quinn, 2010 for proof). Moreover, when the PS is closer to 1 and 0, the augmentation term stabilizes the estimator. After estimating DR_1 and DR_0, the treatment effect is estimated as the difference between DR_1 and DR_0 as shown below:

$$\widehat{ATE}_{DR} = \; DR_1 - DR_2 \tag{2.12}$$

Targeted Maximum Likelihood Estimation: This method is a variant of doubly robust estimators that includes a targeting step to optimizes the bias variance tradeoff (Schuler and Rose, 2017). Similar to other DR estimation techniques, TMLE provides an unbiased estimate of impact if either the treatment or outcome model is correctly specified (Van Der Laan and Rubin, 2006). If the outcome model is not correctly specified, TMLE provides unbiased estimates provided that the treatment model is correctly specified. If the outcome model is correctly specified, the targeting step will preserve the unbiasedness of the outcome model and may remove finite sample bias (Van Der Laan and Rubin, 2006). However, unlike IPWRA and AIPW, which are equation-based estimators and are prone to bias when PSs are close to 0 and 1, TMLE is a substitution estimator and hence is more robust to outliers and sparsity (Schuler and Rose, 2017). While TMLE considers an upper bound of the model, AIPW may result in estimates that are outside of the constraints of a statistical model, such as if the probability is greater than one. Moreover, TMLE uses the ensemble learning technique to maximize the chance of correct model specification (Van Der Laan and Rubin, 2006). This feature is particularly relevant given that impact evaluation in

social science often involves analyzing observational data with numerous variables that exhibit complex relationships and are prone to model misspecification bias. In such conditions, TMLE's flexibility allows the use of machine learning algorithms that maximizes the change of correct model specification.

Implementation of TMLE involves four steps (Schuler and Rose, 2017):

Step 1 - Generate an initial estimate of potential outcomes $E\left(Y|A,X\right)$: This step involves prediction of potential outcomes Y^1 and Y^0, corresponding to $A = 1$ and $A = 0$. Potential outcomes are predicted from a regression model of the conditional expectation of outcomes of interests Y given the exposure status (A) and the other covariates (X). In this case, this step could be considered equivalent to G-computation discussed above (Schuler and Rose, 2017).

Step 2 - Estimate the probability of receiving treatment conditional on observed covariates $\mathbf{P}\left(A = \mathbf{1}, X\right)$: This step involves estimating the predicted probability of receiving either of the treatment conditions given observed covariates, $P\left(A = 1, X\right)$ and $1 - P\left(A = 1, X\right)$ (Schuler and Rose, 2017).

Step 3 - Update initial estimate of our outcome of interest $E\left(Y|A,X\right)$): In this step, the estimated values of Y^1 and Y^0 in Step 1 are used to update the estimates in Step 2 to reduce the bias of confounding variables (Schuler and Rose, 2017). This is done by introducing the clever covariate $H_a\left(A = a,\ x\right) = \frac{I(A=1)}{\hat{\pi}_1} - \frac{I(A=0)}{\hat{\pi}_0}$ (Schuler Rose, 2017). $H_1\left(A = 1,\ x\right) = \frac{1}{\hat{\pi}_1} and H_0\left(A = 0,\ x\right) = -\frac{1}{\hat{\pi}_0}$ are introduced for each observation and fitted in a logistic regression model shown below:

$$logit(E^*\left(Y|A,X\right)) = logit\left(\hat{Y}_a\right) + \ \delta * H_a \tag{2.13}$$

where the δ is a fluctuation parameter composed of two values (δ_1, δ_0) for the model and is used to compute $\frac{1}{\hat{\pi}_1}$ and $-\frac{1}{\hat{\pi}_0}$ and as shown below:

$$logit(\hat{Y}_1^*) = logit\left(\hat{Y}_1\right) + \ \hat{\delta} * H_1) \tag{2.14}$$

and

$$logit(\hat{Y}_0^*) = logit\left(\hat{Y}_0\right) + \ \hat{\delta} * H_0) \tag{2.15}$$

where Ha is the predetermined covariate that is used in the targeting step for the ATE. Then, updated estimates of potential outcomes, $\hat{Y}_1^*$ and $\hat{Y}_0$ generated. $\hat{Y}_1^*$ and $\hat{Y}_0^*$ have the same interpretation as Y1 and Y0, but are numerically distinct (Schuler and Rose, 2017).

Step 4 - Generate estimates of the target parameter: This step involves estimating the treatment effect, in this case ATE, as the difference between $\hat{Y}_1^*$ and $\hat{Y}_0^*$ as shown below:

$$\widehat{ATE} = \ \frac{1}{n}\sum_{i=1}^{n}[\hat{Y}_1^* - \hat{Y}_0^*] \tag{2.16}$$

Instrumental Variable Approach

The methods discussed thus far rely on ignorability, positivity, STUVA, and correct model specification assumptions, which are often difficult to testify. The violation of these assumptions, due to measurement error, unmeasured confounders, or model misspecification, lead to biased estimations of impact. Instrumental variable (IV) approaches provide a valid estimate of impact in conditions where the treatment assignment cannot be credibly viewed as random, even after conditioning on observed covariates provided that instrumental conditions are satisfied (Imbens, 2014). For instrumental variable(s) Z, treatment conditions A, and outcome Y, these conditions are:

1. The relevance condition: Non-zero association between Z and A or Z has a causal effect on A: $Cov(Z, A) \neq 0$.
2. Exclusion restriction: There is no direct effect of Z on Y, i.e. Z affects Y only through its effect on A: $Y(A, Z = 1) = Y(A, Z = 0) = Y(A)$.
3. Instrumental condition: Z does not share a common cause with Y and there are no confounders for the effect of Z on Y: $Y(A = 1) \perp Z$ and $Y(A = 0) \perp Z$.

As shown in Figure 2.2 below, the idea behind instrumental variable estimation is to find a (set) of variable(s) called an instrument(s) (Z) that is (are) not directly associated with the outcome (Y) and affect the outcome only through an endogenous predictor A, in this case the treatment variable (A).

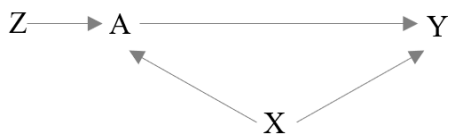

FIGURE 2.2 Diagrammatic representation of the instrumental variable
Source: Imbens, 2014

Where Z is the instrument, A is the treatment condition, Y is the outcome, and X is a confounder between the association of A and Y. The method involves estimating the association of the instrumental variable and the treatment, as well as using predicted values from this model in the outcome regression of the effect of the treatment on the outcomes (Imbens, 2014). The parameter estimates of the instrumental variable are then interpreted as the causal effects of the treatment on the outcome.

Chapter 3

Safety Net and Agriculture

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Bahru, B.A., and Zellr, M. (2021). Gauging the impact of Ethiopia's Productive Safety Net Program on agriculture: Application of targeted maximum likelihood estimation approach.Journal of Agricultural Economics, 73(1), 257-276.

Abstract

The Productive Safety Net Program (PSNP) is Ethiopia's poverty reduction strategy that forms the most important pillar of the country's agricultural transformation into a more productive and competitive sector. However, the extent to which the PSNP is linked to agriculture is unclear. This paper evaluates the impact of the PSNP on a range of agricultural outcomes. We use data from the Living Standard Measurement Study-Integrated Survey on Agriculture and apply the targeted maximum likelihood estimation method. We find no evidence that PSNP participation improved technology adoption, time spent in agriculture, household-level access to agricultural services, or women's control over agricultural assets. However, PSNP participation increased access to credit, the share of non-farm income, hours spent on casual work, community access to irrigation water, ownership of agricultural tools, community service in crop and livestock production, natural resource management, and access to credit. We also observe that PSNP households have a lower level of endowments compared non-PSNP households. Given the observed lack of impact on household-level agricultural outcomes, we recommend integrating household-level interventions, such as increasing the transfer size and provision of productive assets, that could lift household endowments above an asset threshold that would allow the productive use of community assets. This may boost the productive impact of the PSNP at the household-level, facilitate agricultural development and economic growth. To generate additional insights, we recommend further research with sufficient data on the causal pathways between safety nets and agriculture.

3.1 Introduction

Transforming smallholder agriculture into a more productive and competitive sector has received greater attention in Ethiopia's move to eradicate poverty and promote rapid and inclusive economic growth (NPC, 2016). The Productive Safety Net Program (PSNP) is among the most important poverty reduction strategies and pillars of agricultural transformation in Ethiopia. In 2020, the program reached 8 million people in 382 food-insecure districts.

The PSNP aims to reduce socioeconomic risks, vulnerability, extreme poverty, and deprivation (MoA, 2009; MoA, 2014). The program has public work/direct support and complementary asset-building program that may improve agricultural outcomes by increasing certainty, relaxing financial constraints, encouraging investment in agriculture, and improving agricultural production and household welfare. Nevertheless, the extent to which the PSNP improved agriculture has thus far not been thoroughly examined. With few exceptions, available studies provided inconclusive evidence (Table 3.1). Results vary by program modality, geographic area, household characteristics, duration of participation, and outcome type. While some studies report that the PSNP has a positive impact on agricultural asset accumulation, livestock ownership, and adoption of technologies (Berhane et al., 2014; Debela and Hollden, 2014; Hoddinott et al., 2012), others find no impact on such outcomes (Andersson, Mekonnen, and Stage, 2011).

These studies use difference-in-difference, fixed effects, propensity score matching, and regression adjustment to estimate impacts. Although these methods are useful to estimate counterfactual outcomes under solid assumptions, they are prone to model misspecification biases, outliers, and sparsity. This is particularly important considering the program design and complexity in the relationship between PSNP participation and agriculture. Considering the design, PSNP participation is based on community and asset-based criteria. Hence, participants and non-participants are different from what chance would have dictated. Moreover, the relationship between participation in the PSNP and agricultural outcomes is complex and involves several intermediary variables along the causal pathway. Hence, impact estimation in analyzing the complex relationships of two variables using observational data is prone to confounding and model misspecification biases.

To address such shortcomings, we used targeted maximum likelihood estimation (TMLE). TMLE is a variant of a doubly robust estimation technique that integrates machine learning algorithms and double robust property (Van Der Laan and Rubin, 2006). This allows us to eliminate possible model misspecification biases and provide estimates that are less prone to outliers and sparsity. We believe that a better understanding of the impact of the PSNP on agriculture has a higher policy relevance given the Ethiopian government's emphasis on agriculture as a driver of rapid and inclusive economic growth.

TABLE 3.1: Review of studies on the impact of the PSNP on agricultural outcomes

Author (year)	Data source	Sample size	Outcome(s)	Treatment	Model	Results
Andersson, et al. (2009)	Survey in South Wolo	560	TLU # of trees grown	PSNP Other FFW programs	Regression analysis	No impact of the PSNP on livestock holding. Positive impact on tree holding.
Hoddinott et al. (2012)	Food Security Survey	3,038	Agricultural output, productivity, fertilizer use, and investments in water retention	5 PW payment (+ HABP) vs. 1-year PW payment	Dose-response model	No impact of PW on cereal production, area planted, and yield. PW increases the likelihood of investing in fencing. When coupled with HSBP,PW increased yield, the probability of fertilizer use, and investment in terracing and fencing.
Berhane et al.(2014)	Food Security Survey	3,140	TLU Tools and other assets Net transfer	5 PW payment (+ HABP) vs. 1-year PW payment	Dose-response models	5 years PW payment increased livestock holding by 0.38TLU and holding of tools by ETB221. No effect on net private transfers. When 5 years PW payment was coupled with OFSP/HABP, increased livestock holding by 0.999TLU.
Debela & Holden 2014)	Survey in Tigray	400	TLU	PSNP	Endogenous switching regression	Increase livestock holding by 2.68-2.69 TLU.
Zewdu (2015)	Young Lives	1,770	TLU	PSNP other FFW programs	Propensity score matching	Increased livestock holding by: 0.57 TLU for all sample, 0.73 TLU for drought-affected households, 0.78TLU for male-headed households, and 0.88TLU in Tigray region.
Broussard (2017)	Ethiopian Rural Household Survey	FFW:456 FD: 464	Fertilizer use fertilizer use per hectare	FFW and FD	Difference-in- difference; Inverse propensity weighting	FFW increased the likelihood of adopting fertilizer in the short-run (18 months), but has no impact in the long-run (7 years). No impact of FD on fertilizer use. No impact of FFW/FD on fertilizer use per hectare. FFW has a higher impact (3.2%) for each 10% increase in value from the village mean of livestock holdings.
Araya & Holden (2018)	Survey in Tigray	280	Kgs. of fertilizer used	PSNP	Correlated random effect	Increase the likelihood of fertilizer use. No effect on total fertilizer use.

Notes: CFW = Cash for work, FD = free distribution, FFW = food for work, HABP = household asset building program, PSNP = Productive Safety Net Program, PW = public work, OFSP = other food security program, and TLU = Tropical Livestock Unit.

3.2 Method

3.2.1 Description of PSNP

Before 2005, food aid in Ethiopia was mostly addressed via an ad hoc distribution of food following drought. While food aid was effective in sustaining lives, it did not solve the underlying problems of famine. In response, the Government of Ethiopia and development partners launched the PSNP in 2005. The PSNP is a part of Ethiopia's food security program that aims to improve household food security, build household assets, improve livelihoods and resilience to shocks, and break the intergenerational cycle of poverty (Gilligan, Hoddinott, and Taffesse, 2009; MoA, 2014; Sharp, Brown, and Teshome, 2006).

Since its launch, the program has undergone four phases, evolving in its coverage and modality. During phase 1 and 2 from 2005 to 2010, the program reached about 4.8 million people in Amhara, Oromia, Tigray, and the Southern, Nations, Nationalities, and People's regions. Targeting was based on geographic and community criteria. The program had two components: Public Work (PW) and Direct Support (DS). The program targeted the PW component to households who have able-bodied members to participate in labor-intensive public work projects to build community assets, such as rehabilitation and construction of roads, irrigation canals, and water harvesting schemes, for cash or in-kind (food) payments. The DS components were given to households who had no able-bodied members to participate in labor-intensive public work projects. During these phases, the program was complemented by an asset-building program called the Other Food security Program (OFSP). The aim was to increase household income from agriculture and aid asset accumulation via transfer provision and other services, such as access to credit, agricultural extension, seeds, fertilizer, irrigation, water harvesting schemes, and soil and water conservation. Phase 3 of the PSNP operated from 2011 to 2015 with the objective of ensuring food security among chronically food insecure rural households (MoA, 2009). It was targeted to food-insecure households in PNSP woredas using asset-based criteria. During this phase, households in PSNP woredas that become food insecure due to transitory shocks were also included in the program. Vulnerable groups, namely women, youth, and pastoral communities, were given special attention. Two new regions, Somali and Afar, were also included in the PSNP. The program also achieved notable improvements in the quality of public works and timeliness of transfers. A considerable shift from food to cash transfers was also observed. Other sub-components complemented the program: the Household Asset Building Program (HABP), Complimentary Community Investment (CCI), and Resettlement Program. The HABP was aimed at diversifying sources of income and increasing productive asset endowments. The CCI's objective was to ensure access

to enabling infrastructure for PSNP beneficiaries. It targeted food-insecure households who engage in voluntary resettlement and have able-bodied household members. It involves capital intensive community infrastructure development in selected woredas that can best utilize the benefit of CCI. The Resettlement Program's objective was to ensure access to adequate food and income, as well as to enable the natural environment, infrastructure, and services for resettled households. Phase 4 of the PSNP was from 2016 to 2020. This phase's goal was to enhance livelihoods, improve household resilience to shocks, and improve food security and nutrition. It was targeted chronically food-insecure households and households who have suddenly become food insecure due to shocks. This basic criterion was supplemented by other criteria, such as household assets, household agricultural and non-agricultural income, and household vulnerability. As in previous phases, the PSNP had two components: DS and PW. Pregnant and lactating women were also assigned to the PW program, although they received temporary direct support for 12 months. The PSNP was also complemented by other programs, namely livelihoods and social services. The livelihood component is exclusively targeted to PSNP households based on self-selection criteria. The program offers a tailored and sequenced package of support for clients in the on-farm, off-farm, and wage employment pathways to diversify income sources in addition to asset accumulation (Hoddinott et al., 2012; MoA, 2014).

3.2.2 Theoretical Framework

In Ethiopia, there is a greater overlap between social protection beneficiaries and agricultural households. Smallholder agriculture is not only a major contributor to employment, the economy, and hope for economic growth, but is also a source of risk and vulnerability (Dorward, Guenther, and Wheeler, 2008). A high vulnerability to shocks characterizes rural livelihoods (Demeke, Keil, and Zeller, 2011; Dercon and Christiaensen, 2011; Dercon, Hodinnott, and Woldehanna, 2006). Credit and insurance markets are not only imperfect, but are nearly missing.

In such a context, household consumption, production, and labor supply decisions are interdependent – profit and utility maximization decisions are not separable. Households could use transfers given for consumption smoothing purposes for both the consumption of goods and services and the purchase of inputs for farm production. Hence, although improving agricultural productivity is not the primary objective of the PSNP, the PSNP could affect agricultural outcomes both directly and indirectly by altering spending behavior, risk behavior, intrahousehold resource allocation, and participation in social networks, as well as by stimulating the local economy (Tirivayi et al., 2013).

Based on Tirivayi et al., 2013 framework, we identified plausible pathways through which the PSNP and agriculture are linked. First, transfers from the PSNP alleviate credit constraints, improve savings, and reduce liquidity constraints (Figure 3.1). This, in turn, alters household spending, investment, and risk behavior, as well as

encourages investment in agricultural inputs and assets. Second, predictable transfers from the PSNP increases certainty and provides insurance against, for instance, weather-related production shortfalls and/or post-consumption smoothing. Therefore, the PSNP encourages investment in high-risk, high-return activities, reduces the likelihood of taking adverse risk coping mechanisms, such as selling agricultural assets, and improves agricultural outcomes Alem and Broussard, 2018.

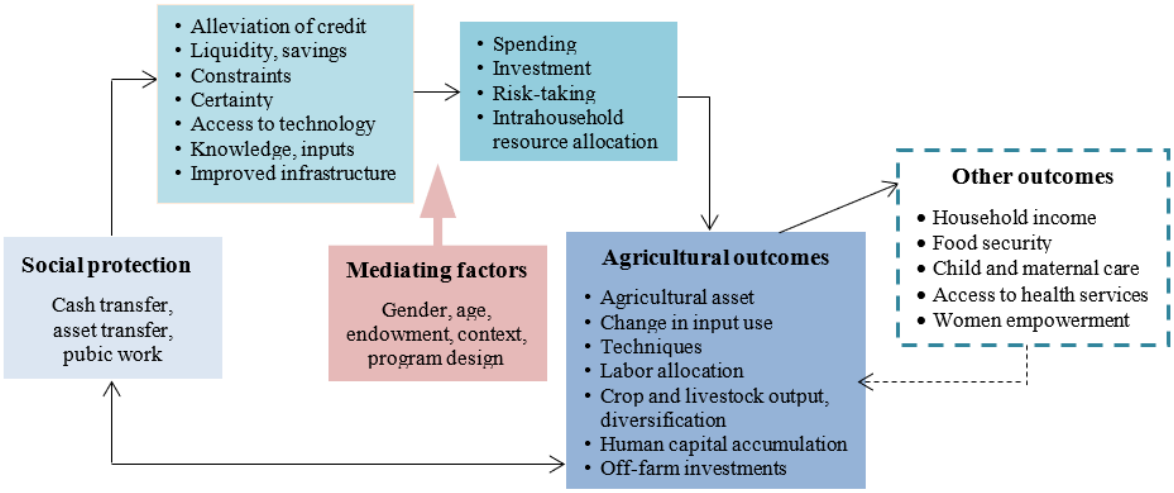

FIGURE 3.1 Conceptual framework of social protection and agriculture linkages
Source:Adopted from Tirivayi et al., 2013

Third, the PSNP could improve access to agricultural inputs, technology, and finance, especially when add-on programs such as the OFSP, HABP, or LH are included. Fourth, public infrastructure constructed as part of the public work program improves access to infrastructure and factors of production, such as roads and irrigation water, and improves community assets and the natural resource base, which positively impacts agricultural outcomes. Fifth, given the sheer size of female recipients in the PSNP, women's access to resources and information from participating in the PSNP improves their bargaining power, increases investments in child human capital (Barrientos, 2012), and positively impacts agricultural production in the long-run. Moreover, improved agricultural production in one of the pathways described above improves agricultural outcomes by improving household income, food security, women's empowerment, and investment in child health and nutrition (see the dashed line in Figure 3.1). Moreover, participation in the PSNP creates a platform for participating households to broaden their social network for risk-sharing and act as social insurance. Furthermore, social protection interventions could have spillover effects to the local economy. For instance, an increase in income from social protection interventions injects cash into the local economy and may alter local demand. This, in turn, stimulates labor markets and demand for goods and services and raises productivity and wages.

Several factors, such as gender, age of beneficiaries, household endowments, program design, and program implementation, mediate the relationship between social protection and agriculture. For instance, while interventions targeted to women increase women's bargaining power and bring about greater investments in child health and education (Barrientos, 2012), the higher time investment in social protection activities may reduce care for young children and affect child welfare negatively. Considering the age, household composition, labor supply, and time use response, a household with a higher number of able-bodied members are less likely to be affected by labor contribution to public work. Concerning initial human capital, wealthier households are more likely to invest income in agriculture than poorer households. Furthermore, the economic, socio-cultural, and environmental context, such as prices, infrastructure, markets, location, susceptibility to natural hazards, social norms, access to services, etc., also play a greater role in how social protection affects agriculture. For instance, high food prices reduce the purchasing power of income from transfers and savings and investment in productive activities, whereas access to services, such as health care, education, and markets, increase the productive impact of social protection and ability to cope with environmental hazards, such as drought, floods, and landslides. Finally, program design, in terms of targeting, choice of delivery, implementation, adequacy, coverage, etc., could affect the impact of social protection on agriculture. For instance, a higher transfer level for a longer duration is proven to have a stronger impact on agricultural assets.

3.2.3 Data

We use the second (2013/14) and third (2015/16) waves of the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for Ethiopia, which is a nationally representative household panel survey. Since we are interested in the link between the PSNP and agricultural outcomes, our analysis is limited to the rural sample of LSMS-ISA. The LSMS-ISA survey employed a two-stage probability sampling method. Primary sampling units/enumeration areas (EAs) were selected in each region based on probabilities proportional to their sizes followed by the selection of households from each EA. For the rural sample, a total of 12 households were randomly selected from each EA, of which 10 were randomly drawn from the sample of 30 agricultural households and two were randomly drawn from non-agricultural households. The survey gathered detailed crop- and plot-level data, along with a rich set of households- and community-level factors. These include socioeconomic, demographic, asset accumulation, technology adoption, time use, agricultural production, livestock production, input use, marketed produce, community access to services, and price level variables. For more details about the data, see http://surveys.worldbank.org/lsms.

Measurement

PSNP participation was measured as a dummy variable – '1' if any household member participated in the PW component of the PSNP and '0' otherwise. The main outcome variables considered are ownership of agricultural assets, the share of non-farm income, log value of land, livestock count, fertilizer and improved seed use, access to irrigation water, and hours spent in agricultural and casual work. Details on how these outcomes were measured and coded, as well as their respective covariates that were used when estimating impact are provided in supplementary file (Table A.1).

3.2.4 Identification Strategy

Causal inference using observational studies is a growing interest to researchers and policymakers. Programs/policies are often administered based on a certain set of criteria to reach a specific population group than chance would detect. This often results in systematic differences in participants and non-participants (hereafter, treatment and control,) making treatment and control groups not directly comparable. In such conditions, the careful adjustment of confounders could be made using causal inference techniques that are based on the Neyman-Rubin potential outcome framework. These techniques rely on structural causal assumptions: conditional exchangeability, positivity, consistency, and correct model specification. Several methods that are based on the Neyman-Rubin potential outcome framework have evolved to become closer to these assumptions. These include propensity score matching, inverse probability treatment weight, and augmented inverse probability treatment weight among others. However, these methods estimate impact under strong assumptions. Often model misspecification is a concern, especially when estimating impacts using observational data with a rich set of variables and potentially complex relationships between them. Recent advances that integrate machine learning techniques to reach the best possible model, such as TMLE, help reduce bias due to model misspecifications.

TMLE is a doubly robust maximum likelihood-based estimation method that includes a secondary "targeting" step to optimize the bias-variance trade-off for the parameter of interest (Van Der Laan and Rubin, 2006). TMLE is a semiparametric method that improves the chances of correct model specification by allowing a flexible estimation using machine-learning techniques, particularly the Super Learner which is a cross-validation based estimator selection approach. TMLE is related to other outcome- and treatment-based models, such as G-computation and propensity score methods, as it involves estimating the outcome model $E(Y|A, X)$ and treatment model $P(A = 1|X)$ (Van Der Laan and Rubin, 2006). However, unlike PSM and G computation that rely on modeling only the treatment or the outcome mechanism, TMLE models both the outcome and treatment model, a characteristic termed as doubly robust. Thus, TMLE yields unbiased estimates of treatment effects

if either the outcome $(E(Y|A,X))$ or the treatment $(P(A=a|X))$ is consistently estimated (e.g., correctly specified in the case of parametric regression) (Van der Laan and Rose, 2011). TMLE has several features that make it particularly attractive for causal inference in observational data (Van der Laan and Rose, 2011). First, TMLE is an asymptotically efficient estimator when both the outcome and exposure mechanisms are consistently estimated. Unlike conventional methods in which analysts choose the functional form, TMLE maximizes the chance of correct model specification using ensemble learning algorithms to reach the best fitting model. Second, TMLE is doubly robust, giving less biased estimates when either the treatment or outcome models are incorrectly specified. Third, unlike other doubly robust estimation techniques, such as Inverse Probability Weighted Regression Adjustment and Augmented Inverse Probability Weighting, TMLE is less sensitive to near positivity violations (estimated propensity scores are close to 0 and 1) and bias due to the overfitting problem from poor overlaps between treatment and control observations.
We followed these steps to implement TMLE:
Step 1 - Generate an initial estimate of outcomes of interests $(E\,(Y|A,X))$: This step involved estimating the conditional expectation of outcomes of interests (Y) given the exposure status of the PSNP (A) and the other covariates (X) to obtain the potential outcomes Y1 and Y0, corresponding to A = 1 and A = 0, respectively. To do this, we used G-computation, a maximum-likelihood-based substitution estimator that relies on the estimation of the conditional expectation of the outcome given the exposure and covariates.
Step 2 - Estimate the probability of receiving the PSNP $\mathbf{P}\,(A=\mathbf{1},X)$: Here, we estimated the conditional probability of receiving PSNP benefits given the observed cofounders, P(A=1 | X). The predicted probability of receiving treatment PSNP benefits given observed covariates, $P\,(A=1,\ X)$, and the predicted probability of not receiving PSNP benefits $P\,(A=1,X)$ and $1-P\,(A=1,X)$was computed for each observation.
Step 3 - Update initial estimate of our outcome of interest $E\,(Y|A,X))$: In this step, the estimated values of Y1 and Y0 from the first step were used to update the estimates to reduce the bias of confounding variables, T. To do so, the clever covariate $H_a\,(A=a,\ x)=\frac{I(A=1)}{\hat{\pi}_1}-\frac{I(A=0)}{\hat{\pi}_0}$ was introduced. In other words, for each observation we calculated $H_1\,(A=1,\ x)=\frac{1}{\hat{\pi}_1} and H_0\,(A=0,\ x)=-\frac{1}{\hat{\pi}_0}$ with each observation's Y, H, and H, in a logistic regression model with the assumption of a constant intercept. This model was fitted as:

$$logit(E^*\,(Y|A,X))=logit\left(\hat{Y}_a\right)+\ \delta*H_a \tag{3.1}$$

where the $\delta$is a fluctuation parameter consisting of two values (δ_1,δ_0)or the model. $1\hat{\pi}_1$ and $-1\hat{\pi}_0$ were used to generate , leading to the following model: as shown

below:

$$logit(\hat{Y}_1^*) = logit\left(\hat{Y}_1\right) + \hat{\delta} * H_1) \tag{3.2}$$

and

$$logit(\hat{Y}_0^*) = logit\left(\hat{Y}_0\right) + \hat{\delta} * H_0) \tag{3.3}$$

where Ha is the predefined covariate used in the targeting step for the average treatment effect (ATE). Then, updated ("targeted") estimates of the set of potential outcomes that incorporate the clever covariate were generated. These potential outcome estimates have the same interpretation as the initial estimates of the potential outcomes obtained in Step 1, but are numerically distinct.

Step 4 - Generate the targeted estimate of the target parameter: With the new individual-specific Y and Y from Step 3, we estimated the targeted average treatment effect (ATE) as:

$$\widehat{ATE} = \frac{1}{n}\sum_{i=1}^{n}[\hat{Y}_1^* - \hat{Y}_0^*], \tag{3.4}$$

where ATE is the causal difference in the outcome of interests that would be observed if all individuals in the population of interest were PSNP beneficiaries compared to no exposure to the PSNP.

Alternatively, the causal model could be explained by Figure 3.2 below:

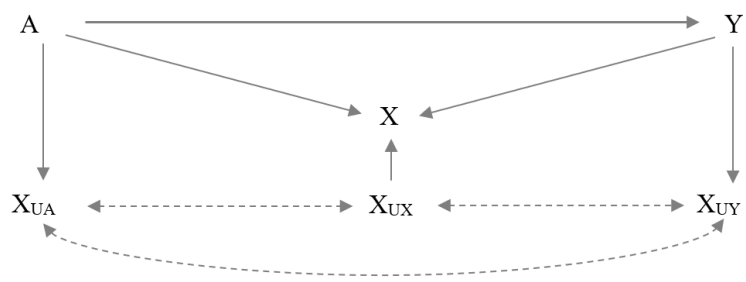

FIGURE 3.2 Diagrammatic representation of TMLE
Source: Authors sketch based on Van Der Laan and Rubin, 2006 and Schuler and Rose, 2017

where A is the treatment, Y is the outcome variable, X is a confounder of the association between the A and Y, and the subscript U denotes unmeasured confounders.

Robustness check: To estimate the average effect of PSNP treatment (or exposure) on outcomes of interests, we did additional analyses using inverse probability of treatment weighted regression adjustment. Results are comparable with findings from the TMLE (Annex Table A.3).

3.3 Result

3.3.1 Demographic and Socioeconomic Characteristics

Table 3.2 shows the demographic and socioeconomic characteristics of the study sample by their respective PSNP participation. As far as household characteristics are concerned, compared to non-PSNP households, PSNP households have less-educated adults members, are more likely to be headed by a literate head, spend less on food and non-food items, own fewer durable assets (but own more agricultural tools), are less likely to have employed household members, are less likely to use fertilizer, herbicide/pesticide, and improved seeds, are more likely to have experienced shocks (drought, illness of a family member, and loss of livestock), are more likely to sell livestock to cope with shocks, own less land, spend more hours on agricultural work (but less on non-agricultural work) in the past 7 days, live farther from large weekly markets, obtain more income from the sale of livestock (but less from the sale of crops), are less likely to participate in agricultural extension and obtain advisory

services, and produce fewer diversified crops.Regarding community characteristics, PSNP households are more likely to live in communities that have experienced improvements in advisory services related to crop production, livestock production, and natural resource management. Moreover, they are more likely to live in communities that are less connected to markets, have better access to improved seeds (but less access to agrochemicals,) are less likely to receive proper rainfall (perceived), and have a higher number of farmers who have access to irrigation.

3.3.2 The Impact of PSNP Participation on Agricultural Outcomes

Table 3.3 presents TMLE results of the effect of participation in the PSNP on different domains of agricultural outcomes. In the asset domain, we find that PSNP participation improved ownership of agricultural tools, as well as the value of land and livestock sales. However, PSNP participation reduced income from crop sales and had no impact on livestock ownership or crop and livestock count. Considering household-level agricultural services, PSNP participation has no impact on access to extension and advisory services. However, PSNP participation improved household participation in watershed activities. Considering input use, we find that PSNP participation has no impact on the adoption and intensity of fertilizer and improved seed use. When it comes to time allocation, we observe that while PSNP participation increases time spent in agricultural work, it had a marginally negative impact on time spent in non-agricultural work and no effect on casual work time. Moreover, PSNP participation improved the share of income obtained from non-farm sources and borrowing on credit over the past 12 months. Regarding women's control over resources, PSNP participation has not improved women's control over resources as measured in land and livestock ownership. PSNP participation improved advisory services for crop and livestock production, natural resource management, and credit

TABLE 3.2: Socioeconomic and demographic characteristics

Factors	Non-PSNP (n = 7,811)	PSNP (n = 843)	P-value
Average age of adult household members*	38.9 (12.6)	38.4 (10.0)	0.21
Number of adult household members*	2.2 (0.9)	2.3 (0.9)	0.23
Adult members who can read and write (%)*	0.4 (0.4)	0.3 (0.3)	<0.001
Household head age (years)*	45.7 (15.4)	45.8 (13.7)	0.88
Household head is male	5,615 (71.9%)	611 (72.5%)	0.72
Household head is literate	3,625 (46.4%)	478 (56.7%)	<0.001
Real expenditure per adult*	2.9 (3.1)	2.5 (2.2)	<0.001
TLU at the time of survey*	2.5 (2.8)	2.5 (3.0)	0.99
Household is in the lowest agricultural asset tercile	2,724 (34.9%)	244 (28.9%)	<0.001
Household is in the lowest durable asset tercile	2,726 (34.9%)	422 (50.1%)	<0.001
Total area (ha)*	1.3 (1.5)	0.8 (1.0)	<0.001
Agricultural work in the past 7 days*	36.0 (46.9)	53.6 (52.2)	<0.001
Non-agricultural work in the past 7 days*	9.0 (23.7)	6.2 (17.9)	<0.001
Casual work in the past 7 days*	2.2 (9.5)	2.3 (9.6)	0.88
Any employment in the past 12 months	1,437 (18.4%)	123 (14.6%)	0.006
Non-farm enterprise in the past 12 months	811 (10.4%)	74 (8.8%)	0.14
Use of credit services	947 (15.0%)	111 (14.1%)	0.5
Distance to the nearest large weekly market (km)*	5.7 (12.2)	11.2 (17.2)	<0.001
Female makes decision on livestock management	442 (7.0%)	50 (6.4%)	0.48
Drought in the past 12 months	1,088 (13.9%)	339 (40.2%)	<0.001
Illness of a household member in the past 12 months	1,141 (14.6%)	143 (17.0%)	0.068
Great loss/death of livestock in the past 12 months	364 (4.7%)	95 (11.3%)	<0.001
Coping strategy: Relied on own savings	1,167 (14.9%)	123 (14.6%)	0.79
Coping strategy: Sold livestock	608 (7.8%)	138 (16.4%)	<0.001
Household uses fertilizer	4,085 (66.1%)	437 (56.1%)	<0.001
Kg of fertilizer used per hectare*	61.9 (639.8)	35.3 (123.4)	0.25
Household used improved seed	1,083 (19.5%)	102 (15.5%)	0.013
Kg of improved seed used per hectare*	0.4 (1.0)	0.4 (1.1)	0.37
Household used pesticide/herbicide	1,669 (21.4%)	115 (13.6%)	<0.001
(Log) value of livestock sold*	3.9 (3.9)	4.5 (3.8)	<0.001
(Log) value of crop sales per hectare*	4.3 (3.7)	3.0 (3.4)	<0.001
Participated in agricultural extension	2,322 (36.8%)	222 (28.2%)	<0.001
Borrowed credit over the past 12 months	947 (15.0%)	111 (14.1%)	0.5
Obtained advisory services	3,536 (56.0%)	373 (47.3%)	<0.001
Simple count of food crops produced*	5.3 (3.9)	3.8 (3.0)	<0.001
Simple count of food livestock produced*	2.5 (1.7)	2.5 (1.6)	0.31
Improved advisory services about crop production**	4,166 (53.3%)	537 (63.7%)	<0.001
Improved advisory services about natural resources**	4,324 (55.4%)	563 (66.8%)	<0.001
Improved advisory services about livestock production **	3,912 (50.1%)	464 (55.0%)	0.006
Able to find fertilizer in the community **	3,266 (41.8%)	354 (42.0%)	0.92
Able to find pest/herb distributors in the community **	1,877 (24.0%)	137 (16.3%)	<0.001
Able to find improved seed in the community **	3,123 (40.0%)	389 (46.1%)	<0.001
# of farmers using an irrigation scheme*	179.5 (346.3)	254.4 (398.0)	<0.001
Proper rain in the past growing season	2,474 (31.7%)	222 (26.3%)	0.001

Notes: HH = Household; TLU= Tropical Livestock Units; * = mean (Standard Deviation); and ** = compared to 2 years ago.

at the community-level. Moreover, PSNP participation improved access to irrigation water and the number of households using irrigation water in the community.

3.4 Discussion

Transforming smallholder agriculture into a more productive and competitive sector has received greater attention in Ethiopia's goal to eradicate poverty and promote rapid and inclusive economic growth (NPC, 2016). Despite being one of the important avenues for agricultural transformation, the extent to which the PSNP has contributed to improving agricultural outcomes is not well-documented. In this paper, we estimate the impact of the PSNP on various agricultural outcomes. Although we find no impact of the PSNP on technology adoption, women's control over income, crop and livestock count, and access to extension service at the household-level, PSNP participation increased ownership of agricultural tools, the value of livestock sale, the share of non-farm income, time spent on agricultural work, access to credit at the household-level, improved community access to irrigation water, and advisory services on natural resource management, credit, and crop and livestock production.

This study finds that PSNP participation improved ownership of agricultural tools, land value, and livestock sales, but had no impact on the crop and livestock count or livestock ownership. Our results are consistent with the previous studies by Berhane et al., 2014, who report a positive impact of the PSNP on ownership of agricultural tools, as well as by Andersson, Mekonnen, and Stage, 2011and Gilligan, Hoddinott, and Taffesse, 2009 who reported no impact of the PSNP on livestock holdings. In contrast, Berhane et al., 2014 find that PW participation alone increased livestock holdings by 0.38TLU and Debela and Hollden, 2014 report a 2.68TLU gain from PW participation in the Tigray region. Zewdu, 2015 also find a significant positive impact of PW on livestock holdings. A positive impact of the PSNP on tree holdings has also been reported (Zewdu, 2015).

Given the strong need to improve agricultural productivity and food security in Ethiopia, understanding drivers of productivity-enhancing modern agricultural inputs is important. Our study finds no impact of the PSNP on the adoption and intensity of fertilizer and improved seed use. Similar to asset ownership, the literature on the impact of the PSNP on fertilizer and improved seed adoption is not definitive – impact varies greatly by household wealth status, sample population, program modality, and duration of participation. Considering only PW as participation and all highland regions, some studies find no impact of the PSNP on adopting fertilizer and improved seed (Gilligan, Hoddinott, and Taffesse, 2009; Hoddinott et al., 2012). Using data from six peasant associations across rural Ethiopia, Alem and Broussard, 2018 find no impact of FFW on fertilizer adoption in the long-run (1999-2009), and find a positive impact in the short-run, and a positive impact for households with

TABLE 3.3: Impact of the Productive Safety net Program on agricultural outcomes

	β	SE
Productive asset ownership		
Own any type of agricultural tool	0.020***	0.007
Livestock (TLU today)	0.024	0.200
Livestock (TLU one year ago)	-0.100	0.200
(Log) value of livestock sale	0.500***	0.200
(Log) value of land reap per hectare	0.013**	0.006
(Log) value of crop sale	-0.900***	0.200
Agricultural services		
Better advice on crop production from an extension agent	0.105***	0.018
Better advice on natural resource management from an extension agent	0.122***	0.016
Better advice on credit from an extension agent	0.081***	0.021
Better advice on livestock production from an extension agent	0.068***	0.019
Community access to irrigation water	0.102***	0.018
# of household in the community who have access to irrigation water	98.900***	17.400
Household received advice from an extension agent	-0.004	0.019
Household borrowed credit in the past 12 months	0.015	0.017
Household obtained advisory services	-0.014	0.019
Household participated in watershed activities	0.148***	0.014
Input use		
Household used fertilizer in the past 12 months	0.002	0.020
Kg of fertilizer use per hectare	-0.300	0.100
Household used improved seed in the past 12 months	-0.010	0.017
Kg of improved seed used per hectare	-0.001	0.006
Count of crops produced	0.200	0.300
Count of livestock produced	0.000	0.100
Time allocation		
Hours spent on agricultural work	9.200***	2.200
Hours spent on non-agricultural work	-0.011**	0.004
Hours spent on casual work	0.001	0.006
Share of non-farm income	10.700***	1.000
Other outcomes		
Borrowed credit over the past 12 months	0.062***	0.020
Female member makes decision about crop and/or livestock production	0.001	0.006

Notes: β is targeted maximum likelihood estimation of average treatment effects. SE = standard error, The model accounted for durable asset quantile, total expenditure, food gap, agroecological zones, household size, number of adults, number of adults who can read and write, adult age, access to credit, shocks (drought, loss of livestock, illness), distance to the market, change in TLU, non-farm enterprise, household head sex, and area of land owned. K.gs. =kilograms.

more livestock. Drawing data from Tigray region and PW participation, Araya and Holden, 2018 find a positive impact of the PSNP on the adoption of fertilizer, but no impact on the intensity of fertilizer use. Moreover,Gilligan, Hoddinott, and Taffesse, 2009 and Hoddinott et al., 2012 find a positive impact of the PSNP on fertilizer and improved seed use when coupled with an asset-building program.

Previous studies in Ethiopia show that safety nets, in particular FFW, can increase fertilizer adoption by acting as insurance for ex-post consumption risk (Alem and Broussard, 2018) and by relaxing liquidity constraints (Bezu and Holden, 2008)). However, low expected consumption in the aftermath of a harvest failure and the lack of insurance to smooth consumption trap households in low-risk, low return activities and perpetuate poverty (Dercon and Christiaensen, 2011). Moreover, evidence shows that the increase in the intensity of fertilizer use is observed for relatively wealthier beneficiaries of FFW (Alem and Broussard, 2018)). A recent meta-analysis also shows a strong effect of wealth on fertilizer adoption (IFAD, 2020). However, in our sample, PSNP households own significantly less livestock, household durables, and agricultural assets and are more likely to experience shocks than non-PSNP households (Table 3.2). This may have hindered farm households from taking high-risk, high return activities. Hence, the lack of impact on technology adoption in our study could be due to risk aversion in fear of an ex-post consummation decline due to shocks and the low asset endowment of beneficiary households. This shows that interventions that increase household endowments via asset transfers in addition to PW transfers, may increase household endowments and enable households to take high-risk, high return activities.

A framework by Tirivayi et al., 2013 shows that cash transfer could improve agricultural outcomes by alleviating credit and liquidity constraints, increasing certainty and insurance against risks, and improving access to inputs. Moreover, cash transfer programs, such as Ethiopia's PSNP that has public work components, could improve access to infrastructure, community agricultural assets, and access to agricultural markets. We also find that PSNP participation increases household access to credit, household participation in watershed activities, and community-level advisory service on crop and livestock production, access to credit, and natural resource management. However, at the household-level, PSNP participation has no impact on extension and advisory services. The lack of impact at the household-level could partly be because the PSNP is a geographically targeted program with most interventions, especially the PW infrastructure, happening at the community-level. Community asset creation does not guarantee that all community members, including PSNP beneficiaries, could utilize assets created due to lack of initial endowments, such as land and livestock, to make created assets more productive, as evident from our descriptive analysis (Table 3.2). Moreover, this finding points out to the fact that transfer levels might be too low to enable households to go above an asset threshold. A combination or level of assets are necessary to engage in productive activities, i.e.,

one needs to have access to a certain plot of land to use irrigation water for crop production (Carter and Barrett, 2007). This finding, along with the low level of endowment of PSNP households, suggests that asset transfers that are high enough to lift households above asset thresholds might create productive impacts.

We find that the PSNP improved community access to irrigation water. Others have also shown that the PSNP improved water harvesting, retention, and utilization approaches including irrigation systems (Solomon et al., 2015). Moreover, implementation of integrated soil and water conservation and soil fertility measures in combination with irrigation and fertilizer on a cropland improves dry matter yield in PSNP areas(Solomon et al., 2015). As shown in other studies, improved access to irrigation water is associated with good welfare outcomes, such as crop diversity, improved food security, better nutrition, and poverty reduction (Cafer et al., 2015; Hagos et al., 2017). Access to irrigation along with credit and extension packages is also seen to enable households to be self-resilient and to lead to graduation (Sabates-Wheeler, Tefera, and Bekele, 2012). However, despite the positive impact on access to irrigation water, no impact was observed on the outcomes at the end of the causal chain, such as income from agriculture. Although improvement in access to irrigation water is a good outcome and may affect households directly through use in agricultural production and indirectly through increasing food production, lowering food prices, and smoothing seasonal price fluctuation, the low endowment of PSNP households may not have enabled them to use the benefit of improved access to irrigation water. This warrants household-level interventions that improve the productive capacity of households to make better use of community assets.

As suggested by Tirivayi et al., 2013), context, gender, age of beneficiaries, initial endowments, program design, and implementation mediates the relationship between social protection and agricultural outcomes. Our data also shows that PSNP household characteristics are not in favor of generating positive mediating effects (Table 3.2). PSNP households have lower household durable and agricultural assets, are more likely to have a woman, older, and less educated household head, have older adult members, have less educated members, and are more likely to experience shocks. For instance, the proportion of households headed by women is higher among PSNP beneficiaries. Hence, participation might have increased women's time burden and allowed them less time for productive activities, such as agricultural production. Moreover, PSNP households were headed by older members and had a higher number of older adult members compared to their non-PSNP counterparts. Therefore, more labor requirements from the PSNP means less time invested in agricultural activities. Considering endowments, PSNP households have fewer adult and educated members, own a smaller plot of land, own less livestock, and have fewer durable assets than non-PSNP households. As far as access to markets is concerned, PSNP households lived farther away from markets compared to their

non-PSNP counterparts. Moreover, while FFW programs could contribute to long-term development when efficiently planned and implemented (Holden, Barrett, and Hagos, 2006), there has been underpayments and delays in transfer in PSNP implementation (Berhane et al., 2011; Gilligan, Hoddinott, and Taffesse, 2009). This may have reduced the predictability of payments and certainty of households and hence the insurance effect of the PSNP and investment in agriculture.

Strength and limitation

This study contributes to a growing body of literature related to social protection and agriculture by providing a rigorous assessment of the impact of the PSNP on a range of agricultural outcomes. The use of a large sample size, a wide range of outcomes considered, and a method that improves model specification and is less prone to outliers and sparsity is among the strengths of this study. Nevertheless, even though the dataset is nationally representative, whether this data has enough power to detect the impact of the PSNP on agricultural outcomes is subject to debate.

3.5 Conclusion

Ethiopia has made significant strides to improve smallholders' agricultural productivity and alleviate chronic food insecurity. Social protection has been implemented to address food insecurity and vulnerability of millions of Ethiopians and was one of the most important pillars of Ethiopia's agricultural transformation into a more productive and competitive sector. In this study, we use two waves of representative panel data from the LSMS-ISA to measure the impact of the PSNP on agricultural outcomes. We use a novel identification strategy that maximizes the chance of a correct model specification, is robust to outliers, and is a near positivity violation. At the household-level, we find no impact of the PSNP on technology adoption, women's control over assets, and access to advisory services. However, PSNP participation increased income from livestock sales, the share of income from non-farm sources, and access to credit. Paradoxically, we observe that PSNP participation improved access to irrigation at the community-level, agricultural advisory services on crop production, livestock production, access to credit, and participation in watershed activities. Although we cannot rule out all pathways, our results suggest that there is a low capability of PSNP households to make use of improved community access to inputs and advisory services, which is reflected by their lower level of endowments. Moreover, others have reported delays and underpayment of entitled public work transfers (Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009), which may have reduced the productive impact of the PSNP. We recommend integrating household-level interventions that could lift household endowments to help lift households above an asset threshold that would allow them to take advantage of the productive use of community created assets. This could be achieved via complementing cash or in-kind transfers with productive asset transfers and improving the

timeliness and size of cash or in-kind payments. Doing so may elevate the impact of the PSNP beyond the improvement in community access to inputs, promoting agricultural development and fueling economic growth. To generate additional insights, we recommend further research on how social protection could be linked to agriculture.

Chapter 4

Agriculture and Nutrition

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Abstract

Improving dietary diversity has attracted greater attention in efforts to improve smallholders' nutrition. Although it is very intuitive to assume that those who produce a wide range of food groups also consume a diverse set of food groups, this assumption has been challenged by studies that report mixed evidence depending on the level of production diversity, as well as market access and participation. Most of these studies are based on cross-sectional data and methods that are prone to endogeneity, making it difficult to discern a causal relationship to inform policy action. Using a nationally representative panel dataset from Ethiopia, this paper estimates the causal impact of on-farm production diversity on household dietary diversity and child chronic undernutrition. It uses an instrumental variable approach to account for the endogenous nature of production and consumption decisions. Results show that production diversity is positively associated with household dietary diversity up to just seven food groups of production, after which the association turns negative. We also find that access to markets is associated with improved dietary diversity even at a higher level of production diversity. As far as child nutrition is concerned, we find no significant relationships. Given that an average farmer in our sample produces about six food groups, promoting diversity further is likely to result in negative returns. Hence, policies that aim to improve smallholders' nutrition should focus on improving conditions for market participation over increasing the diversity of production.

4.1 Introduction

Malnutrition is one of the major causes of premature death, infection, physical and mental growth retardation, and diet-related chronic diseases in low- and middle-income countries (LMICs) (Fanzo et al., 2018). As a result, improving nutrition has received greater attention in development and is included in global commitments to improve humanity (UN, 2005; UN, 2015). Moreover, there is has been nutrition mainstreaming in agricultural policies and programs (Ruel and Alderman, 2013; Russell et al., 2018). Agriculture as a source of both food and livelihoods for the majority of the hungry and malnourished has enormous potential to improve nutritional outcomes. Estimates show that an annual $8 billion investment in agriculture increases the growth rate in crop yields by 0.40 and in livestock by 0.20, generates agricultural GDP growth that increases total GDP by 0.25% and decreases commodity prices, which, in turn, reduces the global prevalence of hunger by 63% and the number of underweight children by 28% in 2050 compared to its 2009 value (Hoddinott, Rosegrant, and Torero, 2013).

Studies suggest several pathways through which agriculture impacts nutrition: food consumed from own production; income from own agricultural production or employment in agriculture; policies that influence agricultural production and inputs, resulting in income and purchasing power changes; and women's access to and control over resources and assets, decision making about the intra-household allocation of resources (food, health, and care), time spent on productive and reproductive tasks and leisure, and health and nutritional status from participation in agriculture (Gillespie, Harris, and Kadiyala, 2012; Hawkes and Ruel, 2008; Herforth and Harris, 2013; Masset et al., 2012; Webb, 2013).

Consumption of own production and income from the sale of agricultural produce are the most frequently cited pathways. Although promoting both seems ideal, empirical evidence shows that one comes at the other's cost, i.e., market participation is associated with lower production diversity (Lipper, Anderson, and Dalton, 2010; Smale, 2005). This poses the question of whether policymakers should promote the diversification of production for more diversified consumption from own production or for the commercialization of agriculture for higher incomes to purchase more diversified foods.

The positive welfare gain from commercialization is well documented (World Bank, 2008; Barrett, 2008). Commercialization improves food security and nutrition via increasing farm income from the sale of agricultural products, increasing off-farm income through employment in the agricultural value chain, and improving access to markets. The gains from commercialization are maximized when institutions and the infrastructure enable the exchange of goods and services and increase input endowments for the production of a marketable surplus by smallholders (Barrett, 2008). However, smallholders' access to these enabling conditions is often limited

and it is questionable whether commercialization improves the nutrition of smallholders. Despite the popular belief that commercialization generally has a positive impact on nutrition (Von Braun and Kennedy, 1994), recent multi-country studies show little evidence of an impact of smallholders' commercialization on nutrition (Carletto, Corral, and Guelfi, 2017).

In the consumption pathway, the role of on-farm production diversity in improving dietary diversity and nutritional outcomes holds important implications (Jones, 2017a; Sibhatu and Qaim, 2018a). Nonetheless, evidence on the impact of production diversity on household dietary diversity and child nutrition is inconclusive (Table 4.1). Moreover, with a few exceptions (Hirvonen and Hoddinott, 2017; Zanello, Shankar, and Poole, 2019), available studies have relied on statistical methods that establish an association rather than causality and are largely based on cross-sectional data, which makes it very difficult to discern a causal relationship for policy action (Jones, 2017a; Sibhatu and Qaim, 2018b). Thus, estimates from available evidence are prone to endogeneity, reverse causality biases, and over- or under- valuing the true relationship between on-farm production diversity and nutritional outcomes. Therefore, further causal evidence using panel data and robust statistical methods is suggested (Jones, 2017a; Sibhatu and Qaim, 2018a). To fill this research gap, this study applies the instrumental variable approach to nationally representative panel data from the Ethiopian Living Standards Measurement Survey-Integrated Surveys on Agriculture (LSMS-ISA) to estimate the impact of production diversity on household dietary diversity and child nutrition.

Nutrition-sensitive agriculture in Ethiopia

Unlike food security, which has always been a priority for Ethiopia's agricultural strategies beginning with the country's five-year plans from the 1960s (Diriba, 2020), nutrition has been neglected in national agricultural strategies. Although nutrition-related indicators were included in earlier agricultural programs, such as the Agriculture Growth Program I (2010-2015), Agriculture Sector Policy and Investment Framework (2010–2020), and Productive Safety Net Program (2005-2015), actual implementation details and how to reach targets was not clearly stipulated (Bossuyt, 2019).

Nutrition was considered as a health and emergency issue and thus the responsibility of the health sector alone. After 2015/16, Ethiopia's National Nutrition-Sensitive Agriculture Strategy was discussed in parallel with the design of the National Nutrition Program II (2016-2020). This allowed agricultural ministries to better understand the agricultural sector's role in improving nutrition. Ethiopia's first National Nutrition-Sensitive Agriculture Strategy was also launched in 2016. The strategy aims to harness agriculture's full potential for nutrition via improving productivity, agricultural income, and women's empowerment. Within the agricultural sector, nutrition has been mainstreamed in extension, horticulture, and post-harvest strategies (MoANR and MoLF, 2016). The agriculture growth program, which was aimed

TABLE 4.1: Review of studies on production diversity and dietary diversity linkages

Author (Year)	Dataset	Modeling approach	Sample Size	Outcome	Result
Jones, et al. (2014)	LSMS-ISA MW	OLS	6,623 HHs	HDDS3 FCS4	PD is positively associated with HDDS and FCS. The association was stronger in female-headed households than male-headed households. Simpson's Diversity index is associated with HDDS, but not FCS.
Dillon et al. (2015)	LSMS-ISA NG	IV	3,000 HHs	HDDS	PD is positively associated with dietary diversity. A 10% increase in PD is associated with a 2.4% increase in DD.
Sibhatu et al. (2015)	LSMS-ISA ET, MW, survey in KE and ID	Poisson estimator	2,045 HHs in ET 674 HHs in MW 397 HHs in KE 5,114 HHs in ID	HDDS	PD is positively associated with DD in MW & ID, but not in ET & KE. PD square is negatively associated with DD in ID & MW but not in ET & KE. Off-farm income has a higher impact on DD than PD.
Hirvonen and Hoddinott (2017)	Data from Ethiopia	OLS, Poisson, linear and Poisson IV	7,011 HHs and 3,448 children (6 to 59 months)	CDDS	One unit increase in PD leads to a 0.49 to 0.62 unit increase in CDDS. For PD (0/1 food group), children living close to markets have a high CDDS than those with no market access. For PD is more than 3 groups, CDDS is not influenced by market access.
Jones (2017)	LSMS-ISA MW	Generalized estimating equations	3,000 HHs	HDDS and daily energy, protein, iron, vitamin A, and zinc intake	PD is positively associated with HDDS and daily energy and micronutrient intake. This effect was not modified by market orientation or distance to the nearest population center. CSR is positively associated with HDDS. High market orientation was associated with earnings from sold agricultural production, which did not lead to diverse food purchases.
Koppmair, et al. (2017)	Survey in MW	Standard and generalized Poisson	408 HHs, 519 children, and 408 mothers	HDDS IDDS	A one food group increase in PD is associated with 0.12, 0.17, and 0.11 increase in food groups consumed by the household, children, and others, respectively. Market distance is negatively associated with DD. The effect of market is not offset by the effect of PD.
Sibhatu and Qaim (2018)	Survery in KE, ID, and UG	Poisson, OLS, and Probit	672 HHs in ID 393 HHs in KE 417 HHs in UG	HDDS, WDDS, calories, fruits, vegetables, and micronutrient intake	One unit increase in PD is associated with a 0.045 - 0.16 increase in food groups consumed. PD is associated with an increase in the consumption of calories, fruits and vegetables, and micronutrients in ID and UG. In less subsistence settings, the cash income pathway has a larger effect on DD than the subsistenc pathway.
Yisgat et al. (2018)	LSMS-ISA NG	Random and fixed effects	6,089 HHs	HDDS	During post-harvest season, PD has a significant positive association with HDDS but no association was observed post-planting. The positive effect was limited to richer HHs.
Zanello et al. (2019)	LCS Afghanistan	Two-stage least squares and OLS	14,079 HHs	FCS	PD positively associated with FCS. Market access is not associated with FCS. The effect of livestock count on FCS is stronger during the lean season. PD has no effect on DD during the lean season. Availability of food in the market has a strong effect in the lean season.
Bellon et al. (2020)	Survey Ghana	Three-stage least squares	637 HHs	Consumption and cash income	PD is positively associated with the imputed value of crops for own consumption and income from crop sales.
Chegere and Stage (2020)	LSMS-ISA TZ	Fixed effects	2,274 HHs	HDDS and child nutrition	PD is positively associated with HDDS but not with child nutrition. The effect is very small. Market orientation is not associated with HDDS.

Notes: LSMS-ISA = Living Standards Measurement Study-Integrated Surveys on Agriculture, MW = Malawi, OLS = ordinary least square, HH = household, HDDS = household dietary diversity score, FCS = food consumption score, PD = production diversity, NG = Nigeria, IV = instrumental variable, ET = Ethiopia, ID = Indonesia, KE = Kenya, CDDS = child dietary diversity score. CSR = crop species richness, UG = Ugnada, IDDS = individual dietary diversity score, WDDS = women dietary diversity score, and LCS = Living Condition Survey.
Source: Authors

only at increasing productivity and commercialization of smallholder farmers in its first phase, incorporated an objective to enhance the production of nutritious foods, household dietary diversity, and household food consumption (World Bank, 2019). The strategy also highlights the importance of promoting diversified production of improved fruits and vegetables for access and consumption of diverse, safe, and nutrition foods, particularly for rural households who have limited access to markets via promoting the production of improved fruit and vegetables at the household- and community-level (MoANR and MoLF, 2016). The productive safety net program also included nutrition sensitive interventions, such as public work waivers for pregnant and lactating women, health and nutrition education, cooking demonstrations, and encouraging visits to health care facilities (MoA, 2014).

4.2 Method

4.2.1 Theoretical Framework

The traditional separable household model is grounded in the assumption that markets are perfect and household production, consumption, and labor supply decisions are independent. However, markets in Ethiopia are far from perfect and farm households are semi-commercial, i.e., they produce goods for both sale and own consumption. Hence, households' production and consumption decisions are better captured using non-separable household models in which household production, consumption, and labor supply decisions are assumed to be interdependent and prices are endogenous. Under the non-separability condition, a household does not behave like a profit-maximizing producer and hence household production, consumption, and labor supply decisions are jointly determined. Thus, the two units of analysis, namely household and firm, are linked to and influence each other. The household faces both utility and profit maximization problems (Dillon et al., 2015). Behrman, 1997 and (Singh, Squire, L., and Strauss, 1986) have extended the standard unitary household model to accommodate the non-separability of households' production and consumption decisions. We draw on this literature to guide our analysis.

In what follows, we highlight the theoretical model underpinning our analysis. In a dynamic utility maximization framework, a household is assumed to maximize inter-temporal utility subject to production, income, and leisure time constraints (Hoddinott and Kinsey, 2001). Hence, household utility (U) is given as follows:

$$U = U\left(U_1, U_2, \ldots U_T\right) \qquad for\ time\ t = 1\ to\ T \tag{4.1}$$

$$U_t = U\left(C_t^{pro},\ C_t^{pur}, C_t^{oth},\ L_t^i;\ \mu_t,\ \varepsilon_t\right) \tag{4.2}$$

where U_t is utility at any time $t; C_t^{pro}, C_t^{pur}, and C_t^{oth}$ are the consumption of food from own production, market purchase, and other sources, respectively; L_t^i is household members' leisure time; and $\mu_t and \varepsilon_t$ are other observable and unobservable household characteristics, respectively. Hence, the optimization problem is to choose the C_t^{pro}, C_t^{pur}, C_t^{oth}, and L_t^i that maximize household utility given $\mu_t and \varepsilon_t$ and subject to production (Q_t), income (W_t), and time (T_t) constraints. Production is given as:

$$Q_t = x_i\lambda + z_i\beta_i + i + ui \tag{4.3}$$

where x_i is a vector of observed covariates that affect household production, such as farm labor, variable inputs, and fixed inputs; z_i is a set of instruments that affects household production and affects household dietary diversity through production only (climatic factors in our case); µi is an unobservable household variable, such as household taste preferences; and u_i is the random error.

The time constraint is given as:

$$E_l = Q_t\ \left(l_t,\ L_t^F,\ L_t^O\right) \tag{4.4}$$

where l_t is household time spent on leisure, and L_t^F and L_t^F are time spent on on-farm and off-farm labor activities.

Wealth, W_t, is defined as a function of wealth in the previous year w_{t-1}, the interest rate (r_t), the net transfer at time t (T_t), non-farm income (Y_t), farm profit (π), and expenditure on food purchases ($P_t^{pur} Cpur_t^i$):

$$W_t = w_{t-1}\left(r_t + 1\right) + T_t + Y_t + \pi_t - \left(P_t^{pur}\mathrm{Cpur}_t^i\right) \tag{4.5}$$

Farm profit, π_t, is defined as:

$$\pi_t = P_t^{pro} Q_t - w_t L_t - P_{vt} V_t - P_{At} A_t \tag{4.6}$$

where w_t is wages, P_{vt} is the price of variable inputs, and P_{At} is the price of fixed inputs.

Finally, maximizing the intertemporal utility, (4.1) function, subject to the constraints given in equations (4.2) through (4.6), will give us a household consumption function, C_t, that includes variable and fixed input prices given as:

$$C_t = C_t(w, P_v,\ P_A,\ P_c,\ W,\ Y,\ \pi,\ z_i,\ \mu_t,\ \varepsilon_t) \tag{4.7}$$

where w is wages; P_v, P_A, and P_c are the prices of variable inputs, fixed inputs, and consumption goods, respectively; W is household wealth; Y is non-farm income; z_i is a set of instruments that affect consumption only through own production; π is profit; μ_t is observed household characteristics; and (ε_t is unobserved household characteristics.

For the child nutrition outcome (N_t), we extend the household consumption specification to accommodate child characteristics (C_t), maternal characteristics (M_t), and community characteristics (Co_t) that affect child nutrition:

$$N_t = C_t\,(W_t, P_v,\ P_A,\ P_c,\ W,\ Y,\ \pi,\ z_i,\ \mu_t, C_t, M_t, Co_t,\ \varepsilon_t) \tag{4.8}$$

Following our theoretical model, we use households' dietary diversity scores as a proxy for household consumption and child stunting (height-for-age Z-score (HAZ)) as a proxy for child nutrition. To account for factor prices, we use agricultural wages and seed, fertilizer, and pesticide prices. To proxy household wealth, we compute the wealth index based on household asset ownership. To proxy farm income, we use the value of crop and livestock sales. We use household head characteristics (age, education, and gender), wealth, and distance to the nearest market to control for observable household characteristics. Since household production diversity is endogenous to factors, such as climate, that affect production decisions and hence affect consumption only through households' own production, we use four instruments (namely agroecological zones, elevation in meters, mean temperature of the wettest quarter, and slope) that have been used previously in a similar context (Hirvonen and Hoddinott, 2017). Production diversity (PD) is thus given by:

$$\mathrm{PD}_i = \beta_1 x_i\ +\ \beta_2 z_i\ +\ e_i\,\varepsilon_t \tag{4.9}$$

where βs are parameter estimates and e_i is the error term. To account for child characteristics, we use data on child age, child sex, whether the child experienced diarrhea within the two weeks prior to the data collection, and whether the child was exclusively breastfed. To account for maternal characteristics, we use maternal age and education level. To account for community-level factors, we use a hospital or health center's availability in the community. Descriptions and measurements of these variables can be found in the methods section.

4.2.2 Data

Our data source is the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), a nationally representative household panel survey from Ethiopia. Since we are interested in the link between on-farm production diversity and nutritional outcomes, our analysis is limited to households that cultivated at least one crop or raised at least one head of livestock. To ensure representativeness, we limit our analysis to the second and third waves of data collected in 2013/2014

and 2015/2016, respectively. The survey employed a two-stage probability sampling method. In the first stage, primary sampling units/enumeration areas (EAs) were selected in each region based on probabilities proportional to their sizes. This was followed by the selection of households from each EA in the second stage. For the rural sample, a total of 12 households were randomly selected from each EA, of which 10 were randomly drawn from the sample of 30 agricultural households and two were randomly drawn from non-agricultural households. The survey gathered detailed crop- and plot-level data, along with a rich set of households- and community-level factors. The household module collected extensive data for socioeconomic, demographic, and child nutrition variables. The agricultural module contained detailed crop and plot-level information and data on livestock production, input use, and marketed produce. The community module contained information on community access to services and price levels. For more details about the data, see http://surveys.worldbank.org/lsms.

Measurement

Agricultural production diversity

We used two common measures of production diversity—crop and livestock count and food group count. We measured crop and livestock count as the sum of crop and livestock species produced by the household over the past 12 months. To measure the food group count, we aggregated the crop and livestock produced over the past 12 months into 12 food groups according to the FAO's dietary diversity score grouping (FAO, 2013) and then summed up the food groups. '

Dietary diversity

We used the FAO's guidelines to measure household dietary diversity scores (HDDSs) (FAO, 2013). We aggregated household consumption of various foods seven days before the survey occurred into 12 food categories: cereals, tubers, beans and pulses, fruits, vegetables, meat, fish, eggs, milk, fats, sugar, and non-sugar condiments. HDDSs were computed as the sum of food groups consumed. Foods included in HDDSs were obtained from households' own production, purchase, and/or gifts and other sources.

Child anthropometry

HAZ was computed using the World Health Organization's (WHO's) latest child growth standards guideline (WHO, 2008). Observations with implausible HAZ values (below –6 or above +6) or missing values of height and/or weight in all waves of the survey were excluded from the analysis.

Wealth index

The wealth index was computed using principal component analysis (PCA). Items used to construct the wealth index included cooking equipment, electronics, furniture, transport equipment, agricultural equipment, and other household assets.

Items received a "yes" or "no" response, and a covariance matrix was used to obtain the weight of the principal components. We used Bartlett's tests and KMO tests ($p = 0.000$ and KMO > 0.8) to test for homogeneity of variance across the samples (Cerny and Kaiser, 1977). We also checked the correlation, internal consistency, and reliability of items and obtained a Cronbach's alpha value of > 0.7 (Tavakol and Dennick, 2011). Items owned by fewer than 5% of households and items with a low correlation with the other items were excluded.

Non-farm income

Non-farm income was computed as the sum of income from wage employment, transfers (remittances, pension, inheritance, and transfers from sources other than the Productive Safety Net Program (PSNP)), investments, sales of assets, rental income, and non-agricultural household business income.

Income from PSNP

Income from PSNP included cash and in-kind (converted to its cash equivalent) transfers from the public PSNP.

Subsistence

The subsistence variable was calculated as the proportion of own produced food in total food consumption.

Market access

We used availability of a weekly large market as a proxy to market access. Since the effect of production diversity on dietary diversity depends on the availability of markets, either to sell own production or purchase from others, we also included the interaction of production diversity and market access in our model.

Crop commercialization index

We computed crop commercialization index following Carletto, Corral, and Guelfi, 2017 as the proportion of total crop production that is marketed.

Market participation

We measure market participation as a dummy variable that takes a value of 1 if a household has sold any proportion of crop and livestock products it produced and 0 otherwise.

Market distance

We measure market distance as household distance (in km) to the nearest market.

Value of crops sold and livestock

We measured the value of crops sold as the total income in Ethiopian Birr (ETB) from crop sales over the past 12 months. Similarly, livestock's value was the total value of livestock owned by the household over the past 12 months.

Head characteristics

Household head characteristics included that person's age, level of education, and sex.

Instruments

We selected a set of four instruments to determine production diversity: agroecological zone, elevation in meters, temperature (mean temperature of the wettest quarter), and slope. Data on agroecological zones was obtained from the International Food Policy Research Institute's standardized agroecological zones, which are classified into eight categories based on elevation and climatology. Elevation in meters was obtained from the National Aeronautics and Space Administration's (NASA) Shuttle Radar Topography Mission 90m dataset. The wettest quarter's average rainfall was obtained from the National Oceanic and Atmospheric Administration's (NOAA) Center for Weather and Climate Prediction rainfall estimates. The plot slope was obtained from the United States Geographical Survey.

Our choice of instruments was informed by both analytical and theoretical considerations. From an analytical perspective, the chosen instruments satisfy both the endogeneity conditions (affecting our outcome variable of interest, dietary diversity, only through production choices and hence production diversity) and the relevance conditions (they affect production diversity). According to the Sargan-Hansen test, we could not reject the null hypothesis that the instruments and error terms are not correlated for the dietary diversity outcome (see Annex Table A.4). It should be noted that although our instruments are pre-determined and assumed to be exogenous, we cannot entirely rule out that they are not correlated with unmeasured covariates of the outcome variables as we expect them to be. Therefore, readers are encouraged to take this into account when interpreting our results. From a theoretical perspective, farmers' production choices are dependent on microclimates, which we proxied using the average temperature in the wettest quarter. Ethiopia's diverse topography includes vast areas of sloped land that are prone to erosion and soil degradation, which, along with other factors that vary by agroecological zone, inform farmers' production choices.

4.2.3 Identification Strategy

We have two dependent variables: household dietary diversity and child HAZ. Although we tried to control a rich set of covariates that affect the outcome variables, our main predictor variable, production diversity, and the outcome variables might be correlated with observed and unobserved factors. Observed factors, such as climate, and unobserved factors, such as household preferences, might affect household production and consumption decisions. Hence, it might give a biased estimation of the true relationship between production diversity and desired outcomes. We applied a linear, instrumental variable generalized method of moments (IV-GMM)

estimation to improve our causal identification. We regressed production diversity on a set of valid exogenous variables, as used in similar contexts by Hirvonen and Hoddinott, 2017 temperature, elevation, altitude, and agroecological zone. We also exploited the panel nature of the data and used household fixed effects to control for household unobservables. Given that we have more instruments than endogenous variables, the moment conditions are greater than the estimated parameters. Hence, standard instrumental variable regression would not allow us to find estimates that would set all moment conditions to zero. Therefore, we used an IV-GMM approach to allow estimates that set the moment conditions to zero by minimizing the objective function, which is comprised of optimal weights of moment conditions as a function of estimates (Baum, Schaffer, Stillman, 2007). The use of GMM also allowed us to obtain efficient estimates in the presence of heteroscedasticity and arbitrary intra-cluster correlations, as well as to control for endogeneity and reverse causality biases (Baum, Schaffer, and Stillman, 2007). Following our theoretical framework, the specification of the IV-GMM equation for household dietary diversity and child nutritional outcomes is given in equations (4.10) - (4.12), respectively:

$$PD_i = \beta_1 x_i \; + \; \beta_2 z_i \; + \; e_i \varepsilon_t \tag{4.10}$$

$$\text{HDDS}_i = \; \gamma_1 PD_i \; + \; \gamma_2 F_i \; + \gamma_3 H_i + \; u_i \varepsilon_t \tag{4.11}$$

$$\text{CN}_i = \; \delta_1 PD_i \; + \; \delta_2 F_i \; + \delta_3 H_i + \delta_4 C_i + \; \varepsilon_i, \varepsilon_t \tag{4.12}$$

where PD, $HDDS$, and CN denote production diversity, household dietary diversity, and child nutrition outcomes, respectively; z_i, F_i, H_i, and C_i represent vectors of instruments, farm level characteristics, household level characteristics, and child level characteristic, respectively; β, γ, and δ are parameter estimates; and e_i, u_i, and ε_i are error terms. Following our theoretical model, we used $HDDS$ and child HAZ to measure consumption (C_t). For the household production function, we used agricultural wage (w), the price of seed, fertilizer, and pesticide (P_v), and land rental prices (P_A) to account for factor prices. To proxy household wealth (W), we used a wealth index, non-farm income, and return on wealth. To proxy farm income (Y), we used the value of crop and livestock sales. A description of the variables and their measurement can be found in the methods section.

Robustness checks To check for robustness of the model, additional fixed-effect estimation and combined instrumental variable, fixed-effect estimation methods were used.

4.3 Result

4.3.1 Demographic and Socioeconomic Characteristics

Table 4.2 presents summary statistics of household dietary diversity from own production, purchase, and gifts and other sources by their respective production diversity level. Household dietary diversity is generally low. On average, households consume fewer than six food groups in the seven days prior to the survey. Dietary diversity from a market purchase is higher than dietary diversity from own production and gifts and other sources. This difference is higher among household who have lower production diversity, more than doubling the dietary diversity from own production. Regardless of households' production diversity levels, food purchased from the market contributes to more than half of the total food groups consumed.

TABLE 4.2: Household dietary diversity and production diversity

	Wave 2 (2013/2014)			Wave 3 (2015/2016)		
	Low PD	High PD	p-value	Low PD	High PD	p-value
HDDS from all sources	5.1 (1.6)	5.2 (1.5)	0.048	5.4 (1.5)	5.8 (1.5)	0.000
HDDS from own production	1.4 (1.1)	2.5 (1.3)	0.000	1.3 (1.2)	2.9 (1.7)	0.000
HDDS from purchase	3.9 (1.9)	3.3 (1.4)	0.000	4.3 (1.8)	3.9 (1.6)	0.000
HDDS from gifts and other sources	0.3 (0.7)	0.2 (0.6)	0.000	0.6 (1.0)	0.4 (0.9)	0.000
N	1,887	1,629		1,818	1,668	

Notes: Results indicate mean values and standard deviations in parentheses of household dietary diversity scores computed based on the FAO 2013 guidelines. Low PD and high PD refers to food group production diversity below and above the mean level of production diversity, respectively. HDDS = household dietary diversity score.
Source: Authors

Moreover, HDDS from gifts and other sources are higher for households with low levels of production diversity compared to households with higher levels of production diversity. Although there are no substantial differences in HDDS, in both waves of the survey, households with higher production diversity (above the population mean) consume a more diversified diet from all sources. As shown in the kernel density plots below (Figure 4.1), many households lie in the middle, i.e., between three and eight, of the food group count distribution. There is a slight decrease in food group count between Wave 2 and Wave 3. Most households fall under the mean value of dietary diversity, yet dietary diversity slightly increased over time. Although household dietary diversity is measured as a count of food groups consumed by households, it has no sign of overdispersion (production diversity: mean = 5.6, variance = 2.4; dietary diversity: mean = 5.4, variance = 1.5).

Table 4.3 presents the socioeconomic characteristics of households by their production diversity level. An average farming household lives 65 km away from the nearest market, consume more than one-third of what they produce, sells about 20% of total crops they produce, sells livestock or related products, owns a little more than one hectare of land, spends ETB 23 on agricultural labor per hectare of land owned, spends ETB 34 per hectare of land used, and obtains ETB 140 in farm income per

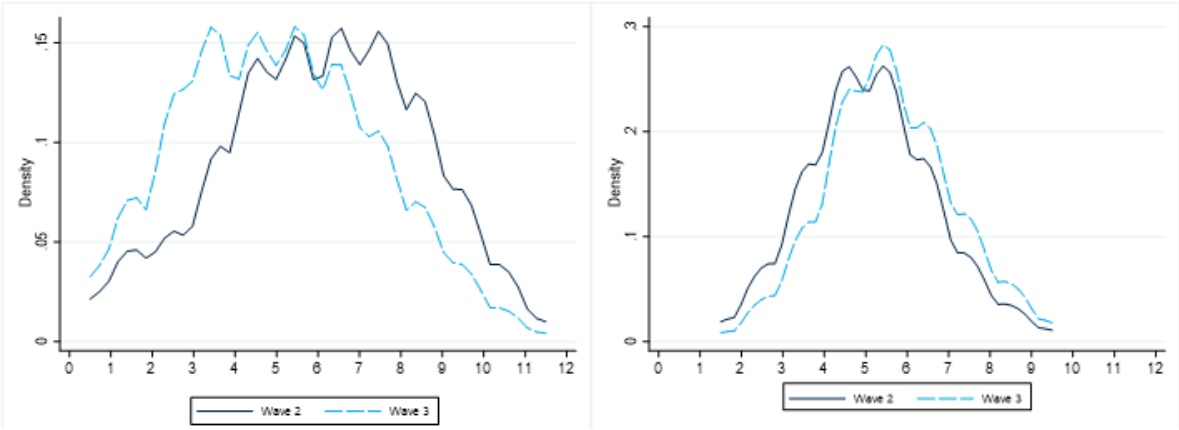

FIGURE 4.1 Distribution of crop and livestock count, food group production count, and number of food items and food groups consumed
Source: Authors

hectare of owned agricultural land. In both waves, households with a higher production diversity consumed a higher proportion of food they produced, live farther away from the market, owned larger plots, spend less on food, spend more on labor and less on land, and have a higher farm income compared to households with low production diversity. Moreover, households with more diversified production own more livestock, receive less income from PSNP, and own fewer durable assets compared to households with less diversified production. Furthermore, households headed by a male and literate head tend to have a higher production diversity.

Although households with lower production diversity have better access to community hospitals and health centers compared to households with higher production diversity, there is no significant difference in child health or anthropometry between the two groups. As far as child characteristics are concerned, children living in households with more diversified production are more likely to have been exclusively breastfed for six months and to have a younger and literate mother.

4.3.2 The Impact of Production Diversity on Nutrition

Table 4.4 reports the IV-GMM estimation results of the relationship between household dietary diversity and production diversity. Production diversity is positively associated with household dietary diversity scores (β = 2.317, SE = 0.653). However, at higher production diversification levels, an increase in production diversity results in a lower HDDS (β = -0.157, SE = 0.046). As far as the role of market is concerned, having a large weekly market is associated with having a more diversified diet (β = 1.333, SE = 0.452). However, the effect of production diversity on dietary diversity reduces with the interaction of access to markets (β = -0.197, SE = 0.069), which implies that positive impact of production diversity on HDDS reduces

TABLE 4.3: Socioeconomic and demographic characteristics

	LSMS-ISA 2013/2014					
Factors	Low production diversity (n = 1,856)	High production diversity (n = 1,629)	p-value	Low production diversity (n = 1,752)	High production diversity (n = 1,668)	p-value
Market distance (km)*	65.2 (52.5)	68.7 (47.1)	0.044	63.9 (50.0)	71.9 (48.6)	<0.001
% of own production consumed*	48.6 (36.6)	68.9 (28.3)	<0.001	38.3 (34.1)	65.9 (29.3)	<0.001
Corp commercialization index*	0.177 (0.253)	0.220 (0.219)	<0.001	0.195 (0.276)	0.189 (0.216)	0.54
Market participation	1,302 (68.2%)	1,438 (92.0%)	<0.001	1516 (76.5%)	1,334 (92.8%)	<0.001
Total area (ha)*	0.9 (1.0)	1.6 (1.2)	<0.001	0.9 (1.0)	1.5 (1.2)	<0.001
Value labor (rph)*	24.2 (47.2)	21.5 (32.1)	0.05	22.6 (40.6)	23.7 (39.7)	0.46
Hectare rental rate (rph)*	38.60 (24.79)	31.45 (19.64)	<0.001	49.95 (37.61)	40.02 (27.52)	<0.001
Food expenditure (rpa)*	0.262 (0.282)	0.137 (0.157)	<0.001	0.284 (0.281)	0.164 (0.156)	<0.001
Farm income (rpa)*	127.3 (343.4)	68.8 (95.8)	<0.001	245.8 (555.9)	107.3 (181.0)	<0.001
Durable asset quantile						
Lower	634 (33.4%)	530 (33.9%)	<0.001	693 (35.3%)	459 (31.9%)	0.083
Medium	575 (30.3%)	581 (37.2%)		637 (32.4%)	509 (35.4%)	
Higher	691 (36.4%)	452 (28.9%)		634 (32.3%)	470 (32.7%)	
Head's gender (m)	1367 (71.9%)	1316 (84.3%)	<0.001	1390 (70.8%)	1184 (82.3%)	<0.001
Head's age	44.0 (34.0, 57.0)	44.0 (36.0, 56.0)	0.17	45.0 (36.0, 58.0)	46.0 (37.0, 58.0)	0.045
Household head is literate	606 (33.1%)	538 (35.7%)	0.12	592 (31.8%)	523 (38.2%)	<0.001
Income from PSNP (rpa)*	0.298 (0.104)	0.162 (0.722)	<0.001	0.257 (0.857)	0.113 (0.549)	<0.001
TLU at time of survey*	0.926 (1.620)	0.758 (0.825)	<0.001	2.560 (3.292)	3.613(2.860)	<0.001
Child's gender (female = 1)	234 (50.8%)	231 (51.1%)	0.95	275 (54.1%)	191 (47.6%)	0.053
Child's age	26.0 (15.0, 37.0)	26.0 (15.0, 38.0)	0.93	50.0 (39.0, 62.0)	51.0 (39.0, 62.0)	0.41
Child diarrhea in the past two weeks	83 (18.0%)	89 (19.8%)	0.5	44 (8.7%)	31 (7.7%)	0.63
Child exclusively breastfed	293 (64.8%)	302 (67.3%)	0.48	281 (55.6%)	209 (52.8%)	0.42
Community hospital/health center	160 (34.9%)	78 (17.4%)	<0.001	181 (35.8%)	97 (24.2%)	<0.001
Mother is literate	149 (32.4%)	115 (25.5%)	0.024	162 (31.9%)	112 (27.9%)	0.22
Maternal age**	29.0 (25.0, 34.0)	30.0 (27.0, 35.0)	<0.001	31.0 (27.0, 36.0)	32.0 (28.0, 38.0)	0.003
Child HAZ*	-1.7 (1.8)	-1.6 (1.8)	0.66	-1.6 (1.8)	-1.7 (1.6)	0.35

Notes: Low production diversity and high production diversity refers to food group production diversity below and above the mean level, respectively. * = mean (standard deviation), ** = median (inter quartile range), rph = real per hectare, and rpa = real per adult, TLU=tropical livestock unit. In households with more than one child, we took a measurement of the youngest child.
Source: Authors

when there is access to market. Nevertheless, the reduced effect of production diversity on HDDS with access to market is smaller and does not nullify the positive effect of market participation. Hence, markets have a positive impact on HDDS even when production diversity is high. However, production diversity has no effect on child chronic undernutrition. Although increased dietary diversity could be one of the pathways through which production diversity may improve child nutrition, we found no impact of household dietary diversity on child nutrition.

Model robustness checks Recall that we chose IV-GMM estimation over other estimation methods to control for endogeneity and reverse causality bias (Baum, Schaffer, and Stillman, 2007) and efficient estimates in the presence of heteroscedasticity and arbitrary intra-cluster correlations under more instruments (moment conditions) than endogenous repressors. Nevertheless, we tested our IV-GMM estimates' robustness using fixed effects regression (see Tables A.5). Results from the IV-GMM does not vary across chosen models except for slight change in magnitude and significance of coefficients (see Table A.5 annexed).

TABLE 4.4: Association of production diversity and dietary diversity in Ethiopia

	Household dietary diversity score	eight-for-age Z-score (HAZ)	Stunting
Production diversity	2.317***	0.705	-0.222
	(0.653)	(1.743)	(0.496)
Production diversity squared	-0.157***	-0.033	0.013
	(0.046)	(0.085)	(0.024)
Large weekly market	1.332***	-0.001	0.013
	(0.452)	(0.119)	(0.036)
Production diversity x weekly market	-0.197***		
	(0.069)		
Household dietary diversity score		0.254	-0.043
		(0.661)	(0.185)
Household dietary diversity score x production diversity		-0.041	0.008
		(0.107)	(0.030)
n	2,367	680	680

Notes: Results are beta-coefficients of instrumental variable general method of moments estimation. Standard errors are given in parentheses. * = p < 0.1, ** = p < 0.05, and *** = p < 0.001. Instrumental variables used are agroecological zones, elevation in meters, mean temperature of the wettest quarter, and slope. Model for household dietary diversity score adjusts for farm income, proportion of crop value sold, value of labor, land size, food expenditure, durable asset index, livestock ownership, household head age, household head gender (Female = 1), and household head literacy. The model for height-for-age z-score and stunting includes children who are six months old and above and adjusts for household dietary diversity dcore, child age, child experienced diarrhea in the past two weeks, and mother is literate in addition to covariates included in the household dietary diversity score model. In households with more than one child, we took a measurement of the youngest child.
Source: Authors

4.4 Discussion

The majority of hungry and malnourished people in the world live in Asia and Sub-Saharan Africa and depend on subsistence agriculture for their livelihoods (Harika et al., 2017; Kumssa et al., 2015). The role of agriculture in improving diets for smallholder farmers is receiving greater attention. Consumption of own produced food and income from the sale of agricultural produce are among the pathways through which agriculture improves nutrition (Gillespie, Harris, and Kadiyala, 2012; Hawkes and Ruel, 2008; Herforth and Harris, 2013; Masset et al., 2012; Ruel and Alderman, 2013; Webb, 2013). Following the well-established evidence that dietary diversity is a good outcome in its own right and is associated with micronutrient adequacy and improved child anthropometry, increasing dietary diversity via production diversity is often seen as a promising strategy to improve diets of smallholders (Jones, 2016; Jones, 2017b; Powell et al., 2015).

The relationship between production diversity and nutrition is complex and can be influenced by several factors (Sibhatu and Qaim, 2018b). Nevertheless, the extent to which agricultural production diversity contributes to smallholders' diets is crucial, given widespread subsistence farming practices and failed rural markets. This paper examined the relationship between production diversity and dietary diversity using an IV-GMM approach to account for endogeneity between production and consumption decisions. In so doing, it provides causal evidence of the association

between production diversity and nutrition outcomes. This study has three principal findings. First, although production diversity is significantly associated with improvements in household diet, higher production diversity is negatively associated with diets. Second, although the positive role of production diversity decreases with access to markets, markets still play an important role for household dietary diversity even when production diversity is higher. Third, neither production diversity nor market access was associated with child undernutrition.

Similarly, previous studies have found a positive impact of production diversity on household dietary diversity (Dillon et al., 2015; Hirvonen and Hoddinott, 2017; Jones, Shrinivas, and Bezner-Kerr, 2014; Koppmair, Kassie, and Qaim, 2016; Kumar, Harris, and Rawat, 2015; Sibhatu, Krishna, and Qaim, 2015). Similar to in Sibhatu, Krishna, and Qaim, 2015 findings in Indonesia and Malawi, this study finds that a high level of production diversity is negatively associated with household dietary diversity. Other studies report a weaker positive (or even negative) association (Dillon et al., 2015; Hirvonen and Hoddinott, 2017; Sibhatu, Krishna, and Qaim, 2015). In a similar context, but using data from just Wave 2 of the LSMS-ISA, Sibhatu, Krishna, and Qaim, 2015 found no significant association between production diversity and dietary diversity.

Considering child chronic undernutrition, we found that production diversity is not associated with child height-for-age Z-scores (HAZ) or the likelihood of stunting. Increased dietary diversity is one of the direct avenues though which production diversity improved child nutrition outcomes. However, we found no impact of household dietary diversity on child undernutrition. There are only a few studies that have reported a significant positive association between production diversity and child HAZ (Kumar, Harris, and Rawat, 2015; Jones, 2016). Instead, most studies have showed either non-existent (Argyropoulou, 2016; M'Kaibi et al., 2017; Purwestri et al., 2017; Shively and Sununtnasuk, 2015) or mixed results (Hirvonen and Hoddinott, 2017; Jones, Shrinivas, and Bezner-Kerr, 2014; Kumar, Harris, and Rawat, 2015; Malapit and Quisumbing, 2015; Cunningham et al., 2016). As far as child diet is concerned, Hirvonen and Hoddinott, 2017 reported a positive impact of production diversity on child dietary diversity scores. Although we cannot rule out all the possible reasons, we attribute the difference to the time-period considered and the identification strategy employed. Although we cannot rule out all possible pathways, the lack of impact on child nutrition metrices could be due to the fact that nutrition is multifaceted and depends on other factors, such as access to health services and proper childcare practices, in addition to dietary quality (UNICEF, 1990).

There are several pathways along which on-farm production diversity improves household diet and child nutrition. First, higher production diversity may improve household dietary diversity through consumption of own production. Our data confirms that this is very likely to be true (see Table A.6 annexed). We not only find that the aggregate dietary diversity score is significantly higher among households with

higher levels of production diversity, but we also find the consumption of nutritious foods (such as root and tubers, vegetables, fruits, eggs, meat, legumes/nuts/seeds, milk, and milk products) is higher among households with higher levels of production diversity (see Table A.6 annexed). Consumption of nutritious foods by households with higher levels of on-farm production diversity was true for all food groups listed above, except meat, when considering all possible food sources and only own production. Second, from an ecological point of view, increased diversification is associated with an soil quality and productivity improvements, which are associated with higher household dietary diversity (Jones, 2017a; Sibhatu and Qaim, 2018a) and child nutritional status (Masset et al., 2012; Ruel and Alderman, 2013). Third, the literature shows that more diversified production translates into a higher risk-bearing capacity, a higher likelihood of adopting new technologies, and improved agricultural productivity, which, in turn, improve household diets (Ecker, 2018; Hirvonen and Hoddinott, 2017; Koppmair, Kassie, and Qaim, 2016; Sibhatu, Krishna, and Qaim, 2015; Sibhatu and Qaim, 2018a).

Nevertheless, despite the positive role of production diversity on household dietary diversity, our results showed that higher levels of diversification (above seven food groups) are negatively associated with household diets. Sibhatu, Krishna, and Qaim, 2015 notes that when production diversity is very high, the association between production diversity and dietary diversity turns negative because of foregone income benefits from specialization. This is very intuitive given that farm household in our setting own on average 1.2 hectares of land. Hence, forgone benefits from specialization might exceed positive dietary diversity gains from own production diversification.

In this study, we found a positive impact of market access on household dietary diversity. Moreover, although the effect of markets on household dietary diversity reduces with increased production diversity, high production diversity does not completely offset the positive effect of market access on household dietary diversity. Similarly, Heady et al. (2019) reported that children living in households near markets that offer more non-staple foods have a more diverse diet. Stifel and Minten, 2017 also reported that households far away from a market have a lower level of consumption and are more food insecure than households close to markets. This is not surprising given that food purchased from the market contributes more than half to household dietary diversity (Table 4.2).

To examine this further, we computed households' market participation using the degree of market participation (via a crop commercialization index) by Carletto, Corral, and Guelfi, 2017 and whether household sold a crop or livestock product. We found that although mere market participation is high, the degree of market participation as measured by the proportion of crop output sold is low, hovering around 20% (see Table A.6). Moreover, market participation is higher among households with a higher levels of production diversity although the rate of participation

is significantly higher in Wave 2 (2013/2014). Hence, even when production diversity is high, markets still play a significant role in improving diets. Intrigued by this finding, we also analyzed the effect of market participation on household dietary diversity, child height-for-age Z-scores, and stunting (see Table A.7). We found that selling a higher proportion of crop produced increases household dietary diversity. However, the degree of market participation has no impact on child chronic undernutrition metrices A.7. Similarly, Carletto, Corral, and Guelfi, 2017 found no impact of market participation on child nutritional outcomes in Malawi, Tanzania, and Uganda.

The role of markets has also been debated among researchers. The positive welfare gain from market participation is well documented (Barrett, 2008). However, more gains from commercialization could be realized if there were institutions and infrastructure that allowed the exchange of goods and services and supported an increase in the endowment of inputs that allowed marketable surplus production by smallholders (Barrett, 2008). Access to these enabling conditions by smallholders is limited. Structural barriers in access to finance, contract enforcement, and limited physical infrastructure raise transaction costs and impede efficient market functioning for smallholders in Africa ((Dillon and Barrett, 2017). Hence, it is questionable whether commercialization benefits accrue to smallholder farmers who constitute most of the hungry and malnourished people in the world. Recent studies in this area tend to confirm the lack of impact. Despite the popular belief that commercialization has a generally positive impact on nutrition (Von Braun and Kennedy, 1994), recent multi-country studies using plot-level data show little evidence of an impact from commercialization on the nutrition of smallholders (Carletto, Corral, and Guelfi, 2017).

Based on these findings, it not clear if a diverse food production or market participation is the better strategy for improving smallholders' diets. While production diversification has a positive effect on household dietary diversity, higher levels of diversification reduced household dietary diversity. Moreover, the rate of market participation, which has a positive impact on household dietary diversity, is high among households with higher production diversity. Moreover, as shown in this study, production diversity and market participation are not always mutually exclusive. An example is that farm households could produce certain food groups entirely for the market, own consumption, or both. Nonetheless, an average farm household in our sample produces about six different food groups, which is just one food group short from where the relationship between production diversity and dietary diversity turns negative. Hence, further diversification is likely to result in negative effects for household diet. Therefore, while we note that conditions for market participation are still in their infancy (Dillon and Barrett, 2017), market participation might be the ultimate avenue for improving the diets of smallholders. This study is not without limitations. Even though seasonality is one of the peculiar features of agricultural

production, market participation, and food consumption in developing countries, this study did not consider the potential role of seasonality. Moreover, in this study the HDDS is measured using week-long recall consumption data, which may not represent consumption throughout the whole season. Moreover, our proxy for the rate of market participation only considers crop production and does not consider livestock products, which may have underestimated market participation.

4.5 Conclusions

Understanding the role of agricultural production diversity on smallholders' diets is crucial given widespread subsistence farming practices and imperfect rural markets. Following the well-established evidence that dietary diversity is good for dietary quality, increasing dietary diversity via production diversity is often seen as a promising strategy to improve diets and nutritional outcomes of smallholders. However, there is contested evidence as to whether commercialization and income from sales of agricultural produce is a better strategy to improve nutrition compared to promoting diversified agriculture production for own consumption. This paper contributes to this debate by analyzing the role of on-farm production diversity on household dietary diversity and child chronic undernutrition. It employs IV-GMM estimation to account for the endogenous relationship between production and consumption decisions. Results show that while production diversification has a positive effect on household dietary diversity, higher levels of diversification reduced household dietary diversity. As far as the role of markets is concerned, access to market in general is associated with more diverse household diets. Although the positive role of markets on household dietary diversity reduces with higher levels of production diversity, markets still play an important role for household dietary diversity even when production diversity is high. We note that the role of markets to improve diets is better realized when conditions for specialization in products where smallholders have a comparative advantage are in place (Barrett, 2008). In the case of Ethiopia, these conditions are lacking (Dillon and Barrett, 2017). Nonetheless, an average farm household in our sample produces about six food groups, which is just one food group shy of the level of production diversity from where the effect of production diversity turns negative. Hence, promotion of further diversification is may negatively affect household diet. Hence, we recommend improving conditions that may increase smallholders market participation and hence improve household nutrition.

Chapter 5

Safety net and nutrition

This chapter has been published as:
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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, child diet diversity, and child 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 the PSNP 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 the 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 the PSNP on household food security, child meal frequency, child dietary diversity, and child anthropometry using the marginal structural modeling approach that takes both selection bias and time-varying confounders into account; and (2) to shed some light on its policy and programmatic implications. Results show that the PSNP has not improved household food insecurity, child dietary diversity, and child anthropometry despite its positive impact on child meal frequency. Household participating in PSNP increased daily child meal frequency by 0.308 unit. Given the consequence of food insecurity and child undernutrition on physical and mental development, intergenerational cycles of poverty, and human capital formation, the program would benefit

[1]Supplementary materials published together are provided under the Annex section.

if it were tailored to nutrition-specific and nutrition-sensitive interventions and integrated with other sectoral programs.

5.1 Introduction

The past two decades have seen a rapid increase in the implementation of social protection programs by African countries with the goals of alleviating poverty, food insecurity, and vulnerability of poor households (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; MoA, 2014). However, evidence on its effectiveness in improving food security, health, and nutritional 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; Groot et al., 2017; Hidrobo et al., 2018).

Studies from Ethiopia also reveal that participation in the PSNP is associated with increased months of adequate food provisioning (Sabates-Wheeler and Devereux, 2010; Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009), number of child meals per day (Berhane et al., 2011), household asset formation (Hoddinott et al., 2012; Gilligan, Hoddinott, and Taffesse, 2009; Debela and Hollden, 2014), resilience to shocks (Knippenberg and Hoddinott, 2017), human capital accumulation (Hoddinott, Gilligan, and Taffesse, 2009), and agricultural productivity and technology adoption (Hoddinott et al., 2012; Gilligan, Hoddinott, and Taffesse, 2009), as well as associated with breaking the intergenerational cycle of poverty (Hoddinott, Gilligan, and Taffesse, 2009), and reducing worries about the availability of food for the household (Porter and Goyal, 2016). In contrast, few studies reported no impact of the PSNP on the number of child meals per day (Gilligan, Hoddinott, and Taffesse, 2009), household dietary diversity, and consumption expenditure per capita (Gebrehiwot and Castilla, 2018; Berhane, Hoddinott, and Kumar, 2017).

Evidence on the impact of the PSNP on child nutrition is mixed. Some studies reported positive impacts (Debela, Shively, and Holden, 2015; Porter and Goyal, 2016), whereas others found no impact (Berhane, Hoddinott, and Kumar, 2017; Gebrehiwot and Castilla, 2018) (Table 5.1). This may be due different study designs, 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, and Abuye, 2014),

TABLE 5.1: Review of studies on the impact of PSNP on food security and nutrition

Authors (year)	Dataset	Model	Study population	Outcome(s)	Sample size	Summary of results
Gilligan et al. (2009)	Food Security Survey	PSM DID	HH level	Caloric acquisition, food gap, child meals frequency	3,700	No impact (1), 2educed likelihood of having very low caloric intake (1+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).
Wheeler and Devereux (2010)	Survey in highland regions	OLS	HH level	Food gap	960	Food and mixed recipients experienced 1.24 months of lower food shortage compared with non-beneficiaries (7)
Tafere and Woldehanna (2012)	Young Lives	PSM DID	11.5-15.5 years old	Monthly per capita consumption expenditure	569	Decreased per capita consumption expenditure¥ (5)
Berhane et al. (2014)	Food Security Survey	DID PSM	HH	Food gap, caloric acquisition		Increase in months of adequate household food provisioning by 1.2814 and 1.515 months. No effect on household caloric availability
Debela et al. (2015)	Survey in northern Ethiopia	Exogenous switching regression	<5 years old	WHZ	519	Increased mean WHZ mediated by female labor engagement in PSNP (12)
Motbainor et al. (2015)	Survey in northern Ethiopia	Logistic regression	Mothers with children <5 years old	BMI	4,110	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 PSM	3-5, 5-8, and 12-15 years old	HAZ	1,605	Improved HAZ8,9,10,11; siblings at the age of 5 had a significantly higher HAZ than the pre-PSNP conditions11 compared with those who did not receive PSNP or received PSNP in 2006 and 2009
Berhane et al. (2017)	Food Security Survey	IPWAR	<5 years	HAZ, WAZ, stunting, and wasting	1,728	No significant impact on HAZ, WAZ, stunting, and wasting (12)
Gebrehiwot & Castilla (2019)	LSMS-ISA	2SLS, IV, GPSM	Household, 0-56 months old children	Dietary diversity score; consumption of calories, protein, and iron; and HAZ	3,797HHs 688 children	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 = Sothern, Nations, Nationalities and People, 1 = any payment from the PSNP, 2 = food/cash worth 90 Birr, 3 = Other Food Security Program, 4 = households living in areas where the PSNP operates 5 = children from households who participated in both wave 2 and 3 compared with those who participated only in wave 3 (195+30), 7 = non-PSNP beneficiary versus only food only, cash, and mixed (cash and food) beneficiaries, 8 = matched sample, 9 = shortlisted for the PSNP, 10 = participated only in 2006, 11 = participated only in 2009, 12 participated in the public work component of the PSNP vs. non-PSNP households, 13 = membership in the PSNP, 14 = one year of participation in public work, and 15 = five 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.
Source: Authors

propensity score matching (Gilligan, Hoddinott, and Taffesse, 2009), inverse-probability-weighted regression-adjustment (Berhane, Hoddinott, and Kumar, 2017), difference-in-difference (Gilligan, Hoddinott, and Taffesse, 2009), and exogenous switching regression methods (Debela, Shively, and Holden, 2015).

However, these studies did not take into account the effect of time-varying confounders and hence, might have resulted in biased estimation (Kawachi et al., 2016). For instance, while estimating time-varying impact of the PSNP on food insecurity, neglecting to control for prior PSNP participation increases the risk of confounding, but statistically controlling for it may also introduce bias because of the intermediary relationship between PSNP participation and food insecurity status (Kawachi et al., 2016), which makes it difficult to comprehend a causal relationship. Moreover, the PSNP by design was not random: It was administered to chronically food-insecure households on asset-based criteria and is thus prone to selection bias. Moreover, reducing food insecurity was one of the desired outcomes of the program. Participation in the PSNP is not only expected to improve a household's food security status, but may also predict future PSNP eligibility by altering household's food insecurity status, thereby confounding the association between household PSNP participation and food security status. Hence, by considering this complexity, we evaluated the magnitude of the association of the PSNP with household food security and child nutritional outcomes using the marginal structural model (MSM). Findings of this study have important policy implications to make social protection nutrition-sensitive (Alderman, 2014; Ruel and Alderman, 2013).

5.2 Method

5.2.1 Description of PSNP

The 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 (FDRE, 2004; MoA, 2009; MoA, 2014). The 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 as cash or in-kind (food). DS is administered to households whose breadwinners are the elderly or disabled and hence cannot take part in labor-intensive activities.

The 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 five million people in four major regions of Ethiopia: Amhara, Oromia, Southern Nations, Nationalities, and Peoples' Region (SNNPR), and Tigray (Sharp, Brown, and Teshome, 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 eight million people (FDRE, 2004).

The PSNP uses a mix of geographic and community targeting criteria to choose vulnerable households. Beneficiaries are households that experienced a 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 (FDRE, 2004). 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 (FDRE, 2004).

5.2.2 Theoretical Framework

5.2.3 Data

We used the Young Lives (YL) cohort study dataset. YL is a longitudinal cohort study of 1,000 "older" (initially 7.5-8.5 years of age) and about 2,000 "younger" children (6-18 months of age) in Ethiopia, India, Peru, and Vietnam. This study uses the Ethiopia data on younger cohorts. In Ethiopia, the first wave of data collection started in 2002 and the second, third, fourth, and fifth waves of surveys were conducted in 2006–2007, 2009–2010, 2012–2013, and 2016–2017, respectively (Woldemedihin, 2014; Young Lives, 2018). YL collected data in four major regions (Amhara, Oromia, Southern Nations Nationalities and People, and Tigray) and one administrative city (Addis Ababa) (Woldemedihin, 2014; Young Lives, 2018). The survey is comprised of modules on child health and anthropometry, household food security, caregiver characteristics, educational status, PSNP participation, socioeconomic characteristics, and household composition. Although the PSNP began in 2005, households' participation was measured starting from the third wave of the YL survey (2009/2010) 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 waves of the survey (n = 1,200).

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 participated in the 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, number of meals consumed per day, and child anthropometry. Food insecurity (a time-varying confounder) was measured using the Household Food Insecurity Access Scale (HFIAS). Following Coates, Bilinsky, and Coates, 2007, the HFIAS score was computed and households were classified as severely food insecure, moderately food secure, mildly food insecure, or food secure. Households were categorized as food insecure and coded as "1" if they were severely or moderately food insecure and "0" otherwise. The number of meals consumed by a child was computed as the number of meals a child consumed in the past 24 hours prior to the survey. Child dietary diversity was measured using a 24-hour dietary recall questionnaire. A child's consumption of one or more different foods was aggregated into nine food groups according to the Food and Agriculture Organization's (FAO) individual dietary diversity score guidelines (FAO, 2013). Food groups were summed to generate a child dietary diversity score (DDS). To measure child anthropometry, the 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 one 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's child growth standard (Onis et al., 2007; M et al., 2006). 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 waves 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 the PSNP, 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 expenditures per adult. Sex of the household head was measured as a dummy variable where "1" indicates male and "0" indicates female. The 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 that the household experienced drought in the past 12 months. Household land ownership was measured as a dummy variable that takes a value of "1" if a household owns land and zero otherwise. Access to credit is 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" 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 household head sex with PSNP participation. For nutritional outcomes, we added child characteristics (child's nutritional status during the prior 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, 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 examined ($p = 0.000$ and KMO > 0.8) (Cerny and Kaiser, 1977). Item correlation, internal consistency, and reliability were checked. A recommended value of Cronbach's alpha (>0.7) was obtained (Tavakol and Dennick, 2011). Items with low correlation with the rest of the items were excluded. Using the computed wealth index, households were classified into wealth terciles of low (1), medium (2), and high (3). YL 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.

5.2.4 Identification Strategy

We used MSM to estimate the causal association of a time-dependent treatment (the PSNP) in the presence of a time-dependent covariate (food security status) that is simultaneously a confounder and an intermediate variable (Robins, Hernán, and Brumback, 2000). The hypothesized temporal ordering and impact pathway of the PSNP on household food insecurity and child nutritional outcomes is presented in Figure **??**. Accordingly, the PSNP1 (PSNP participation during wave 3 of the YL survey) might be associated with FS1 (food security status measured during wave 3 of the YL survey) and time-invariant covariates (V). In turn, this affects both participation in the PSNP2 (PSNP participation during wave 4 of the YL survey) and FS2 (food insecurity status measured during wave 4 of the YL survey). Similarly, the PSNP2 (PSNP participation during wave 4 of the YL survey) might be associated with FS2 (food security status measured during wave 4 of the YL survey) and baseline covariates (V). In turn, this affects both participation in the PSNP3 (PSNP participation during wave 5 of the YL survey) and FS3 (food insecurity status measured during wave 5 of the YL survey). To phrase it differently, participation of households

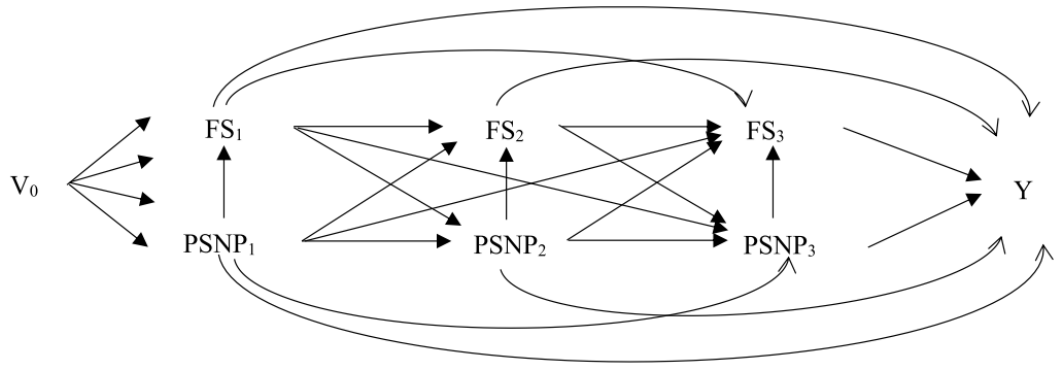

FIGURE 5.1: Diagrammatic representation of the causal association of participation in PSNP and household food security status, child dietary diversity, number of meals consumed by a child per day, and child anthropometry.

Note: V represents time-invariant covariates, PSNP1, PSNP2 and PSNP3 represent participation in the third, fourth, and fifth waves of the YL survey, respectively, FS1, FI2, and FS3 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), FS1 is a confounder and intermediate variable in the association of PSNP2 and FS2, and FS2 is a confounder and intermediate variable in the association of PSNP3 and FS3. Similar hypothesis holds for the causal impact of PSNP on other outcomes (Y).

Source: Authors.

in the subsequent PSNP (PSNP2), is affected not only by previous food security status (FS1), but also by prior PSNP enrolment (PSNP1). Previous food security status (FS1), could affect future food security status (FS2 and FS3) directly or indirectly by predicting future participation in the PSNP (PSNP2 and PSNP3). Therefore, food security status, FS1 and FS2, is both a confounder (i.e., a time-variant confounder of the association of PSNP1 and FS2 and PSNP2 and FS2, respectively) and an intermediary variable (between two treatment conditions, PSNP1 and PSNP2 and PSNP2 and PNSP3, respectively). Besides, covariates associated with PSNP1 and PSNP2 may also be associated with FS1 and FS2, respectively, so that observed response differences cannot be attributed directly to exposure to PSNP1 and PSNP2. Therefore, while neglecting to control for prior treatment status might increase the risk of confounding, statistically controlling for it (by just including the regression model) may also introduce bias because of the intermediary relationship between the PSNP and FS (Kawachi et al., 2016). Furthermore, not adjusting for prior food security status might lead to an invalid comparison of treatments. Similarly, statistically controlling for the PSNP would also not allow for the disentangling of the causes and effects of PSNP households with different treatment statuses. Therefore, following Robins, Robins, Hernán, and Brumback, 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 (Robins, Hernán, and Brumback, 2000). MSM

estimation controls for time-varying confounders and loss 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. In the second stage, the outcome model is fit, including sensitivity analyses that take into account weight distributions (Williamson and Ravani, 2017).

Treatment model: Inverse probability treatment weights

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

$$logitPr[PSNP_k = 1|PSNP_1, \ldots, PSNP_{K-1}, V_0, FS_1 \ldots FS_{K-1} = \beta_o + \beta_1 PSNP_1 + \ldots + \beta_{k-1} PSNP_{k-1} + \beta FS_{1\ldots k} + \beta_5 V_0 \tag{5.1}$$

where $PSNP_K$ denotes participation in the PSNP at time K, V_0 denotes baseline covariates from time 1 to K, and $FS_1 \ldots k$ 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:

$$W(t) = \prod_{k=0}^{t} \frac{1}{f\{PSNP_K|PSNP_1, \ldots., PSNP_{K-1}\ ,\ V_0,\ \ FS_1 \ldots FS_{K-1}\}} \tag{5.2}$$

where W(t) is the IPTW at time t. Those who received the treatment are assigned a weight of 1/P(Z=1/V)S 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 and Robins, 2019). Such weights are referred to as "unstabilized weights" and are prone to a higher variation. That is, observations that received the treatment but have a lower propensity of receiving the treatment based on covariate values, will have a much larger weight and hence the analysis will be heavily dependent on those observations (Hernán and Robins, 2019). To correct for this, we used the following stabilized weights (Robins, Hernán, and Brumback, 2000):

$$SW(t) = \prod_{k=0}^{t} \frac{p\{PSNP_K|\ PSNP_1, \ldots, PSNP_{K-1},\ V_0}{p\{PSNP_K|\ PSNP_1, \ldots, PSNP_{K-1},\ V_0,\ FS_1,\ \ldots,\ FS_{K-1}} \tag{5.3}$$

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 did not receive a treatment are given a

weight of 1 - P(Z=1)/ (1 - P(Z=1/V))

Stabilized weights give estimates that have a small variance and higher precision and hence are always preferred over the unstabilized weights (Hernán Robins, 2019b). The distribution of both stabilized and unstabilized weights are available in the Supplementary Table A.8. Once IPTWs are computed, they can be used in any desired outcome model to estimate treatment effects (Hernán and Robins, 2019).

Outcome model: Estimation of the MSM
We evaluated the effect of the PSNP on household food insecurity and child dietary diversity, number of meals, and child anthropometry if households were part of the PSNP, compared to households who did not receive the PSNP. The MSM was fitted by regressing the outcomes on the predictors in the MSM weighting the contribution of each subject using 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:

$$E\left[Y_{PSNP}|V = v\right] = \beta_0 + \beta_1 a_t + \beta_2 a_{t-1} + \gamma\beta_1 \tag{5.4}$$

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

5.3 Result

Demographic and Socioeconomic Characteristic Table 5.2 presents the socioeconomic and demographic characteristics of respondents by their PSNP enrollment during waves 3, 4 and 5, respectively. During wave 3, children in PSNP households have a lower dietary diversity score ($p < 0.001$), higher number of meals ($p < 0.001$), are more likely to be underweight ($p < 0.01$), have less educated ($p < 0.001$) and older (< 0.05) mothers, and have a poor health condition ($p < 0.005$) compared to children in non-PSNP households. There is no significant difference in terms of child sex, age, HAZ score, BMI z-score, stunting, underweight, and general health status. Considering household characteristics, PSNP household own fewer household durables ($p < 0.001$), spend less on food and non-food items ($p < 0.001$), have a female household head ($p < 0.001$), have more dependent members ($p < 0.01$), are more likely to experience drought ($p < 0.001$), are more likely to own livestock and borrow with credit ($p < 0.05$), and are less likely to own land ($p < 0.05$) compared to non-PNSP households. There is no significant difference in household food security.

During wave 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

TABLE 5.2: Socioeconomic and demographic characteristics

	Wave 3			Wave 4			Wave 5		
	Non-PSNP	PSNP		Non-PSNP	PSNP		Non-PSNP	PSNP	
Characteristics			P-value			P-value			P-value
	740 (61%)	482 (39%)		796 (67%)	391(33%)		882 (76%)	275 (24%)	
Child sex, **	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*	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 age (in months)*	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
Child HAZ score at wave 1*	-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
Chile number of meals*	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
Child HAZ score*	-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
Child BMI z-score*	-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
Child Stunting**	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
Child Underweight**	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**	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 real per adult (2006 ETB)	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**									
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)**	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**									
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*	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*	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 in the past 12 months**	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 in the past 12 months**	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 in the past 12 months**	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 wave **	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

Note: * = mean (standard deviation), ** = percentage (standard deviation), HAZ = height-for-age z-score, BMI = body mass index, and ETB = Ethiopian Birr.
Source: Authors

was no significant difference in child sex, age, dietary diversity score, daily number of meals, HAZ score, stunting, underweight, and health status. Regarding household characteristics, PSNP households own fewer household durables ($p < 0.001$), spend less on food and non-food items ($p < 0.001$), are more likely to be headed by a female ($p < 0.001$), are more likely to be food insecure ($p < 0.001$), have more dependent members ($p < 0.005$), are more likely to experience drought ($p < 0.01$), and are more likely to borrow with credit ($p < 0.001$) compared to non-PSNP households. There is no significant difference in maternal education, maternal age, and livestock and land ownership.

During wave 5, children in PSNP households eat a less diversified diet ($p < 0.001$), eat a smaller number of meals ($p < 0.005$), and have less educated mothers ($p < 0.01$) compared to children in non-PSNP households. There is no significant difference in child age, sex, HAZ score, BMI z-score, stunting, underweight, and health status. PSNP households own fewer durable assets ($p < 0.001$), spend 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 is observed in maternal age, livestock ownership, and borrowing with credit.

The Impact of PSNP on Food Security and Nutrition

Tables 5.3 and 5.3 present the MSM results of the causal association of participation in the PSNP and household food security 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 an increased number of meals consumed by a child (β = 0.308, SE = 0.121) (Table 5.3).

TABLE 5.3: Association of PSNP, household food security, child dietary diversity, and number of meals

	Household is food insecure	Child meal frequency	Child dietary diversity score
	0.022	0.308**	-0.183
PNSP	[-0.493–0.536]	[0.070–0.545]	[-0.413–0.047]
	(0.262)	(0.121)	(0.117)
n	3,305	3,292	3,295

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

Similarly, PSNP also has no effect on 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) among children in households who participate in the PSNP as compared with those who do not (Table 5.4).

TABLE 5.4: Association of the PSNP and child anthropometry

	Height-for-age z-score	Stunting	Body mass index z-score	Underweight
	-0.032	0.017	-0.032	0.103
PNSP	[-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	3,231	3,285	3,227	3,292

Notes: Rrobust standard errors are given in parentheses. A mixed effects logistic regression model is used for dichotomous outcomes and a linear mixed effects model is used for continuous outcomes. Models are adjusted for household durable asset quantile, dependency ratio, maternal education, maternal age, log of total real expenditures per adult, access to credit, ownership of livestock and land, household head sex and its interaction with PSNP participation, exposure to drought and its interaction with PSNP participation, and the age, sex, dietary diversity, and general health of the child.
Source: Authors

For all outcomes considered, we observe similar patterns of relationships in terms of the direction and significance with a slight change in the magnitude of estimates when comparing results from the Inverse Probability Weighted Regression Adjustment, mixed effects logistic regression, and linear mixed-effects model with MSM (see Tables A.9 - A.14).

5.4 Discussion

Evidence linking investment in child health and nutrition and economic growth is well established (Perkins et al., 2017; Vasquez and Daher, 2019). However, child nutrition remains one of the most pressing challenges in low-and middle-income countries and is exacerbated by poverty, shocks, and household vulnerability. To address these 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 and Alderman, 2013; Manley, Gitter, and Slavchevska, 2013; Davies and Davey, 2008). 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 the PSNP, which is the second largest social protection scheme in Sub-Saharan Africa, on household food insecurity and child nutritional 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 the PSNP on household food security, child dietary diversity, and child nutrition despite positive impacts in increasing the number of meals consumed in a day for the child in the household.

Many studies conceptualized that social protection programs could improve child nutrition through increased resources for food security, health, and/or health care

(Leroy, Ruel, and Verhofstadt, 2009). Such programs improve access to the quality of food, food production, productive assets, sanitation, and access to health care. In turn, in combination with appropriate feeding practices and a good health status, food security and dietary diversity could affect child nutrition. In this analysis, we found no impact of the PSNP on child undernutrition. Evidence from previous studies are also mixed. Berhane, Hoddinott, and Kumar, 2017 and Gebrehiwot and Castilla, 2018 did not find a significant impact of PSNP participation on child linear growth. Other studies found no significant impact on child BMI z-score or the likelihood of being stunted and underweight. The recent systematic review also shows no statistically significant association between social protection programs and height-for-age z-scores (Manley, Gitter, and Slavchevska, 2013). On the contrary, a study byPorter and Goyal, 2016 provides evidence of improvements in nutritional outcomes due to the PSNP. Debela, Shively, and Holden, 2015 report that children living in PSNP households have a higher weight-for-Height z-score (WHZ) than their non-PSNP counterparts. Differences in these studies can be due to several factors.

Chronic undernutrition is highly dependent on nutritional status during the 1,000 day window (Victora et al., 2008). Even though we attempted to control for nutritional status during the 1,000 day window, our sample children were over eight years of age, which is an age group for which improvements in long-term nutritional status may not be easily realized (Georgiadis et al., 2016). Moreover, the PSNP targets households with a history of chronic food insecurity. Therefore, children in these targeted households have a lower likelihood of having a good nutritional status. The absence of an 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 the PSNP are different from those households that are not enrolled in the PSNP (Table 5.2). They have lower dietary diversity, lower maternal education, lower expenditures, 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 and Begum, 2011), which, in turn, is associated with better child nutrition and nutrient adequacy (Ruel, 2003). In this study, the fact that the education level of mothers and the availability of public health facilities were lower among households participating in the PSNP (see Table 5.2) may have also contributed to poor child feeding practices, dietary quality, and child health. Along the same line, Berhane, Hoddinott, and Kumar, 2017 also reported a lack of good child feeding practices and contact with health extension workers among PSNP beneficiary mothers. Woldehanna, 2010 also reports the role of intra-household dynamics on child nutritional status. Porter and Goyal, 2016 point out that the PSNP has produced both intended and unintended outcomes for children, particularly with regard to their time use.

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 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(HLPE, 2012). This is also evident from previous impact evaluation studies of the PSNP where access to both the PW and OFSP component of the PSNP 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 about 30% of total beneficiaries benefited, such activities were not well integrated into the 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 transfers matter for programs to have an impact on nutrition. As indicated in Leroy, Ruel, and Verhofstadt, 2009, higher amounts and a longer duration of the transfer are likely to produce a greater impact. If transfer size exceeds the minimum amount required for consumption and to encourage investment, it will likely generate future income that could be spent on food security and nutrition-promoting activities. However, studies show that the PSNP mainly operates for six months of the year (January through June) and beneficiaries receive less than half of the intended transfer amount, which is too small to cover a consumption need, let alone encourage investment in assets(Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009). Moreover, there were payment delays (Gilligan, Hoddinott, and Taffesse, 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 improvements in household food security and child nutrition is questionable.

Previous studies report that the PSNP improves household food security (Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009; Porter and Goyal, 2016). Gilligan et al. (2009) examine the effect of the PSNP on the food gap (number of months the household reports having difficulty meeting food needs), calorie intake, and number of meals consumed by children 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 the PSNP on food security as the years of participation increase. On the contrary, our study shows no evidence to this claim. Similarly, Gebrehiwot and Castilla, 2018 find no impact of the 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 (e.g.,. Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009; Porter and Goyal, 2016 use propensity score matching, difference-in-difference, and

dose-response models. To measure food insecurity, we use HFIAS, whereas Gilligan, Hoddinott, and Taffesse, 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, Gebrehiwot and Castilla, 2018 use intake of calorie, iron, and protein, and others use a dietary diversity score (Berhane et al., 2014; Woldehanna, Mekonnen, and Alemu, 2008; Gilligan, Hoddinott, and Taffesse, 2009). 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, Hoddinott, and Taffesse, 2009 and Berhane et al., 2014 are based on a survey undertaken in areas where the PSNP operates, Gebrehiwot and Castilla, 2018 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 2007/2008 and 2011/2012 food price spike and drought at the time of the survey may have also 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. Hence, the income or substitution effects of food price shocks among households that received the 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. Error in the measurement of food security could also have introduced bias in the results. Berhane et al., 2014 and Gilligan, Hoddinott, and Taffesse, 2009 note that households' responses to the food gap survey questions are sensitive to whether or not households received payments in the month prior to the survey whereby payments received close to the survey period trigger positive answers to the food security questions. Hence, such inconclusive results warrant further investigation.

Studies show that child undernutrition is sensitive to dietary quality Dewey and Begum, 2011, which in turn, is associated with better child nutrition and nutrient adequacy (Ruel, 2003). However, empirical evidence on the impact of the 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 dietary diversity. Evidence from Kenya, Malawi, and South Africa show that social protection program have improved households dietary diversity (Groot et al., 2017). In Ethiopia, (Berhane et al., 2014) found no impact of the PSNP on dietary diversity. Similarly, we found no impact of the PSNP on child dietary diversity. In our sample, dietary diversity was generally low among the sample children, but significantly lower among children in PSNP households.

In this study, PSNP participation by households leads to a 0.302 increase in the number of daily meals consumed by a child in the household. Similarly, Berhane et al., 2011 reported that the PSNP increased the number of child meals per day by 0.15 units while Gilligan, Hoddinott, and Taffesse, 2009 found no impact of the PSNP

on the number of meals per day during the hungry season. As studies show, the PSNP increased borrowing for productive purposes, the use of improved agricultural technologies, agricultural productivity, and consumption expenditures, while it decreased the number of months of food shortages (Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009; Hoddinott et al., 2012) all of which are correlated with better child nutrition. However, whether the immediate gains in consumption translate into long-term improvements in child nutrition requires further study.

Our results have implications for the design of health and nutrition improving safety nets in Ethiopia. Unless the 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 the impact of social protection on food security and nutrition is better realized when such programs are integrated with other sectoral programs that provide infrastructure, and appropriate training and information on food utilization. Therefore, integrating the 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 sizes, 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 MSM gives accurate estimates of the effect of the PSNP on household food security and nutritional outcomes compared with conventional modeling approaches. MSMs do not suffer from collider stratification because it uses weighting (as opposed to conditioning). Moreover, this study also attempted to check the necessary assumptions required for using MSMs. Among these, conditional exchangeability and the absence of unmeasured confounding inducing correlation between treatment (exposure) and residuals were 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. The results show that substantial residual unmeasured confounding was needed to explain away the observed significant associations of the treatment (PSNP) with the outcomes 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 the descriptive statistics (see Tables A.8 and 5.2). Additional assumptions of the correct model specification were likely to hold, given that stabilized weights have a mean of around 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. A given household could use the 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 relied only on known factors. Moreover, it is important to emphasize that 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 and 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 IPWRA methods.

5.5 Conclusion

Both food insecurity and child undernutrition remain public health challenges in Ethiopia. In this study, we found no evidence that the PSNP improved household food security and child nutrition despite its positive impact on the number of daily meals consumed by a child. 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.

Chapter 6

Discussion and Implications

Ethiopia implemented several policy reforms to alleviate poverty and food insecurity and to accelerate agricultural transformation (NPC, 2016). These include the introduction of a safety net program in 2005 that entailed a shift from an ad hoc food distribution approach to a program that addresses both the immediate and underlying causes of food insecurity. Since 2015, Ethiopia has also tried to mainstream nutrition in its agricultural and social protection interventions (MoA, 2014; MoANR and MoLF, 2016; World Bank, 2019). However, whether these interventions have been effective in improving agricultural outcomes, reducing food insecurity, and improving nutrition is inconclusive (see table 3.1, table 4.1, and table 5.1). As far as the impact of PSNP is concerned, while some studies show that the PSNP has improved agricultural outcomes, food security, and nutrition, others report no impact of the program on such outcomes. Moreover, previous studies have relied on methods that are prone to time varying confounders and model misspecification biases that are pertinent to the program design. Regarding the impact of one of the nutrition-sensitive interventions we studied, namely agricultural diversification, evidence is not only limited, but is also based on studies that have not addressed endogeneity involved in production and consumption decisions of farm households.

Following the conceptual framework described in section 1.2 that highlights the linkages between social protection, agriculture, and nutrition, we assessed the contributions of social protection for agricultural production, food security, and nutritional outcomes. We also examined the role of agriculture, particularly production diversification, in improving nutritional outcomes. In Chapter 3 we evaluated the impact of the PSNP on agricultural asset ownership, technology adoption, crop and livestock production diversity, access to advisory services, and women's control over resources. In Chapter 4 we assessed the impact of production diversity on household dietary diversity and child nutritional outcomes. In Chapter 5 we evaluated the impact of a safety net program on household food security and child nutritional outcomes. To this end, we used two longitudinal quantitative data sets, namely the LSMS-ISA (2012/2013-2015/2016) and the YL cohort study. We applied targeted maximum likelihood estimation, instrumental variable generalized method of moments approach, and marginal structural models to improve causal identification.

Doing so we improved causal identification and addressed methodological limitations in the existing literature, especially those related to time varying confounding, model misspecification, and endogeneity biases. In what follows, we provide a summary of major findings, which is followed by a discussion and conclusion, implications of the study, and areas for further research.

6.1 Summary of Major Findings

Scholars argue that participation in the PSNP could improve agricultural outcomes by alleviating liquidity and credit constraints and related risks, improving risk-bearing capacity, insuring against risks, building community agricultural assets, and improving access to inputs, infrastructure, and agricultural markets. In Chapter 3, we evaluated the impact of PSNP participation on agricultural outcomes. We found that, at the household level, PSNP participation increased ownership of agricultural tools, the value of livestock sales, the share of household income from non-farm sources, time spent on agricultural work, and access to credit. We also found that the PSNP has improved community access to irrigation water and advisory services on natural resource management, credit, and crop and livestock production. However, we found that PSNP participation has no impact on technology adoption, women's control over income, crop and livestock count, and household access to extension services. Moreover, PSNP participants have a lower endowment of durable assets, human capital, and land, which might hinder improved community access to inputs and advisory services for improved agricultural outcomes at the household level. To the best of our knowledge, this is the first study to assess the impact of the PSNP on agricultural outcomes by applying a method that is less sensitive to outliers and maximizes the chance of correct model specification using machine learning algorithms. This is also the first study to consider various outcomes along the causal pathway of the impact of a safety net program on agricultural outcomes.

Agriculture as a source of food and livelihood for most of the hungry and malnourished people has a great role in alleviating malnutrition and its associated welfare consequences. Especially in a context like Ethiopia where subsistence agriculture constitutes the sheer size of agricultural production, market access and participation is low, and markets do not function well, own production plays a crucial role in household food security and nutritional outcomes. In Chapter 4, we tackled this important subject by assessing the role of agricultural diversification on household and child nutritional outcomes. The literature is not definitive as to whether production diversity improves nutrition and is dominated by studies that use methods that do not consider the endogenous relationship between own production and consumption. Using a nationally representative plot level longitudinal data, we examined the impact of production diversity on household and child nutritional outcomes while addressing the endogenous relationship between production diversity, dietary diversity, and child undernutrition using an IV-GMM approach. We found

that higher production diversity is associated with improvements in household diet up until production diversity reaches seven food groups. If a household produces eight or more food groups, the effect of production diversity on household dietary diversity is negative. The positive effect found for up to seven food groups could come through three possible pathways: consumption, improved agroecology due to production diversification, and improved risk-bearing capacity. We find that the consumption of more nutritious foods (eggs, fish, fruits, legumes, nuts, seeds, meat, roots, tubers, milk, milk products, and vegetables) to be higher among households with higher levels of production diversity (see Table S3). From an ecological perspective, studies show that increased diversification improves soil quality, which, in turn, improves agricultural productivity and household dietary diversity (Jones, 2017b; Sibhatu and Qaim, 2018a) and child nutritional status (Masset et al., 2012; Ruel and Alderman, 2013). Considering risk, more diversified production is associated with a higher risk-bearing capacity and a greater likelihood of adopting new technologies, which improve agricultural productivity and household diets (Ecker, 2018; Hirvonen and Hoddinott, 2017; Koppmair, Kassie, and Qaim, 2016; Sibhatu, Krishna, and Qaim, 2015; Sibhatu and Qaim, 2018a). However, production diversity after seven food groups is negatively associated with household dietary diversity. As far as the role of markets is concerned, we observed that markets have a strong positive impact on household dietary diversity, even at higher levels of production diversity. Given that an average farmer in our sample produces about six food groups, promoting more diversification is likely to negatively impact household diets due to negative returns to excess diversification.

In Chapter 5, we evaluated the impact of the PSNP on household food security and child nutrition outcomes. Only a few studies have examined the impact of the PSNP on child nutritional outcomes (Debela, Shively, and Holden, 2015; Berhane, Hoddinott, and Kumar, 2017; Porter and Goyal, 2016). These studies have applied methods that are prone to bias due to time-varying confounders that are pertinent to the program design and implementation. We tried to fill this gap in the literature by applying marginal structural models that account for not only time-varying but also time-invariant confounders and evaluated the impact of the PSNP on household food security and child nutritional outcomes. We found that PSNP had no impact on household food security measured by the household food insecurity access scale. We also found no impact of the PSNP on child dietary diversity, height for age z-score, body mass index z-score, the likelihood of stunting, and the likelihood of being underweight. However, PSNP participation increased child meal frequency by 0.34 meals a day. We also observed that children in the PSNP households have a lower dietary diversity score, lower maternal education, lower health service utilization, and higher food insecurity, which might have contributed to lack of impact.

6.2 Implications of the Study

6.2.1 Policy and Program Implications

This dissertation contributes to a growing body of literature related to social protection, agriculture, and nutrition by providing a rigorous assessment of the impact of the PSNP on a range of agricultural outcomes, the impact of agricultural diversification on household and child nutrition, and the impact of a safety net program on food security and child nutritional outcomes. The results of this dissertation have several policy implications that could be used to elevate the impact of safety nets beyond immediate consumption smoothing and address the root cause of poverty, human capital formation, and associated outcomes, thus contributing to inclusive economic growth. The findings of this dissertation also have implications for the design of nutrition-sensitive interventions.

In Chapter 3, we showed that the PSNP brought improvements in several community-level agricultural outcomes, such as improvement of advisory services for crop and livestock production, natural resource management, access to credit, and improved access to irrigation. However, at the household level, its impact is only limited to improvements in agricultural tool ownership, access to credit, and income from livestock sales. Moreover, we have noted that households participating in the PSNP have low physical and human capital endowments, which might have hindered households from benefiting from created community-level assets for improved agricultural production. We also did not find an impact of the PSNP in adopting high-risk high-return activities, such as improved seed and fertilizer use, indicating a lack of impact of the PSNP in either improving risk-bearing capacity or reducing risk exposure and thereby altering household risk behavior. Therefore, we recommend household-level interventions that could lift households' endowment levels to create an asset threshold that would allow the productive use of created community assets to be integrated into the PSNP. This would help elevate the program's impact beyond improvements in community access to inputs. This could be achieved by increasing the transfer level and complementing cash and/or in-kind transfers with productive asset transfers (Banerjee et al., 2015). Moreover, as noted by Gilligan, Hoddinott, and Taffesse, 2009, there are delays and underpayments of entitled transfers in the implementation of the PSNP. This might have contributed to the lack of impact found on households' risk exposure and risk behavior and technology adoption. Hence, improving timeliness and the amount of cash and/or in-kind payments is also critical for creating certainty and altering household risk behavior.

There are two strands in the literature on agriculture and nutrition linkages. One strand of the literature advocates production diversification and the other advocates commercialization for improved nutrition (Jones, 2017b; Sibhatu and Qaim, 2018a). In Chapter 4, we have shown that production diversity is associated with

improved household dietary diversity; however, after a production diversity level of seven food groups, this association turns negative. We have also shown the strong positive role of markets in improving household dietary diversity, even at a higher level of production diversity. Given that an average farmer in our sample produced six food groups, promoting further diversification is likely to affect household dietary diversity negatively. This could be because the gains in further diversification are outweighed by the complementary losses from reduced specialization. We also observed that the level of market participation is positively associated with household dietary diversity. Hence, we recommend improving conditions for market participation by smallholders. These could be achieved by improving infrastructure, storage facilities, and access to factors of production that increase marketable surplus and hence the rate of market participation.

In Chapter 5, we showed that the PSNP has no impact on household food insecurity and child undernutrition, except for a positive impact on children's number of meals per day. This finding is contrary to a study conducted using similar data set but different methodological approach (Porter and Goyal, 2016). Studies show that child age, transfer size, and household conditions are important determinants of the impact of cash transfers on nutrition (Leroy, Ruel, and Verhofstadt, 2009). However, children in PSNP households have a lower dietary diversity score, lower maternal education, lower health service utilization, and greater food insecurity, which may contribute to the observed lack of impact. Moreover, while experts show that sectoral linkages with other programs are critical for programs to improve child nutrition (HLPE, 2012), the PSNP lacks coordination with other nutrition-sensitive interventions related to health and agriculture. Therefore, we recommend the integration of 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 (Groot et al., 2017; Leroy, Ruel, and Verhofstadt, 2009; Hoddinott, Ahmed, and Roy, 2018).

6.2.2 Methodological Implications

This dissertation contributes to the literature that applies advanced methods in impact evaluation using observational studies (Abadie and Cattaneo, 2018; Hernán and Robins, 2019; Imbens, 2014; Imbens and Wooldridge, 2009). The use of repeated measure, large sample size, a wide range of outcomes considered, a method that improves causal identification, and estimations that are based on a less-stricter assumption are among the methodological strengths of this study. In Chapter 3, we used targeted maximum likelihood estimation that uses machine learning algorithims to maximize the chance of correct model specification and is more robust to outliers and sparsity biases. In Chapter 4, we used instrumental variable approach to account for the endogenous relationship between agricultural production diversity and dietary diversity in households where both production and consu-

mption decisions are jointly determined. In Chapter 5, we used marginal structural models that takes into account both time-variant and time-invariant confounders and are robust to collider and stratifica-tion bias. Hence, we believe that this thesis provides a more robust and accurate estimation of impact. Moreover, this thesis has also attempted to check the validity of the assumptions underlying causal inference in observational studies, namely conditional exchangeability, positivity, and correct model specification. For conditional exchangeability, we conducted sensitivity analyses for unmeasured confounding. For positivity, we compared descriptive statistics of treated and un-treated households. For correct model specification, we checked the mean of stabilized weights and used machine learning approaches, namely ensemble learning, to maximize the chance of correct model specification. Furthermore, although methods used in this study are increasing in popularity, their application in the field of agricultural economics has been rare with their use mainly found in the epidemiological and statistical literature. We believe that this dissertation has contributed to impact evaluation in the field of agricultural economics by applying these methods in situations where their unique properties improve causal identification, thus bringing these methods to the attention of agricultural economists.

6.3 Limitations of the Study and Recommendation for Future Research

This dissertation is not without limitations. Although the dataset used for Chapters 3 and 4 is nationally representative and dataset used for Chapter 5 is more inclined to poorer households, whether this data has enough power to detect the impact of the PSNP on agricultural outcomes, household food security, and child nutrition is subject to debate. Hence, a more powered study with the primary objective of answering the effectiveness of the PSNP with respect to outcomes considered would help to get more accurate results. Such data may also allow causal mediation analysis to identify the mechanisms through which social protection improves agricultural and nutritional outcomes.

Another limitation of the datasets used in this study is that although seasonality is one of the peculiar features of agricultural production and food security in Ethiopia, it is not captured in this study. Moreover, probable measurement error due to recall biases in the measurement of consumption data used in Chapters 4 and 3 are another limitation. Therefore, studies that account for seasonality via bi-annual or more frequent data collection would provide estimates that are less prone to bias due to seasonality and improve our understanding of the linkages between agriculture and nutrition under seasonal variations. Furthermore, although this study applied identification strategies that are less prone to bias due to model misspecification, outliers, sparsity, endogeneity, and time-varying confounders, the validity of the val-

idity of assumption that these methods rely on are difficult to verify. Particularly, the consistency assumption – which entails that the observed outcome is precisely the causal outcome under the observed treatment history – is less likely to hold true due to possible misclassification and lack of compliance. Although we have conducted sensitivity analysis for unobserved confounders and found favorable results, we cannot rule out the possibility of unmeasured confounders and hence the validity of the conditional exchangeability assumption.

While it is not the scope of this study to assess the linkages between social protection, agriculture, and nutrition, the theoretical rationale presented in Chapter 1.2 and the growing multi-sectoral approach of programs means that research and policy would immensely benefit from exploring such interlinkages. However, due to data limitations, namely the lack of enough child nutrition indicators in the LSMS-ISA, this dissertation has not explored these interlinkages. We recommend future research that assesses these interlinkages. In addition, while created community assets from PW activities are one of the probable pathways through which the PSNP improves agricultural and nutritional outcomes, due to data limitations we were not able to quantify this effect. Furthermore, although the interlinkages between agriculture and nutrition are more complex and involve other pathways such as women's status (Webb, 2013), we only explored two pathways – consumption and income in their very simplistic definition. Hence, we might have under- or over-estimated the true relationship between agriculture and nutrition.

Finally, while implementation challenges, such as timeliness and the amount of entitled payments, are frequently cited in the literature (Berhane et al., 2014; Gilligan, Hoddinott, and Taffesse, 2009) and could limit effectiveness of the PSNP in improving nutrition and agricultural outcomes, this study did not capture program implementation challenges. Hence, qualitative data that provide in-depth insights into the implementation process of the program would have been valuable to supplement our understanding of program's roll-out and implementation.

6.4 Concluding Remarks

Despite the potential of safety nets to address the root cause of poverty by improving household resilience via productive impacts on agriculture and breaking the intergenerational cycle of poverty via improving child nutrition, these impacts are largely nonexistent in one of the largest social protection programs in Africa. While we cannot rule out all possible pathways, the lack of endowments among beneficiaries in terms of human capital, assets, expenditure, and food insecurity, might have resulted in a lack of impact on such metrics. We recommend integrating nutrition-sensitive interventions and asset transfers to alleviate these constraints, as well as to elevate the contribution of safety nets beyond the short-term impact on nutrition and impacts at the early stage of the causal pathway from safety nets to agriculture.

Moreover, we have shown that production diversity is positively associated with improvements in household diet until a production level of 7 food groups, one food group above the average level of production diversification. Hence, promoting further diversification is likely to negatively impact housed diets. Hence, policies that aim to improve stallholders' diet should focus on improving conditions for market participation over production diversification.

Appendix A

Appendix

A.1 Appendix for Chapter 3

A.2 Appendix for Chapter 4

A.3 Appendix for Chapter 5

TABLE A.1: Variable description

Description of variables	Variables included in the model
Own agricultural tool - '1' for households that own a sickle/ax/pickax/ plow/water pump and '0' otherwise	Durable asset quantile, total expenditure quantile, food shortage, lowland dummy, household size, number of adults, average adult age, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, change in the stock of livestock, female head, female head and durable asset interaction, household non-farm owns enterprise, hectares of land owned, and proportion of adults who can read and write.
Tropical Livestock Unit (log) income from livestock sale and (log) income from crop sale	Total expenditure quantile, durable asset quantile, food shortage, lowland dummy, household size, number of adults, average adult age, proportion of adults who can read and write, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, hectares of land owned, female head, female head and durable asset interaction, and household owns a non-farm enterprise.
Advise on crop/ livestock produciton, credit and natural resource management '1' if the community experienced betterment in these services and '0' otherwise.	Total expenditure quantile, durable asset quantile, food shortage, lowland dummy, household size, number of adults, average adult age, the proportion of adults who can read and write, the dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, hectares of land owned, female head, female head, and durable asset interaction and household owns a non-farm enterprise.
Irrigation -'1' if the community has access to irrigation and '0' otherwise	Total expenditure quantile, durable asset quantile, food shortage, lowland dummy, household size, number of adults, average adult age, proportion of adults who can read and write, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, hectares of land owned, female head, female head, and durable asset interaction, and household owns a non-farm enterprise.
Irrigation - # of hoseholds using irrigation water	
Share of non-farm income in total income	Total expenditure quantile, food shortage, lowland dummy, household size, number of adults, average adult age, proportion of adults who can read and write, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, change in stock of livestock in TLU, hectares of land owned, female head, female head and durable asset interaction, household owns a non-farm enterprise, and proportion of adults who can read and write.
Log of value of land in local currency	Durable asset quantile, total expenditure quantile, food shortage, lowland dummy, household size, number of adults, average adult age, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, change in stock of livestock in TLU, non-farm enterprise, female head, female head and durable asset interaction, household owns a non-farm enterprise, and household owns agricultural assets (sickle and plough).
# of livestock/crop species raised by the household	Total expenditure quantile, durable asset quantile, food shortage, lowland dummy, household size, number of adults, average adult age, proportion of adults who can read and write, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, hectare of land owned, female head, female head and durable asset interaction, and household owns a non-farm enterprise.
Kilogram of fertilizer/ improved seed per hectare	
Hours spent on non-agricultural, agricultural, and casual work in the past 7 days	Total expenditure quantile, food shortage, lowland dummy, household size, number of adults, average adult age, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, change in the stock of livestock in TLU, hectares of land owned, female head, female head and durable asset interaction, household owns a non-farm enterprise and proportion of adults who can read and write.
'1' if the community has obtained credit, extension, or advisory services and '0' otherwise	Total expenditure quantile, durable asset quantile, food shortage, lowland dummy, household size, number of adults, average adult age, the proportion of adults who can read and write, the dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, hectares of land owned, female head, female head, and durable asset interaction and household owns a non-farm enterprise.
Female members have sole ownership of livestock or land	Durable asset quantile, total expenditure quantile, food shortage, lowland dummy, household size, number of adults, average adult age, dependency ratio, time dummy, credit in the past 12 months, drought in the past 12 months, livestock loss in the past 12 months, illness in the past 12 months, distance to the nearest market in kilometers, change in the stock of livestock, female head, household owns a non-farm enterprise, hectares of land owned, and proportion of adults who can read and write.

Source: Authors

TABLE A.2: Community characteristics by PSNP participation

Factor	PSNP (N=3036)	non-PSNP (N=5665)	p-value
Rain comes at the right time	820 (27.0%)	1865 (32.9%)	<0.001
Land used for farming (%)	2419 (79.7%)	3285 (58.0%)	<0.001
Land used as bush (%)	20.7 (21.4)	12.4 (20.4)	<0.001
Land used as forest (%)	11.7 (14.6)	9.6 (13.9)	<0.001
Main road in the community is Asphalt	625 (20.6%)	2015 (35.6%)	<0.001
Distance to the nearest Asphalt (kms)	32.0 (41.8)	30.8 (48.4)	0.23
Distance to the nearest bus station (kms)	15.4 (24.1)	13.0 (32.8)	<0.001
Community resides in a woreda town	374 (12.3%)	1978 (34.9%)	<0.001
Distance to the nearest woreda town (kms)	24.1 (23.0)	20.1 (22.4)	<0.001
There is a large weekly market in the community	1553 (51.2%)	3318 (58.6%)	<0.001
Distance to the nearest primary school (kms)	1.0 (6.5)	2.5 (28.6)	0.004
Primary school is electrified	2632 (87.0%)	4864 (86.2%)	0.31
Health post in the community	2544 (90.3%)	3967 (83.7%)	<0.001
Health post in the community is electrified	1028 (36.4%)	1460 (33.6%)	0.015
There is MFI in the community	707 (23.4%)	2273 (40.1%)	<0.001
There is a water service in the community	1037 (34.3%)	2652 (46.8%)	<0.001
Large weekly market in the community	1553 (51.2%)	3269 (58.4%)	<0.001
Distance to the nearest weekly market (kms)	8.2 (14.2)	5.1 (11.9)	<0.001
(log) distance to the nearest weekly market (kms)	1.3 (1.4)	0.9 (1.2)	<0.001
Development agent in the community	2704 (89.1%)	3575 (63.9%)	<0.001
Better advice on crop production	2027 (66.8%)	2653 (47.4%)	<0.001
Better advice on natural resource management	2070 (68.2%)	2794 (49.9%)	<0.001
Better advice on agricultural credit	1476 (48.6%)	2020 (36.1%)	<0.001
Better advice on livestock production	1766 (58.2%)	2599 (46.5%)	<0.001
Better advice on livestock major crop production	820 (27.0%)	1865 (33.3%)	<0.001
Compared to 2 years ago, farmers find fertilizer. distributors in your community more	1469 (48.4%)	2151 (38.4%)	<0.001
Compared to 2 years ago, farmers find pest/herb distributors in your community	656 (21.6%)	1347 (24.1%)	0.010
Compared to 2 years ago, farmers find improved seed distributors in your community	1506 (49.6%)	2006 (35.9%)	<0.001

Source: Authors

TABLE A.3: Impact of PSNP on agricultural outcomes

	TMLE		IV		AIPW	
	ATE	SE	ATE	SE	ATE	SE
Productive asset ownership						
Own any type of agricultural tool	0.020***	0.01	0.059*	(0.034)	0.019	(0.012)
Livestock (TLU today)	0.02	0.2	-0.190	(0.760)	0.007	0.12
Livestock (TLU one year ago)	-0.1	0.2	-0.382	0.662	-.0152253	0.11
(log) value of livestock sale	0.500***	0.2	0.720*	(0.414)	0.515***	(0.155)
(log) value of land reap per hectare	0.013**	0.01	0.187	(0.237)	0.117**	(0.051)
(log) value of crop sale	-0.900***	0.2	-2.034***	(0.585)	-0.488***	0.13
Agricultural services						
Better advice on crop production from extension agent	0.105***	0.02	0.125	(0.102)	0.121***	(0.019)
Better advice on natural resource management from extension agent	0.122***	0.02	0.147**	(0.072)	0.133***	(0.018)
Better advice on credit from extension agent	0.081***	0.02	0.131	(0.144)	0.078***	(0.019)
Better advice on livestock production from extension agent	0.068***	0.02	0.109	(0.103)	0.060***	(0.019)
Community has access to irrigation water	0.102***	0.02	0.136	0.082	0.122***	(0.019)
# of household in the community who have access to irrigation water	98.900***	17.4	32.05*	39.175	88.784***	(20.167)
Household recived advice from extension agent	-0	0.02			-0.005	(0.017)
Household borrowed on credit over the past 12 months	0.02	0.02			0.024*	(0.014)
Household obtained advisory services	-0.01	0.02			0.006	(0.018)
Household participated in watershed activities	0.148***	0.01			0.203***	(0.017)
Input use						
Household used fertilizer	0	0.02	0.055	(0.097)	0.015	(0.016)
Kg of fertilizer per hectare used by households	-0.3	0.1	-27.733	(24.029)	-14.396	(18.127)
Household used improved seed	-0.01	0.02	-0.062	(0.042)	-0.005	(0.016)
Kg of improved seed used per hectare	-0,001	0.01	-0.155	(0.119)	0.013	(0.046)
Count of crops produced	0.2	0.3	-0.010	(0.463)	-0.489***	(0.102)
Count of livestock produced	0	0.1	0.045	(0.256)	0.227***	(0.071)
Time allocation						
Hours spent on agricultural work	9.200***	2.2	13.625*	(7.420)	9.663***	(2.043)
Hours spent on non-agricultural work	-0.011**	0	-0.958	(0.984)	-1.235**	(0.615)
Hours spent on casual work	0	0.01	-1.082	(0.728)	0.331	(0.405)
share of non-farm income	10.700***	1	0.390***	(0.083)	0.208***	0.04
Other outcomes						
Borrowed on credit over the past 12 months	0.062***	0.02	-0.012	(0.079)	0.030**	(0.014)
Female member make decision making	0	0.01			-0.005	(0.008)

Notes: ATE is targeted maximum likelihood estimation of average treatment effects. SE stands for standard errors. The model accounted for durable asset quantile, total expenditure, food gap, agroecological zones, household size, number of adults, number of adults who can read and write, adult age, access to credit, shocks (drought, loss of livestock, illness), distance to market, change in TLU, non-farm enterprise, head sex, area of land owned, Kgs. =kilograms.
Source: Authors

TABLE A.4: First stage regression results based on the linear model

Tropic-warm/semiarid	-0.059	0.070
	(0.249)	(0.120)
Tropic-warm/sub humid	-1.5223***	-0.567 ***
	(0.161)	(0.111)
Tropic-cool/sub humid	0.426***	0.309***
	(0.103)	(0.07)
Precipitation (wet quarter mean)	-0.0002*	-0.0001
	(0.0001)	(0.0001)
Elevation (meter)	-0.0001	-0.0002
	(0.0004)	(0.0002)
Plot slope (meter)	-0.0008	0.004
	(0.003)	(0.003)
Weak-identification tests		
Kleibergen-Paap rk LM statistic		
Cragg-Donald F-statistic	2.570	1.48
Angrist-Pischke F-test of excluded instruments	30.67	28.61
— p-value	0.000	0.000
Over identification test:		
Hansen-J	26.940	17.526
— p-value	0.0001	0.0036

Notes: Results are beta-coefficients of the first stage regression of the instrumental variable general method of moments estimation. Standard errors are shown in parentheses. * = p < 0.1, ** = p < 0.05, and *** = p < 0.001.
Source: Authors

TABLE A.5: Association between production diversity nutritional outcomes

	Household dietary diversity score			Height-for-age Z-score		Stunting	
	IV-GMM	Linear FE	Poisson	IV-GMM	Linear FE	IV-GMM	Linear FE
Production diversity	2.317***	0.123**	0.023	0.705	-0.105	-0.222	-0.002
	(0.653)	(0.062)	(0.024)	(1.743)	(0.182)	(0.496)	(0.053)
Production diversity squared	-0.157***	-0.006	-0.001	-0.033	0.003	0.013	0.003
	(0.046)	(0.005)	(0.002)	(0.085)	(0.012)	(0.024)	(0.003)
Large weekly market	1.332***	0.081	0.024	-0.001	0.103	0.013	-0.021
	(0.452)	(0.164)	(0.064)	(0.119)	(0.132)	(0.036)	(0.038)
Production diversity * weekly	-0.197***	-0.002	-0.002				
	(0.069)	(0.023)	(0.009)				
Household dietary diversity score				0.254	0.061	-0.043	0.017
				(0.661)	(0.141)	(0.185)	(0.041)
Household dietary diversity score X production diversity				-0.041	-0.006	0.008	-0.003
				(0.107)	(0.020)	(0.030)	(0.006)
(log) farm income (rph)	0.202	0.763***	0.131	0.438	0.615	-0.009	-0.070
	(0.385)	(0.244)	(0.091)	(0.941)	(0.627)	(0.243)	(0.183)
Proportion of crop value sold	-0.034	-0.154	-0.026	0.106	0.093	0.009	-0.016
	(0.161)	(0.134)	(0.051)	(0.312)	(0.341)	(0.098)	(0.099)
(log) value of labour (rph)	-0.036	0.030	0.005	-0.021	-0.013	-0.015	-0.016
	(0.039)	(0.028)	(0.011)	(0.076)	(0.072)	(0.022)	(0.021)
Land size (ha)	-0.004	0.027	0.004	0.093	0.102	-0.024	-0.029
	(0.052)	(0.043)	(0.016)	(0.109)	(0.105)	(0.034)	(0.031)
(log) food expenditure	0.563***	0.576***	0.111***	0.065	0.038	-0.003	0.004
	(0.037)	(0.030)	(0.012)	(0.108)	(0.084)	(0.030)	(0.024)
Durable asset index	0.133*	0.156***	0.023	-0.248	-0.192	0.060	0.044
	(0.076)	(0.057)	(0.021)	(0.188)	(0.149)	(0.049)	(0.043)
Livestock (TLU)	-0.068***	0.057***	0.009**	-0.010	0.098***	0.001	-0.021***
	(0.025)	(0.010)	(0.004)	(0.051)	(0.028)	(0.015)	(0.008)
Household head age (years)	0.009	0.024***	0.005*	0.018	0.045**	0.002	-0.006
	(0.010)	(0.007)	(0.003)	(0.028)	(0.022)	(0.006)	(0.006)
Household head is female	0.553	0.096	0.025	-1.113	-1.279**	0.223	0.303
	(0.459)	(0.305)	(0.122)	(0.678)	(0.650)	(0.180)	(0.189)
Household head is literate	-0.130	-0.103	-0.019	0.151	0.175	-0.028	-0.036
	(0.111)	(0.091)	(0.035)	(0.205)	(0.207)	(0.055)	(0.060)
(log) income from PSNP	-0.040	-0.051	-0.010	-0.339	-0.402	0.074	0.088
	(0.119)	(0.094)	(0.037)	(0.246)	(0.269)	(0.070)	(0.078)
Child age (months)				-0.096***	-0.027***	0.021***	0.005***
				(0.013)	(0.005)	(0.004)	(0.001)
2*Child diarrhea (past 14 days)				-0.057	-0.157	0.006	0.026
				(0.191)	(0.176)	(0.058)	(0.051)
Mother is literate				0.078	0.094	-0.008	-0.023
				(0.223)	(0.186)	(0.064)	(0.054)
Health post in the community				0.052	-0.033	-0.059	-0.038
				(0.254)	(0.262)	(0.066)	(0.076)
Constant	0.819***			2.456***	-5.450	-0.574***	0.802
	(0.149)			(0.456)	(4.533)	(0.131)	(1.320)
n	2,367	4,800	4,800	663	1,480	663	1,480

Note: Results are beta-coefficients. Robust standard errors are shown in parentheses. *** = p < 0.01, ** = p <0.05, and * = p < 0.1. IV-GMM stands for instrumental variable generalized method of moments approach, FE stands for fixed effect. rpa represents real per adult and rph stands for real per hectare. Instrumental variables used are used are agroecological zones, elevation in meters, mean temperature of the wettest quarter, and slope. In households with more than one child, we took a measurement of the youngest child.
Source: Authors

TABLE A.6: Consumption of 12 food groups by production diversity level and data sources

	Wave 2			Wave 3		
	Low PD (n = 1,856)	High PD (n = 1,629)	p-value	Low PD (n = 1,752)	High PD (n = 1,668)	p-value
Cereal from own production	1,049 (57.2%)	1,379 (84.9%)	<0.001	847 (48.8%)	1,347 (81.1%)	<0.001
Cereal from purchases	964 (52.5%)	511 (31.4%)	<0.001	1046 (60.3%)	666 (40.1%)	<0.001
Cereal from other sources	223 (12.2%)	75 (4.6%)	<0.001	451 (26.0%)	202 (12.2%)	<0.001
Cereal from all sources	1,791 (97.6%)	1,594 (98.1%)	0.35	1,709 (98.4%)	1,631 (98.2%)	0.60
Root and tuber crops from own production	135 (7.4%)	300 (18.5%)	<0.001	179 (10.3%)	432 (26.0%)	<0.001
Root and tuber crops from purchases	110 (6.0%)	92 (5.7%)	0.72	137 (7.9%)	171 (10.3%)	0.017
Root and tuber crops from other sources	33 (1.8%)	16 (1.0%)	0.045	31 (1.8%)	64 (3.9%)	<0.001
Root and tuber crops from all sources	248 (13.5%)	397 (24.4%)	<0.001	305 (17.6%)	566 (34.1%)	<0.001
Vegetables from own production	45 (2.5%)	153 (9.4%)	<0.001	144 (8.3%)	424 (25.5%)	<0.001
Vegetables from purchases	1291 (70.4%)	1197 (73.7%)	0.031	1414 (81.5%)	1394 (83.9%)	0.063
Vegetables from other sources	22 (1.2%)	17 (1.0%)	0.75	62 (3.6%)	62 (3.7%)	0.85
Vegetables from all sources	1,328 (72.4%)	1,269 (78.1%)	<0.001	1,489 (85.8%)	1,498 (90.2%)	<0.001
Fruits from own production	45 (2.5%)	171 (10.5%)	<0.001	52 (3.0%)	177 (10.7%)	<0.001
Fruits from purchases	248 (13.5%)	140 (8.6%)	<0.001	239 (13.8%)	209 (12.6%)	0.31
Fruits from other sources	15 (0.8%)	10 (0.6%)	0.55	8 (0.5%)	33 (2.0%)	<0.001
Fruits from all sources	300 (16.3%)	319 (19.6%)	0.013	297 (17.1%)	405 (24.4%)	<0.001
Meat from own production	24 (1.3%)	28 (1.7%)	0.33	17 (1.0%)	23 (1.4%)	0.34
Meat from purchases	327 (17.8%)	230 (14.2%)	0.003	262 (15.1%)	206 (12.4%)	0.025
Meat from other sources	14 (0.8%)	8 (0.5%)	0.39	16 (0.9%)	18 (1.1%)	0.73
Meat from all sources	362 (19.7%)	263 (16.2%)	0.007	292 (16.8%)	244 (14.7%)	0.090
Eggs from own production	118 (6.4%)	214 (13.2%)	<0.001	52 (3.0%)	150 (9.0%)	<0.001
Eggs from purchases	106 (5.8%)	24 (1.5%)	<0.001	96 (5.5%)	59 (3.6%)	0.007
Eggs from other sources	10 (0.5%)	7 (0.4%)	0.81	5 (0.3%)	13 (0.8%)	0.058
Eggs from all sources	234 (12.8%)	242 (14.9%)	0.075	152 (8.8%)	220 (13.2%)	<0.001
Fish from own production	9 (0.5%)	9 (0.6%)	0.82	20 (1.2%)	3 (0.2%)	<0.001
Fish from purchases				16 (0.9%)	1 (0.1%)	<0.001
Fish from other sources	9 (0.5%)	9 (0.6%)	0.82	1 (0.1%)	0 (0.0%)	1.00
Fish from all sources	9 (0.5%)	9 (0.6%)	0.82	33 (1.9%)	4 (0.2%)	<0.001
Legumes/nuts/oil seeds from own production	314 (17.1%)	726 (44.7%)	<0.001	227 (13.1%)	703 (42.3%)	<0.001
Legumes/nuts/oil seeds from purchases	939 (51.2%)	742 (45.7%)	0.001	908 (52.3%)	734 (44.2%)	<0.001
Legumes/nuts/oil seeds from other sources	87 (4.7%)	62 (3.8%)	0.21	144 (8.3%)	100 (6.0%)	0.011
Legumes/nuts/oil seeds from all sources	1,241 (67.6%)	1,319 (81.2%)	<0.001	1,168 (67.3%)	1,312 (79.0%)	<0.001
Milk/milk products from own production	534 (29.1%)	514 (31.6%)	0.11	423 (24.4%)	540 (32.5%)	<0.001
Milk/milk products from purchases	202 (11.0%)	68 (4.2%)	<0.001	172 (9.9%)	73 (4.4%)	<0.001
Milk/milk products from other sources	68 (3.7%)	38 (2.3%)	0.023	65 (3.7%)	50 (3.0%)	0.26
Milk/milk products from all sources	767 (41.8%)	615 (37.8%)	0.018	646 (37.2%)	657 (39.6%)	0.17
Oil and fats from own production	23 (1.3%)	65 (4.0%)	<0.001	102 (5.9%)	299 (18.0%)	<0.001
Oil and fats from purchases	83 (4.5%)	64 (3.9%)	0.40	1,263 (72.8%)	1,238 (74.5%)	0.24
Oil and fats from other sources				128 (7.4%)	54 (3.3%)	<0.001
Oil and fats from all sources	114 (6.2%)	134 (8.2%)	0.021	1,406 (81.0%)	1,341 (80.7%)	0.86
Sweets from own production	3 (0.2%)	5 (0.3%)	0.49	2 (0.1%)	6 (0.4%)	0.17
Sweets from purchases	1116 (60.8%)	652 (40.1%)	<0.001	107 (6.2%)	76 (4.6%)	0.048
Sweets from other sources	8 (0.4%)	6 (0.4%)	0.80	4 (0.2%)	4 (0.2%)	1.00
Sweets from all sources	1128 (61.5%)	664 (40.9%)	<0.001	112 (6.5%)	85 (5.1%)	0.11
Spice/condiments from own production	218 (11.9%)	471 (29.0%)	<0.001	319 (18.4%)	696 (41.9%)	<0.001
Spice/ condiments from purchases	1,803 (98.3%)	1,597 (98.3%)	1.00	1,709 (98.4%)	1,631 (98.2%)	0.60
Spice/condiments from other sources	78 (4.3%)	59 (3.6%)	0.38	139 (8.0%)	124 (7.5%)	0.56
Spice/condiments from other sources	1,818 (99.1%)	1,615 (99.4%)	0.34	1,721 (99.1%)	1,648 (99.2%)	0.85

Notes: Low PD and high PD refers to food group production diversity below and above the mean level of production diversity, respectively. Displayed figures are frequencies and proportion in parenthesis.
Source: Authors

TABLE A.7: Association between market participation and nutritional outcomes

	Household dietary diversity score	Height-for-age Z-score	Stunting
Crop commercialization index*	0.107**	0.142	-0.042
	(0.053)	(0.152)	(0.045)
Large weekly market	0.108	0.178	-0.047
	(0.113)	(0.329)	(0.092)
(log) farm income (rph)	1.847**	2.642	-0.691
	(0.814)	(2.559)	(0.742)
(log) value of labor (rph)	0.028	0.123	-0.056
	(0.064)	(0.231)	(0.067)
Land size (ha)	0.129	0.036	-0.010
	(0.095)	(0.231)	(0.069)
(log) food expenditure (rpa)	0.434***	-0.199	0.077
	(0.088)	(0.279)	(0.082)
Durable asset index	0.122	-0.659	0.187
	(0.139)	(0.592)	(0.168)
Livestock (TLU)	-0.018	-0.030	0.010
	(0.031)	(0.079)	(0.022)
Household head age (years)	0.032*	0.088	-0.020
	(0.018)	(0.086)	(0.025)
Household head gender (Female = 1)	0.086	-1.224	0.295
	(0.493)	(1.001)	(0.246)
Household head is literate	-0.290	-0.075	0.045
	(0.211)	(0.487)	(0.135)
(log) income from PSNP	0.137	-0.276	0.062
	(0.249)	(0.538)	(0.158)
Household dietary diversity score		0.011	-0.002
		(0.111)	(0.031)
Child age (months)		-0.108***	0.023***
		(0.024)	(0.007)
Child experienced diarrhea in the past two weeks		0.102	-0.045
		(0.386)	(0.106)
Mother is literate		0.048	0.010
		(0.419)	(0.115)
Health post in the community		0.623	-0.232
		(0.850)	(0.243)
Constant	0.427***	2.684***	-0.629***
	(0.134)	(0.670)	(0.191)
n	2,367	680	680

Notes: Low PD and high PD refers to food group production diversity below and above the mean level of production diversity, respectively. Displayed figures are frequencies and proportion in parenthesis.
Source: Authors

TABLE A.8: Distribution of the estimated stabilized and unstabilized and weights

Weights	Mean	Standard Deviation	Percentile 1	Percentile 25	Percentile 50	Percentile 75	Percentile 99
Wave 3							
Unstabilized weight	2.102	1.187	1.066	1.393	1.718	2.340	7.065
Stabilized weight	1.006	0.074	0.871	0.952	1.020	1.035	1.228
Wave 4							
Unstabilized weight	2.032	1.180	1.044	1.304	1.558	2.337	6.622
Stabilized weight	0.994	0.074	0.862	0.940	0.985	1.034	1.225
Wave 5							
Unstabilized weight	1.817	1.019	1.051	1.264	1.445	1.888	5.955
Stabilized weight	1.000	0.075	0.856	0.947	1.016	1.035	1.244

Notes: Low PD and high PD refers to food group production diversity below and above the mean level of production diversity, respectively. Displayed figures are frequencies and proportion in parenthesis.
Source: Authors

TABLE A.9: Association of the PSNP and household food insecurity

	Melogit1	IPWRA2	MSM3
PNSP¥	0.461*	-0.027	0.022
	(0.252)	(0.43)	(0.262)
Wealth tertile 1 vs. 2	-0.051	-0.199	-0.097
	(0.102)	(0.182)	(0.104)
Wealth tertile 1 vs. 2	-0.496***	-0.701**	-0.532***
	(0.156)	(0.276)	(0.161)
Maternal education none vs. primary	0.474***	0.583**	0.466***
	(0.153)	(0.253)	(0.153)
Maternal education none vs. above primary	-0.215**	-0.510***	-0.224**
	(0.107)	(0.182)	(0.11)
Dependency ratio	-0.204***	-0.147	-0.202***
	(0.071)	(0.126)	(0.073)
(log) total real expenditures per adult	-0.905***	-1.023***	-0.930***
	(0.1)	(0.174)	(0.103)
Household borrowed with credit	0.369***	0.695***	0.398***
	(0.102)	(0.18)	(0.105)
Own any animal	-0.18	-0.257	-0.091
	(0.163)	(0.32)	(0.169)
Maternal age (years)	-0.036***	-0.096***	-0.037***
	(0.007)	(0.015)	(0.008)
Head sex (male)	-0.492***	-0.856***	-0.631***
	(0.171)	(0.301)	(0.18)
Head sex (male) * PSNP¥	0.322	0.815*	0.4
	(0.268)	(0.457)	(0.279)
Drought	0.866***	1.381***	0.899***
	(0.127)	(0.207)	(0.13)
Drought * PSNP¥	-0.958***	-1.643***	-0.928***
	(0.22)	(0.356)	(0.222)
Constant	6.750***	10.339***	7.067***
	(0.608)	(1.106)	(0.624)
n	3,393	3,305	3,305

Note: ¥=Productive Safety Net Program, 1 = mixed effects logistic regression, 2 = Inversed Probability Weighted Regression Adjustment, 3 = Marginal Structural Model, Standard errors are shown in parentheses. * = p < 0.1, ** = p < 0.05, and *** = p < 0.01.
Source: Authors

TABLE A.10: Association of the PSNP and child meal frequency

	LME1	IPWRA2	MSM3
PNSP	-0.213*	0.014	-0.183
	(0.116)	(0.126)	(0.117)
Wealth tertile 1 vs. 2	0.101**	0.080	0.091*
	(0.049)	(0.058)	(0.051)
Wealth tertile 1 vs. 2	0.310***	0.248**	0.308***
	(0.083)	(0.106)	(0.083)
Maternal education non vs. primary	-0.085	-0.041	-0.084
	(0.071)	(0.085)	(0.077)
Maternal education non vs. above primary	0.109*	0.120*	0.109*
	(0.056)	(0.063)	(0.057)
Dependency ratio	-0.003	0.013	0.005
	(0.037)	(0.042)	(0.037)
(log) total expenditure real per adult	0.101**	0.112**	0.097*
	(0.048)	(0.056)	(0.050)
Household borrowed on credit	0.104**	0.107*	0.090*
	(0.051)	(0.055)	(0.050)
Own any animal	0.100	0.199*	0.131
	(0.086)	(0.104)	(0.091)
Child sex (male)	-0.029	-0.021	-0.032
	(0.049)	(0.050)	(0.049)
Child age (months)	0.063***	0.073***	0.064***
	(0.000)	(0.000)	(0.000)
Maternal age (years)	-0.002	-0.001	-0.001
	(0.004)	(0.004)	(0.004)
Head sex (male)	0.088	0.105	0.114
	(0.082)	(0.086)	(0.081)
Head sex (male) * PSNP¥	0.051	-0.112	0.003
	(0.124)	(0.137)	(0.126)
Drought	-0.268***	-0.227***	-0.265***
	(0.058)	(0.061)	(0.057)
Drought * PSNP¥	0.062	0.031	0.087
	(0.095)	(0.103)	(0.094)
Household is food insecure	-0.205***	-0.151***	-0.194***
	(0.049)	(0.055)	(0.049)
Constant	-1.680***	-2.646***	-1.808***
	(0.541)	(0.606)	(0.550)
n	3,383	3,295	3,295

Notes: ¥=Productive Safety Net Program, 1=liner mixed effects model, 2=Inversed Probability Weighted Regression Adjustment, 3=Marginal Structural Model, Standard errors in parenthesis. *=p<0.1, **=p<0.05, ***=p<0.01.
Source: Authors

TABLE A.11: Association of the PSNP and child height-for-age z-score

	LME1	IPWRA2	MSM3
PNSP	-0.039	0.001	-0.032
	(0.081)	(0.099)	(0.091)
Wealth tertile 1 vs. 2	0.021	0.015	0.030
	(0.033)	(0.035)	(0.034)
Wealth tertile 1 vs. 2	0.079	-0.054	0.072
	(0.059)	(0.075)	(0.061)
Maternal education non vs. primary	-0.024	-0.079	-0.031
	(0.064)	(0.066)	(0.062)
Maternal education non vs. above primary	0.087	0.054	0.083
	(0.054)	(0.061)	(0.053)
Dependency ratio	0.017	-0.002	0.007
	(0.025)	(0.029)	(0.026)
(log) total expenditure real per adult	0.167***	0.133***	0.180***
	(0.030)	(0.035)	(0.034)
Household borrowed on credit	0.019	0.002	-0.000
	(0.032)	(0.037)	(0.034)
Own any animal	-0.165***	-0.136	-0.125
	(0.059)	(0.099)	(0.078)
Child sex (male)	-0.311***	-0.297***	-0.320***
	(0.053)	(0.054)	(0.053)
Child age (months)	-0.021***	-0.019***	-0.022***
	(0.004)	(0.004)	(0.004)
Child is in a good health condition	0.035	0.034	0.038
	(0.034)	(0.035)	(0.034)
Maternal age (years)	0.002	0.003	0.002
	(0.004)	(0.004)	(0.004)
Head sex (male)	-0.010	-0.038	-0.022
	(0.055)	(0.072)	(0.069)
Head sex (male) * PSNP¥	0.029	-0.003	0.029
	(0.084)	(0.100)	(0.092)
Drought	-0.055	-0.036	-0.056
	(0.035)	(0.036)	(0.035)
Drought * PSNP¥	0.144**	0.137**	0.138**
	(0.056)	(0.058)	(0.056)
Child dietary diversity score	-0.001	-0.007	-0.001
	(0.011)	(0.012)	(0.011)
Constant	-0.636*	-0.528	-0.623**
	(0.325)	(0.329)	(0.315)
n	3,317	3,231	3,231

Notes: ¥=Productive Safety Net Program, 1=liner mixed effects model, 2=Inversed Probability Weighted Regression Adjustment, 3=Marginal Structural Model, Standard errors in parenthesis. *=p<0.1, **=p<0.05, ***=p<0.01.
Source: Authors

TABLE A.12: Association of the PSNP and child stunting

	Melogit1	IPWRA2	MSM3
PNSP	-0.011	0.071	0.017
	(0.345)	(0.509)	(0.354)
Wealth tertile 1 vs. 2	-0.086	0.128	-0.121
	(0.156)	(0.246)	(0.162)
Wealth tertile 1 vs. 2	-0.496*	0.522	-0.419
	(0.294)	(0.484)	(0.302)
Maternal education non vs. primary	0.111	0.430	0.138
	(0.257)	(0.330)	(0.261)
Maternal education non vs. above primary	-0.232	-0.274	-0.188
	(0.211)	(0.250)	(0.216)
Dependency ratio	-0.087	0.030	-0.023
	(0.114)	(0.165)	(0.119)
(log) total expenditure real per adult	-0.761***	-0.861***	-0.843***
	(0.171)	(0.244)	(0.178)
Household borrowed on credit	-0.115	-0.048	-0.009
	(0.159)	(0.244)	(0.164)
Own any animal	0.474	0.526	0.403
	(0.336)	(0.476)	(0.341)
Child sex (male)	1.029***	2.035***	1.087***
	(0.196)	(0.318)	(0.200)
Child age (months)	0.078***	0.105***	0.081***
	(0.018)	(0.029)	(0.019)
Child is in a good health condition	-0.126	-0.089	-0.119
	(0.168)	(0.251)	(0.172)
Maternal age (years)	0.016	0.037**	0.019
	(0.015)	(0.016)	(0.015)
Head sex (male)	-0.270	-0.120	-0.252
	(0.260)	(0.373)	(0.274)
Head sex (male) * PSNP¥	-0.198	-0.422	-0.230
	(0.372)	(0.545)	(0.382)
Drought	0.361**	0.531**	0.387**
	(0.173)	(0.247)	(0.178)
Drought * PSNP¥	-0.329	-0.487	-0.334
	(0.282)	(0.402)	(0.289)
Child dietary diversity score	-0.008	0.021	-0.016
	(0.052)	(0.080)	(0.054)
Constant	-4.744***	-9.996***	-4.922***
	(1.548)	(2.575)	(1.592)
n	3,373	3,285	3,285

Notes: ¥=Productive Safety Net Program, 1=mixed effects logistic regression, 2=Inversed Probability Weighted Regression Adjustment, 3=Marginal Structural Model, Standard errors in parenthesis. *=p<0.1, **=p<0.05, ***=p<0.01
Source: Authors

TABLE A.13: Association of the PSNP and child body mass index z-score

	LME	IPWRA	MSM
PNSP	0.013	-0.032	-0.032
	(0.092)	(0.114)	(0.114)
Wealth tertile 1 vs. 2	0.117***	0.087**	0.087**
	(0.038)	(0.037)	(0.037)
Wealth tertile 1 vs. 2	0.307***	0.231***	0.231***
	(0.066)	(0.072)	(0.072)
Maternal education non vs. primary	0.098	0.161**	0.161**
	(0.067)	(0.067)	(0.067)
Maternal education non vs. above primary	0.164***	0.172***	0.172***
	(0.055)	(0.063)	(0.063)
Dependency ratio	0.014	-0.005	-0.005
	(0.028)	(0.036)	(0.036)
(log) total expenditure real per adult	0.071**	0.044	0.044
	(0.035)	(0.038)	(0.038)
Household borrowed on credit	0.082**	0.087*	0.087*
	(0.037)	(0.046)	(0.046)
Own any animal	0.094	0.230*	0.230*
	(0.068)	(0.120)	(0.120)
Child sex (male)	-0.275***	-0.274***	-0.274***
	(0.051)	(0.052)	(0.052)
Child age (months)	-0.061***	-0.061***	-0.061***
	(0.004)	(0.004)	(0.004)
Child is in a good health condition	0.094**	0.060	0.060
	(0.040)	(0.042)	(0.042)
Maternal age (years)	0.002	0.001	0.001
	(0.004)	(0.004)	(0.004)
Head sex (male)	-0.034	-0.036	-0.036
	(0.064)	(0.085)	(0.085)
Head sex (male) * PSNP¥	0.010	0.027	0.027
	(0.097)	(0.117)	(0.117)
Drought	0.042	0.074*	0.074*
	(0.041)	(0.043)	(0.043)
Drought * PSNP¥	0.024	0.018	0.018
	(0.066)	(0.067)	(0.067)
Child dietary diversity score	0.018	0.017	0.017
	(0.012)	(0.013)	(0.013)
Constant	1.934***	1.997***	1.997***
	(0.378)	(0.366)	(0.366)
n	3,313	3,227	3,227

Notes: ¥=Productive Safety Net Program, 1=liner mixed effects model, 2=Inversed Probability Weighted Regression Adjustment, 3=Marginal Structural Model, Standard errors in parenthesis. *=p<0.1, **=p<0.05, ***=p<0.01.
Source: Authors

TABLE A.14: Association of the PSNP and child underweight

	Melogit1	IPWRA2	MSM3
PNSP	0.120	0.224	0.103
	(0.352)	(0.590)	(0.371)
Wealth tertile 1 vs. 2	-0.436***	-0.666***	-0.456***
	(0.146)	(0.234)	(0.150)
Wealth tertile 1 vs. 2	-1.263***	-1.966***	-1.295***
	(0.288)	(0.518)	(0.299)
Maternal education non vs. primary	-0.340	-0.533	-0.349
	(0.241)	(0.409)	(0.248)
Maternal education non vs. above primary	-0.415**	-0.728**	-0.442**
	(0.200)	(0.308)	(0.207)
Dependency ratio	0.063	0.133	0.035
	(0.116)	(0.177)	(0.122)
(log) total expenditure real per adult	-0.235	-0.216	-0.215
	(0.144)	(0.224)	(0.147)
Household borrowed on credit	-0.487***	-0.860***	-0.532***
	(0.146)	(0.248)	(0.152)
Own any animal	0.080	-0.298	0.060
	(0.264)	(0.416)	(0.277)
Child sex (male)	0.858***	1.568***	0.916***
	(0.184)	(0.239)	(0.190)
Child age (months)	0.188***	0.271***	0.196***
	(0.019)	(0.030)	(0.020)
Child is in a good health condition	-0.280*	-0.245	-0.280*
	(0.163)	(0.251)	(0.167)
Maternal age (years)	-0.010	-0.030*	-0.012
	(0.015)	(0.018)	(0.015)
Head sex (male)	0.281	0.639*	0.263
	(0.252)	(0.375)	(0.267)
Head sex (male) * PSNP¥	-0.394	-0.657	-0.385
	(0.381)	(0.652)	(0.404)
Drought	0.144	0.080	0.115
	(0.166)	(0.256)	(0.171)
Drought * PSNP¥	0.026	0.145	0.055
	(0.286)	(0.441)	(0.290)
Child dietary diversity score	0.004	0.045	0.000
	(0.049)	(0.080)	(0.050)
Constant	-13.334***	-19.803***	-13.797***
	(1.604)	(2.506)	(1.660)
n	3,380	3,292	3,292

Notes: ¥=Productive Safety Net Program, 1=mixed effects logistic regression, 2=Inversed Probability Weighted Regression Adjustment, 3=Marginal Structural Model, Standard errors in parenthesis. *=p<0.1, **=p<0.05, ***=p<0.01.
Source: Authors

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I, Bezawit Adugna Bahru
Born in Addis Ababa, Ethiopia, declare that this dissertation titled, "The role of social protection and agriculture for improved nutrition in Ethiopia" and the work presented in it are my own. I confirm that:

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- I did not accept any assistance from a commercial doctoral agency or consulting firm.

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