The Double-Edged Sword of Social Transfers: evidence from Ethiopia

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Abstract

This article examines how cash versus in-kind transfers affect local economies using Ethiopia's Productive Safety Net Program (PSNP), Africa's largest social protection program. Exploiting the progressive nationwide rollout and using a staggered difference-in-differences approach, I analyze impact on local prices and market adjustments from 2001-2015 to identify causal effects. Cash transfers increase local prices by 5%, while in-kind transfers show no significant average price effects. However, prices of the food items distributed fall significantly in localities receiving in-kind transfers. Effects are strongest in districts with higher treatment intensity, more isolated, and lower initial agricultural productivity. A one percentage point increase in transfer share drives a 1.02% price increase in cash-dominant districts versus a 0.82% decrease in food-dominant districts. Several mechanisms explain these differential effects: cash transfers relax supply constraints by improving agricultural productivity through increased fertilizer application, partially offsetting price inflation. Market power among suppliers and a lack of market access amplify price effects in cash-receiving areas. However, the increase in price entail welfare costs: children under five show higher rates of underweight and wasting in cash-dominant districts. These findings highlight the importance of tailoring social protection program design to local market conditions and considering transfer modality effects when scaling up interventions.

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1. Introduction

Social safety net programs provide livelihood assistance to the poorest part of the population to minimize vulnerability and risks (World Bank, 2015). These welfare programs covers more than 2.5 billion individuals worldwide (Gentilini et al., 2022) and aim to improve participants welfare (Banerjee et al., 2015; Haushofer and Shapiro, 2016). Transfers can be made in cash or in-kind (e.g., poultry, grains) with potential direct and indirect effects on local economies, which can be amplified when these programs are scaled up (Basu, 1996; Bryan et al., 2023; Gazeaud and Ricard, 2024; Sadoulet et al., 2001). By relaxing beneficiaries' budget constraints, social transfers shift local demand and affect local prices when markets are imperfectly integrated. However, their potential general equilibrium effects remain an open and newly studied question in sub-Saharan Africa (SSA) (Banerjee et al., 2024; Egger et al., 2022; Franklin et al., 2024; Walker et al., 2024). Understanding the extent of these effects and their heterogeneity across transfer types can improve social protection program design, such as targeting and transfer modalities, to limit unintended impacts. The type of transfers differs across programs, but cash and in-kind transfers are the main used in SSA (Gentilini et al., 2022). Despite their importance, we have limited evidence of the differential effects of food and cash transfers when implemented at scale due to data limitations (Correa et al., 2023).[1]

This paper analyzes this question by focusing on the impact of social protection transfers on local markets. More specifically, it focuses first on local prices and then tests for evidence of indirect effects by investigating supply and demand-side adjustments. To study this question, I focus on Ethiopia's Productive Safety Net Program (PSNP) transfers targeting food-insecure communities. I exploit the progressive roll-out of this nationwide public works program launched in 2005 and use a staggered difference-in-differences strategy to estimate its causal effects on local prices. PSNP provides monthly transfers, either cash or in-kind (i.e., cereals and legumes) or both, to 10% of the population (8 million people in 2009) during the non-agricultural season. PSNP transfers are sizeable and represent, on average, around 35% of annual household expenditures, and it is one of the largest social protection programs to date in Africa (Gazeaud and Stephane, 2022).

I combine several existing datasets on monthly retail price panel data, newly digitized administrative program implementation data, and nationally representative income, ex-

[1] I will use in-kind and food transfers interchangeably in this paper.

penditure, and agricultural production data.[2] Before estimating the causal effects of the PSNP, I first provide novel descriptive evidence at the national level suggesting that local food markets are imperfectly integrated and that local prices vary with local demand and supply adjustments. Then, I causally test whether the PSNP has any effect on local markets using a staggered difference-in-differences strategy and estimate robust estimators for staggered designs (Borusyak et al., 2024). I find that only the cash component of PSNP has an effect on local prices, increasing local prices by 5%. I further show that these effects are proportional to treatment intensity levels and derive price elasticities of transfer instensity.[3] My results highlight that when the transfer share in *woreda* (i.e., district) expenditures increases by 1% in cash (food) dominant *woredas*, it leads to an increase (decrease) of about 1.02% (0.82%) in prices. Finally, analysis at the food group level suggests that cereal and legume prices are driving these effects.

While the total amount a district received is almost constant over time, its transfer composition can vary annually according to the quantity of food procured. Leveraging this annual within-district variation, I can estimate the effects of switching from a transfer type dominant regime to another on prices. My results suggest that switching from a food to cash-dominant regime yields a 8 % price increase, but the opposite does not impact prices. An additional question to address is the existence of spatial spillover. To answer this question, I construct buffers of varying radii around each district to identify spillover effects and find limited effects.[4] If anything, these effects are spatially concentrated and decayed quickly with distance. These results suggest that social transfers significantly affect local markets, thus understanding the mechanisms through which these happen could be particularly informative for policymakers.

Building on this result, I investigate potential mechanisms through which transfers affect local prices. First, competition among suppliers can impact price responses. Consistent with Attanasio and Pastorino (2020)'s theoretical approach to detect sellers market power, I find that price effects are higher in cash-dominant *woredas* where suppliers have market power because there are fewer sellers in these districts. Second, I find that price effects are concentrated in less integrated and more remote *woredas*, locations where local prices are highly correlated with variations in local demand (Cunha et al., 2019). Third, distributional

[2] I digitize annual administrative program reports containing the number of beneficiaries and the amount transferred for food and cash transfers at the *woreda* (district) level to define exposure to PSNP at the extensive (i.e., receiving a transfer regardless of its nature) and intensive (i.e., the proportion of a *woreda*'s population receiving a transfer and transfer share in aggregated *woreda* expenditures) margins.

[3] I use two measures of treatment intensity: (i) the share of the *woreda* population treated; (ii) the share of the transfer represented in pre-treatment total *woreda* expenditures.

[4] I construct buffers ranging from 10 to 50km with a 10km steps.

effects can emerge when districts with larger agricultural production have greater ability to respond to demand shocks. I find distributional effects across *woredas* with different pre-treatment agricultural production levels, with food transfers affecting the least productive *woredas* disproportionately more. Finally, consistent with recent literature investigating implementation issues in at-scale policies (Angrist and Dercon, 2024; Mobarak, 2022), I highlight that implementation failures also contribute to observed price effects. Price effects are even higher in cash-dominant *woredas* when NGOs are implementing the program, suggesting efficiency differences with government agencies when dealing with cash transfers. NGOs may face issues in delivering cash-transfers on a monthly basis to beneficiaries, therefore providing the bulk of the annual transfers at the same time.

Given the price effects found, the next step is to quantify whether these effects are purely nominal or translate into real-world impacts. First, I use twelve waves of repeated cross-sectional, nationally representative data on agricultural production to measure supply adjustments following PSNP implementation. I provide suggestive evidence that cash transfers relax supply constraints by improving agricultural productivity, which may attenuate the price effects of transfers. This result contrasts with Gazeaud and Stephane (2022), who find that PSNP has no effect on agricultural production, with differences stemming from variations in the data sources used for agricultural production and program implementation.[5] Consistent with Gilligan et al. (2009), this productivity differential is primarily attributable to heightened fertilizer application rates observed in cash-receiving districts.

Second, I estimate the PSNP's effect on the demand side. Due to limited availability and scarcity of nationally representative high-frequency consumption data, I use Demographic and Health Survey (DHS) data. Using the DHS data relies on the assumption that consumption shocks affect children's anthropometric status in a sustained way (Galasso et al., 2016). I find suggestive evidence that the previous productivity gains are accompanied by meaningful welfare trade-offs in children's acute malnutrition outcomes. Children in cash-dominant districts (i.e., those most affected by price increases) are 15 and 10 percentage points more likely to be underweight and experience wasting, respectively, than those in food-dominant districts. This negative outcome likely represents a direct consequence a reduction in purchasing power resulting from PSNP-induced price inflation. These

[5]While Gazeaud and Stephane (2022) relies on remote-sensing data to measure agricultural outcomes at the district level, I use nationally representative data, which are more accurate and representative. Additionally, they draw implementation data from Figure 4 of Van Domelen and Coll-Black (2010)'s report, which is less detailed than the administrative data I rely on. For instance, it does not specify the year of program rollout or consider some treated districts in Oromia and SNNP regions as control district.

results suggest that transfer modality may have significant implications for household welfare beyond immediate economic productivity effects. However, this analysis is based on a subsample of the initial data due to the partial geographic overlap between districts covered in DHS data and those in the retail price dataset. Despite this limitation, these results provide additional evidence that social protection transfers may harm children's nutritional status in targeted communities (Filmer et al., 2021).

This work contributes to the literature in three ways. First, I provide additional empirical evidence regarding the price effects of cash and in-kind transfers on a large panel of food items and the mechanisms at play. Existing work finds mixed evidence according to the food group studied and focus on interventions not scale-up at the nation-scale . Attanasio and Pastorino (2020) and Cunha et al. (2019) show that cash transfers in Mexico did not lead to significant food price effects, except in remote villages for the latter. Egger et al. (2022) find no price effects on food products following a cash transfer program in Kenya. While Filmer et al. (2021) find a sustained positive price effect for protein-rich foods (i.e., eggs) in the Philippines, they do not find such effects on other food products (i.e., rice and sugar). Compared to these papers, I focus on a nation-scale program and find an overall positive price effects of cash-transfers and negative price effect following food-transfers for cereals and legumes, the food items transferred. I go one step further by quantifying the effects at extensive and intensive margins, which helps identify the mechanisms in place. In line with Walker et al. (2024), the price effects eventually arise once the size of external transfers becomes sufficiently large. I also describe the mechanisms at play, showing that the impacts are concentrated in highly exposed *woredas*, located in remote areas, and with lower agricultural production, suggesting that social protection designs should be tailored to the local context.

Second, this paper relates to the literature tracing the indirect and heterogeneous effects of social protection transfers (Angelucci and De Giorgi, 2009; Egger et al., 2022; Gerard et al., 2021). I contribute to this literature by showing that cash transfers increase local agricultural investments and production but also negatively affect children's nutritional status. I confirm previous findings that productive workfare programs have positive effects on production outcomes (Christian et al., 2015; Egger et al., 2022; Franklin et al., 2024; Gehrke, 2019). In addition, the negative effect on children's nutritional outcomes aligns with Filmer et al. (2021)'s results in the Philippines showing that untreated children in treated communities experience nutritional losses. Overall, the findings highlight the significant potential role of indirect price effects and the importance of designing social protection programs that reduce exposure to these adverse effects through locally procured in-kind transfers, indexing cash transfers to prices more regularly, or providing them jointly with other policies.

Finally, this paper is also related to the growing literature focusing on the scale-up of development programs by analyzing the effects of a flagship social protection program in Ethiopia that has been rapidly scaled up (Angrist and Dercon, 2024; Banerjee et al., 2017; Egger et al., 2022). I present new evidence that at-scale social transfer programs could impact local markets and might affect both the overall net benefit of the program as well as the identity of the beneficiaries. However, further research would be needed to estimate targeted parameters and calibrate theoretical models allowing for counterfactual simulations.

The rest of the paper proceeds as follows. In section 2, I describe the Ethiopia's Productive Safety Net Program. Section 3 presents the data. In section 4, I present a simple conceptual framework of price responses to cash and food transfers. Then section 5 outlines the empirical strategy. Section 6 shows the results for the impact of PSNP transfers on local prices and discusses some of the underlying mechanisms. The discussion and conclusion ensue.

2. The Ethiopia's Productive Safety Net Program

Objective. Before 2005, emergency assistance in Ethiopia was unpredictable and often provided after the need for it had passed, failing to address the underlying causes of food insecurity and not helping households to prevent against future shocks. The Productive Safety Net Program (PSNP) was started in February 2005 as a means to provide a comprehensive and sustainable response to chronic food insecurity in rural Ethiopia. The program initially aimed to phase out non-emergency food aid towards systematic cash transfers. In addition, food-insecure households in chronically food-insecure *woredas* (districts) received monthly cash and/or in-kind transfers to address food consumption gaps, prevent asset depletion, and enhance asset creation at the community level (GFDRE, 2004; 2010a). The PSNP was designed as a safety net program with a public work (PW) and an unconditional direct support (DS) components, ensuring that all types of households were catered to. Households with non-disabled adults are involved in the PW, and those with elderly or disabled members receive DS.

Coverage and targeting. A one-year transition period was designed to ease the transition from emergency relief towards a productive and development safety net logic. It was scaled up quickly and reached approximately 8 million beneficiaries in 2009 (10% of the population at the time), becoming the largest workfare program in Africa and one of the largest safety net programs in the world. Although the PSNP was initially put in place for three years (until 2009), it has been gradually extended through several phases until its fifth phase (PSNP5) scheduled to end in 2025. Initially, PNSP started in the four main regional states of Ethiopia (i.e., Amhara, Oromia, SNNP, and Tigray) before being expanded to the agropastoral regions of Afar and Somali in 2006 and to new *woredas* in the four initial regions later. Figure 1 shows PSNP coverage and the first year of implementation for targeted *woredas*. While the number of *woredas* included in the program has increased from 201 to 315 between 2005 and 2010, this roll-out does not follow clearly articulated or published criteria (Stephen and Bruce, 2007). *Woredas* and households targeting are based on a combination of geoic, administrative, and community-based targeting to identify food-insecure households in chronically food-insecure *woredas*. At the *woreda* level, the initial criteria was to target *woredas* which had received food aid for three consecutive years before 2005. Requests for food assistance were partly due to idiosyncratic shocks (e.g., droughts, floods, locusts). The aid amount allocated to each *woreda* is determined at the federal level using food aid historical amount. The household selection process is decentralized, with local institutions at the core of it.[6] The Community Food Security Task Force (CFSTF) identifies households using three main criteria. Households should be members of the treated community ex ante, reducing risks of selective migration, and (i) must have faced at least three months of food shortages in the last three years; (ii) suddenly became food insecure following assets depletion; or (iii) does not have access to other means of social protection and support.[7] In practice, the Community Food Security Task Force relies on previous years' food aid recipients lists and refines it using the first and third criteria (Stephen and Bruce, 2007). PSNP is a graduation program, meaning that beneficiaries exit the program when they transition out from extreme poverty. Households remain in the program until the CFSTF considers them as food-sufficient and ready to graduate.

[6]The *Woreda* Food Security Task Force applies the national guidelines for beneficiary selection to the local level and trains the Kebele Food Security Task Force (KFSTF). Once trained, the KFSTF introduces a Community Food Security Task Force in each village, which has to prospect potential eligible households and produce a beneficiary list.

[7]With these conditions, PSNP also reduces seasonal and permanent migration out of targeted communities (Lavers, 2013).

Public work. The public work component covers approximately 80% of program beneficiaries and focuses on developing community assets such as roads, soil and water conservation structures, or schools (Hoddinott et al., 2015).[8] Most public works and transfers happen during the non-agricultural season from mid-January to mid-July to avoid conflict with agricultural activities. Each household member is allotted five days of work per month for this period. For instance, a five-member household with a non-disabled adult will receive 25 work days per month for the period. Public works must be labor intensive, benefit the entire community, be approved by the community and targeted households. These projects are only implemented in targeted rural areas. In highland areas, public works are located within one hour from beneficiaries' homes. This last condition differs in pastoral areas where public works are implemented at specific locations easily accessible for beneficiaries (e.g., close to villages, next to range lands). The number of projects approved can vary each year, with the local planning process driving this number. This local planning process aims to reflect and be representative of the needs of the whole community, resulting in a community development plan that must be approved at every administrative level involved in PSNP implementation.

Transfers. Beneficiary households received either food, cash, or both transfers according to local market conditions. Households received 6 Birr (0.27 Purchasing power parity US Dollars) per workday in 2005 or 3kg of cereals (wheat essentially) and 0.8kg of pulses (GFDRE, 2010b).The daily wage rate of the cash transfer is based on the equivalent market price for 3kg of cereals and 0.8 kilograms of pulses. The food transfers supplied per workday are based on the assumption that beneficiaries must work five days to receive it. The daily wage is adjusted each year based on the closest market prices such as beneficiaries could buy 15kg of cereals and 4kg of pulse per month. Thus, cash transfers have been reevaluated, reaching 14 or 18 Birrs per workday in 2015. Decision to provide cash or food transfers does not follow clear criteria. PSNP decision-makers encourage cash rather than food transfers for this potential positive spillover effects for smallholder farmers, local food markets, and agricultural production (Filipski et al., 2016; Gilligan et al., 2009). Food transfers follow a top-down approach, from the federal level towards *woredas*. They are essentially procured from international sources. Significant delays in cash and food transfers characterized the first two years of the program. For instance, only 11% of transfers had been paid by June 2005, which remained unsatisfactory the following year despite improvement with 53% of payments made in the same period in 2006 (Coll-Black et al., 2011). Cash payments

[8] Figure B.1 shows an example of infrastructure done under PSNP.

represent the majority of the transfers made, representing 73% of total transfers in 2014, and 89% of the beneficiaries experienced at least one cash payment during this period (Hirvonen and Hoddinott, 2021). Overall, figure B.6 shows that transfers are sizable and represent, on average, around 40% and 30% of annual household expenditures in 2007.

3. Data and descriptive statistics

To estimate the effect of the PSNP, I combine several existing datasets covering Ethiopia over the 2001-2015 period. The resulting dataset contains monthly retail prices panel data on 119 markets between 2001 and 2015, annual administrative data about PSNP implementation, four waves of repeated cross-sectional nationally representative income and expenditure data between 2000 and 2015, twelve waves of repeated cross-sectional nationally representative agricultural production data between 2000 and 2015, and remote-sensing data.[9] In this section, I further describe the data used in this paper and summarize data coverage in figure B.10.

3.1. Retail Price data

I use retail price data from the Ethiopia's Central Statistical Agency (CSA). CSA collects monthly retail prices from 119 markets for 360 relatively homogeneous food and non-food products. The survey covers all 11 regional states of the country, with the number of markets approximately proportional to the population region's size (Headey et al., 2012). Markets are located in rural towns and urban centers (i.e., larger than 1,000 inhabitants). Enumerators live in *woredas* where markets are located. They collect price and quantity data from at most three different retailers during the first half of each Gregorian calendar month and are encouraged to survey the same retailers every months if possible. The original purpose of these data is to calculate the national consumer price index. I focus on the period between 2001 and 2015, during which the markets and the price survey instrument remained consistent, for a total of 20,618 market-month observations and 402,852 non-missing price observations. Figure B.2 shows markets' locations in the CSA retail price survey. Because each market is located in a different *woreda*, I use market and *woreda* interchangeably.

[9]An issue that arises in merging these datasets over this period is that there were redistricting of zones and *woredas* over time. I homogenize *woredas* coding using the 2007 Ethiopian Central Statistical Agency identifiers.

Food classification. Following WHO (2008)'s food classification recommendation, I aggregate food items into eight food groups: (i) grains, roots, and tubers; (ii) legumes and nuts; (iii) dairy products; (iv) flesh foods; (v) eggs; (vi) vitamin-A rich fruits and vegetables; (vii) other fruits and vegetables, and (viii) others (e.g., cooking oil, butter, sugar).[10] I complement this classification with two additional food groups (i.e., spices and processed cereal-based products) to consider diet transformation in Ethiopia (Worku et al., 2017). Table A.1 shows the complete mapping of these items into the ten food groups.

Food prices in level. I express all prices in 2005 Birr terms per calorie to allow comparison overtime and across food items. High inflation episodes during the last two decades (Bachewe and Headey, 2021) can threaten items' comparability over time. I deflate nominal prices using regional consumer price index to express all prices in 2005 Birr terms. Then, I convert each CSA food item into calory equivalent using estimates of the item's edible portion and energy content from the United States Department of Agriculture (USDA) National Nutrient Database (USDA, 2013) and express each item in Birr per calorie. I use the median price for each product-market-month and then calculate linear log-price indices, weighting prices by *woreda*-specific household expenditure shares using expenditures data from the 2004-2005 Household Income and Consumption Survey (HICES).[11]

3.1.1. Measuring market integration

In a well-integrated market, changes in local demand or supply following transfer influx should not affect local prices since supply is infinitely elastic, with prices set at a broader level. Integrated markets are connected through a price arbitrage process and satisfy the law of one price: all prices are related over time and locations. Following that law, if markets are perfectly integrated, local markets will absorb the additional demand following PSNP transfers without impacting local prices.

[10] Most dietary guidelines and recommendations are based on food groups because these are easier to follow than guidelines specifying the desired macro or micronutrient intake (Arimond and Ruel, 2004; Ruel, 2003). There are several recommended food groupings depending on the purpose and target population. A common theme in food group-based dietary guidelines is grouping food items based on their nutritional qualities. For example, in the minimum dietary diversity for women developed by FAO (2016), vitamin A-rich fruits and vegetables have been separated from other fruits and vegetables. At the same time, protein-rich animal-source foods are grouped into three categories (flesh foods, eggs, and dairy). These food groupings aim to ensure a sufficient intake of essential macro and micronutrients while maintaining flexibility across food items within food groups. Such flexibility is needed, for example, to account for the seasonal availability of fruits, vegetables, and other food products.

[11] I rely only on the 2004-2005 HICES round and prefer not to use next rounds expenditure data which are potentially endogenous to the PSNP.

I test for market integration with respect to the capital city food price. Addis Ababa is central to the national food trade because of its geoical location and the lack of alternative roads to ship foods from supply to demand areas (Gabre-Madhin, 2001; Osborne, 2005). I measure the extent to which monthly market prices are correlated with last month's Addis Ababa prices. If market prices respond immediately and perfectly to changes in Addis Ababa, one should expect a coefficient of correlation of 1 (i.e., Addis Ababa price variation leads to local price adjustment of same magnitude). Figure 2 shows regional price correlation with Addis Ababa's price between 2001 and 2015. While there is a strong correlation between local market prices and Addis Ababa (i.e., average Pearson correlation equals 0.77), this correlation differs across time and regions, suggesting imperfect market integration. This result is close to previous findings in east-African countries documenting a lack of food market integration (e.g., Abay et al., 2023 in Sudan, Jones and Salazar, 2021 in Mozambique, Minten et al., 2014 and Osborne, 2005 in Ethiopia, and Van Campenhout, 2007 in Tanzania).

3.1.2. Food price seasonality

Figure B.3 plots monthly price differences with annual mean (i.e., price seasonality) for each food group. It shows that food group prices experience high seasonality. Some food groups are especially affected: grains, vitamin A-rich fruits and vegetables, and eggs. Price seasonality follows the agricultural cycle for grains and vitamin A-rich fruits and vegetables. Grain prices peak during the growing season from late May to early October and are low during the marketing season. For vitamin A-rich fruits and vegetables, prices peak in the growing season, occurring during the secondary rainy season from February to April.[12] For egg prices, prices are lower from March to May, which coincides with the main Ethiopian fasting period (i.e., *Hudadi* fast lasts for 55 days before *Fasika*—Orthodox Easter). This result suggests that measuring PSNP price effects months before and after the first transfer could capture a "natural" seasonality pattern rather than treatment effects. To avoid this bias, I construct a market-month-year panel dataset (e.g., comparing market i January prices over year).

[12] See figure B.4 for regional rainfall patterns.

3.2. Productive Safety Net Program Data

To construct my treatment variable, I rely on a newly comprehensive dataset I assembled from Ministry of Agriculture and Livestock Resource (MOA) annual reports. I digitized MOA annual reports containing granular implementation information at the *woreda* level between 2005 and 2015. These reports provide *woreda*-level information regarding the total number of beneficiaries, the number of beneficiaries receiving food and cash, and the amount of money and food transferred.

Treatment definition. Figure 1 shows the location of treated *woredas* along with their first year of PSNP implementation. A *woreda* starts being affected by the PSNP when it is first mentioned in MOA annual reports. Among treated *woreda*s, 67% are first exposed to the program in 2005, 18% in 2006, 7% in 2007 and 2008, and less than 1% in 2010 and 2011. I complement this extensive margin treatment definition with two intensive treatment measures at the *woreda* level: the proportion of the population covered by the PSNP and the transfers share in the *woreda*'s total household expenditures.[13] Figure 3 illustrates the *woreda*-level spatial variation in the annual average coverage (3A) and total transfer per beneficiary in US Dollars (3B).

Transfers. Figure B.5 shows a clear shift from food to cash transfers over time. While cash and food transfers per beneficiary represent roughly 40 and 125 US Dollars in 2007, cash transfer value has quadrupled, reaching 150 US Dollars per beneficiary in 2014, and food transfer has declined by almost 30 US Dollars. PSNP transfers represent a significant share of household expenditures in treated *woredas*. Figure B.6 plots the share of cash and food transfers represent in annual household expenditures from 2007 to 2014 (i.e., years for which this information is available). It shows that in *woreda*s where food is the primary transfer type, transfers represent slightly more than 40% of annual household expenditures in 2007 but decreased by half in 2014. The situation differs for cash transfers, representing roughly 30% of household expenditures during the entire period.

[13]I convert food transfers in cash using the equivalent market price for of cereals and 0.8 kg pulses the previous season on the nearest market. I use the 2004/05 round of the Ethiopian Household Income Consumption and Expenditure Survey (i.e., the last pre-PSNP wave available) to calculate aggregated expenditures at *woreda*-level.

3.3. Production and Consumption data

Agricultural Production. I rely on household-level data from the Ethiopian Agricultural Sample Survey (AgSS), a nationally representative annual survey administered by the Central Statistical Agency (CSA). The data contains information at the plot level on the crops produced, the quantity produced, land allocation, irrigation, and input usage. I use twelve waves of repeated cross-sectional nationally representative between 2000 and 2015.[14] The AgSS data do not necessarily follow the same households over time and do not contain geocoded information on the location of individual households. Therefore, I conduct the analysis at the *woreda* level, the lowest level administrative level for which a reliable panel could be constructed. I group crops into 5 groups similar to those available in the retail price data (i.e., cereals, vitamin A-rich fruits and vegetables, other fruits and vegetables, legumes and nuts, and spices) and consider also two local specific cash crops, coffee and khat.[15] Figure B.7 shows the evolution of production (B.7A) and land occupation (B.7B) share across these groups. It clearly shows that cereal is the main food group representing roughly 80% of total production and 75% of land under cultivation.

Consumption and Expenditures. I exploit the 2004/05 round of the Ethiopian Household Income Consumption and Expenditure Survey (HICES) data set, covering 21,530 households. The HICES is a repeated cross-sectional survey and serve as the official source for poverty statistics in Ethiopia. It contains information on household characteristics, occupation, and a detailed consumption/expenditure module. The 2004/05 survey was conducted in two short rounds after the main growing season (*meher*) and in the lean period (January–February and July-August).

Anthropometric indicators. I use household surveys from the Demographic and Health Surveys (DHS), which provide nationally and regionally representative cross-sections of children under 5 years old in 2000, 2005, 2011, and 2016.[16] DHS data contains anthropometric information for children under 5 years old. I derive appropriate indicators of acute malnutrition from the weight for age, height for age, and weight for height z-scores. Following WHO classification, I classify an individual as under-weighted, stunted, or wasted

[14]One wave in 2000, then 11 successive waves without gap between 2004 and 2015. See figure B.10.

[15]Khat is a chewable green leaf that has an euphoric effect and widely consumed in Ethiopia and exported to nearby countries.

[16]The surveys were designed to be nationally and regionally representative for the purpose of policy planning. All of my analysis which follows uses the appropriate sampling weights provided in the data.

if their z-score is larger than 2 standard deviations for the relevant index.[17] Each measure capture a different aspect of lack of access to healthy and sufficient diet in terms of magnitude and time. Underweight reflects short to medium-term food deprivation and can indicate wasting, stunting, or both. Stunting captures prolonged undernutrition and lack of access to healthy and sufficient diet with longer term consequences throughout a person life (e.g., delayed cognitive development). Lastly, wasting captures rapid weight loss or insufficient weight gain and can results from major disruption in food access or health conditions such as severe food shortages, recent illnesses.

Figure B.9 shows the evolution of the proportion of children under 5 years affected by acute malnutrition from the 2000 to 2016. It shows that the share of children stunted and under-weighted has decreased while the proportion affected by wasting slightly increased over time.

3.4. Additional variables

Roads data. I use detailed GIS data on the evolution of the road network in Ethiopia for the period 2004-2016. I obtained data from the Ethiopian Roads Authority (ERA) for highways and regional roads, and the Regional Roads Authorities for regional and community roads. The data provides information on the length, starting and completing year of construction for every link in the network.

I use this data to compute pre-PSNP *woreda*-level market access measure following Donaldson and Hornbeck (2016). This approach captures benefits from both direct and indirect connectivity, and accounts for the density of the network to which a *woreda* is connected. This measure is calculated every two years using the entire road network and the distribution of population in 2000 across Ethiopian *woredas*.[18] Figure B.24 plots the distribution of market access induced by the road network expansion between 2004 and 2016.

[17]Underweight refers to children weighting less than what is considered healthy for their age and is measure using weight for age z-score. Stunting is a condition where a child growth is hindered yielding them to fall share of their growth potential. Height for age is used to measure stunting. Lastly, wasting, or acute malnutrition, happens when a child's weight is too low relatively to their height.

[18]See Appendix C for further details.

4. Conceptual Framework

In this section, I sketch a conceptual framework underlying the main drivers of the impacts of cash and food transfers on local markets and economies. The relative impacts of these transfers depend on initial market integration, whether food transfers can be resold locally, and the magnitude of the income elasticity of the demand.

In a small open economy where the supply is infinitely elastic with prices determined at the world level, local demand or supply variation should not affect prices. It is unlikely to be the case for Ethiopian local markets, which are more typically partially closed economies where prices depend on local conditions (figure 2). I consider a *woreda* as an economy where goods are consumed and produced. Household consumption correlates with their own production (home production represents 44% of household expenditures in the 2004/05 HICES data).

First, I consider a simple model where a rural market is perfectly competitive but not integrated with other markets. In that case, if the supply curve increases monotonously with prices, changes in local demand will affect local prices. High transportation costs to other markets due to poor or lack of infrastructure is one potential reason for increasing marginal costs in the short run. Therefore, local traders and aggregators must travel to nearby markets to meet higher demand.

Figure 4 shows the market for a normal good in a *woreda*. The demand and supply curves depict the aggregate demand local suppliers face and the available aggregate supply. First, the figure shows the effects of a cash transfer on the local market. The income effect following the transfer shifts the initial demand curve (D_0) rightward to D_C, yielding a higher equilibrium price, P_C. With X_C the cash transfers amount, the first prediction is:

$$\frac{\partial P}{\partial X_C} > 0 \tag{1}$$

Proposition 1. Where markets are not integrated, a cash transfer will raise local prices, with the effect being greater for a larger amount transferred.

Next, consider a food transfer, with X_F its equivalent cash value.[19] Accordingly, a food

[19] Food transfer is valued at the market price because the transfer is inframarginal (i.e., the transfer is less than what the household spends on the transferred good after the transfer). In addition, Hirvonen and Hoddinott (2021) show that food transfers reselling is rare: 90% of households never sold any food transfers over the 2006-2014 period.

transfer triggers an income effect yielding a similar rise in demand than a cash transfer. In addition, food transfer satisfies part of the local demand with food supply procured outside of the local market, which decreases local demand on the market (D_F). This shift leads to a new equilibrium E_F with the post-food transfer price (P_F) lower than the post-cash transfer price P_C. The net price effect of a food transfer relative to the original market price equilibrium (P_0) is theoretically ambiguous and is a function of the size of the transfer: a larger transfer can yield to $P_F < P_0$. The second prediction is the following:

$$\frac{\partial P}{\partial X_C} > \frac{\partial P}{\partial X_F} \tag{2}$$

Proposition 2. The price should be lower under food than cash transfer for the transferred goods, with the difference being larger for higher amounts transferred.[20]

In my setting, the supply side consists of periodic markets with only 13 percent operating daily (Hirvonen and Hoddinott, 2021). While these markets are large, with 72 percent having more than 50 traders, these markets are isolated from urban centers, suggesting that these locations are less integrated with more inelastic supply and that local demand and supply changes would lead to higher price variation (Atkin and Donaldson, 2015).

Proposition 3. The greater the market integration is, the smaller the magnitude of the price effects.

These propositions will be tested empirically in the next section. To detect the transfer effects, I narrow the analysis on the food groups provided (i.e., grains and legumes) in the Ethiopian Productive Safety Net Program. Without conditions on how cash should be spent, the rise in demand due to the income effect is spread across several items, yielding a small demand increase per good. The effects on average prices depend on food groups' transferred share in total expenditures, with more significant effects where shares are higher.

[20]Under several standard preference classes (e.g., homothetic), prices should decline with an in-kind transfer relative to no transfer. For the price to increase, a food transfer with aggregate value X would need to increase aggregate demand for this item by more than X (i.e., being a luxury good).

5. Empirical Strategy

Following the above analytical framework, I describe the empirical strategy to estimate price price variation due to the Productive Safety Net Program.

5.1. Estimator choice

In this section, I examine the direct static and dynamic effect of each transfer modality of the Productive Safety Net Program. My main specification uses the following event-study model:

$$y_{ijkt} = \alpha_i + \gamma_t + \delta_{kt} + \sum_{h=-a}^{b} \tau_{h,1} \mathbb{1}[t = E_j + h] \times \mathbb{1}[\text{Cash}] + \sum_{h=-a}^{b} \tau_{h,2} 1[t = E_j + h] \times \mathbb{1}[\text{Food}] + \epsilon_{ijkt} \quad (3)$$

where y_{ijkt} is my outcome of interests (i.e., log-price indices or agricultural production variables) for market i in *woreda* j at time t in region k. t is the month-year when the outcome is related to market price and the year of observation otherwise. α_i and γ_t are market and time fixed effects. δ_{kt} captures regional linear trend. E_j is the year in which a *woreda* receives its first PSNP transfer and h, the relative time, corresponds to the distance in years between the year of observation and the year when treatment starts. h is negative for units observed in pre-treatment years. In other words, the set of $\mathbb{1}[t = E_j + h]$ dummies are the lead/lag indicator variables tracking the number of years since the year of the first PSNP transfer, E_j. Cash (Food) is a dummy for whether cash (food) transfers represent more than 50% of *woreda* i transfers value during the treatment period. $\tau_{h,1}$ ($\tau_{h,2}$) captures the ATT for receiving mostly cash (food) transfers relative to all periods before a *woreda* enters the PSNP.[21] Each of the event study dummy variables is set to zero for all *woredas* that remain unexposed by 2015. I include these non-exposed in my estimation sample to help identify time effects and avoid multicollinearity issue (Borusyak et al., 2024).

Estimating equation (3) with two-way fixed estimators can lead to biased estimates when there is staggered treatment timing and heterogeneous treatment effects across cohorts (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille,

[21] I use this measure to overcome the lack of data regarding transfers during the first years of the program. MOA reports contain detailed transfers information starting in 2007.

2020; Goodman-Bacon, 2021). In what follows, I use Borusyak et al. (2024)'s imputation estimator to estimate the average treatment effect across cohorts for each post-treatment time period.[22] In addition, I also rely on Borusyak et al. (2024)'s estimator to compute treatment-on-the-treated (ATT) coefficients, which provide an unbiased estimate of the average treatment effect across all cohorts and time periods. All standard errors are clustered at the program implementation level (i.e., *woreda*). The coefficients on the set of event study dummy variables $\tau_{h,1}$ ($\tau_{h,2}$) capture the ATT relative to all periods before a cash (food) dominant *woreda* receives the PSNP.

Estimation (3) can lead to biased estimates if it captures existing differences between food and cash-dominant *woredas*. For instance, $\tau_{h,1}$ can capture effects of cash transfers and other *woreda* characteristics such as better market-integration. Overall, Table A.2 shows that cash and food-dominant *woredas* are fairly similar, excepting that cash-dominant *woredas* are more likely to be located in the highland. *Woreda* and time fixed-effects already capture highland/lowland differences and also other potential differences such as local elites preferences or local population tastes.

Within-*woreda* estimation. Finally, I estimate a modified version of equation (3) to estimate the effect of switching from a food to cash dominant regime, as well as from cash to food dominant. I estimate this equation restricting my sample to treated *woredas* as follows:[23]

$$y_{ijkt} = \alpha_i + \gamma_t + \delta_{kt} + \sum_{h=-a}^{b} \tau_{h,1} \mathbb{1}[t = E_j + h] \times \mathbb{1}[\text{Cash}] + \sum_{h=-a}^{b} \tau_{h,2} 1[t = E_j + h] \times \mathbb{1}[\text{Food}] + \epsilon_{ijkt} \quad (4)$$

where Cash (Food) is a dummy for whether *woreda* i switches from cash (food) to food (cash) dominant transfers (i.e., represent more than 50% of *woreda* i transfers) $\tau_{h,1}$ ($\tau_{h,2}$) captures the ATT for switching from cash (food) dominant transfers to food (cash) transfers relative to all periods before a *woreda* switches while being in the PSNP.

[22]This estimator takes an "imputation" form and is constructed in three steps: i) unit and period effects are fitted by regression on untreated observations only; ii) unit and period effects are used to impute the untreated potential outcomes and obtain an estimated treatment effect; and iii) a weighted average of these treatment effect estimates is taken with weights, corresponding to the estimation target τ_h . Borusyak et al. (2024) show that the presence of a never-treated group is essential for implementing this estimator and generate counterfactual estimates for all treated observations. For this purpose, the presence of many never-treated *woredas* is plays in favor of my empirical strategy.

[23]This restriction means that never switcher *woredas* are considered as never-treated.

5.2. Testing for parallel trends

The imputation estimator assumes that potential outcomes without treatment would follow parallel trends. Borusyak et al. (2024) provide an empirical test for this assumption using OLS on untreated *woredas* only:

$$y_{ijkt} = \alpha_i + \gamma_t + \delta_{kt} + \sum_{h=-H}^{-1} \mu_h \mathbb{1}[t = E_j + h] + \epsilon_{it} \tag{5}$$

In this model, the observations from *woredas* which will be treated 1 to H years later are compared to all the observations from never treated *woredas* or from those which will be exposed more than H years later. Borusyak et al. (2024) show that this procedure is robust to treatment effect heterogeneity and improves the power of treatment effects estimation because all untreated observations can be included in the control group for ATT coefficients imputation. Although the placebo test and ATT imputations are performed separately, I provide parallel trends evidence along with ATT coefficients in a single .

5.3. Continuous treatment

My estimates have relied so far on an extensive margin definition of PSNP treatment. I further measure treatment effects at the intensive margin.

Treatment intensity . I use two measures of treatment intensity. First, the share of the *woreda* population who benefited from the PSNP. Second, the transfers share in the *woreda*'s total household expenditure. Then, I construct 25% quantile based on transfert share distribution. For instance, a *woreda* is in the cash intensity first quantile ($Q1$) if its cash transfers share in its total transfers value is among the bottom 25% of the transfers share distribution. I modify equation (3) by interacting τ_h with 25% quartile indicators of treatment intensity:

$$y_{ijkt} = \alpha_i + \gamma_t + \delta_{kt} + \sum_{h=-a}^{b} \tau_{h,q=1} \mathbb{1}[t = E_j + h] \times \mathbb{1}[Q1] + \ldots + \sum_{h=-a}^{b} \tau_{h,q=4} \mathbb{1}[t = E_j + h] \times \mathbb{1}[Q4] + \epsilon_{it} \tag{6}$$

$\tau_{h,q}$ captures the ATT for being in quartile q relative to all periods before a *woreda* receives the PSNP.

6. Results

In this section, I investigate the effects of the PSNP on local prices, potential mechanisms, and supply adjustments. First, I estimate the differential effects of transfers type (i.e., cash and in-kind) on local prices. Second, I investigate potential mechanisms explaining the main results. Third, I estimate whether the PSNP yields to supply-side adjustments that may attenuate or excacerbate price effects.

6.1. Cash versus food transfers effect on local prices

6.1.1. Main transfers type

The richness of the MOA annual reports allows me to study the differential impacts of transfer types on local markets. In particular, the reports measure the number of beneficiaries per transfer type at the *woreda* level and the total amount transferred in cash and food-monetary equivalent. Using this information, I classify a *woreda* as cash (food) dominant if cash (food) transfers represent more than 50% of *woreda* transfers value during the treatment period. 68% of *woredas* are cash-dominant *woredas*, 32% are food-dominant *woredas*. In addition, I construct two measures of intensity using 25% quantile based on the share of the *woreda*'s population covered by the PSNP and the transfers' share in *woredas* total household expenditure.

Across *woredas* effect. First, I estimate equation (3) to examine whether treatment effects vary with the primary transfer type received in a *woreda*. Figure 5 shows the results by transfer type and pre-trend coefficients. The pre-trend coefficients are generally much smaller and never statistically different from zero, which provides additional support to the validity of the empirical strategy. For cash-dominant *woredas*, point estimates are large, positive, and significant at the 5% level for all treatment periods except the first two years.[24] This result suggests that the transfer has an immediate small effect, less than 2% in the first two years. This positive effect reaches 5% three years later and levels out at that level until the end of the period. In food-dominant *woredas*, prices fall slightly in the program's first two years, but this drop does not last afterward.

[24]Implementation issues may explain why transfers have a weak effect on prices in the first two years. Coll-Black et al. (2011) highlight that only 11% and 53% of planned transfers were disbursed by June 2005 and 2006.

Table 1 presents coefficients for the average yearly effect of cash and food transfers on average monthly price for the entire year, outside transfer time, and during transfer time. For cash-dominant *woredas*, the point estimate suggests that PSNP transfer caused prices to increase by 4% (column 1) and that this effect is roughly equal outside and during transfer time (columns 2 and 3).[25] In food-dominant *woredas*, prices drop by five percentage points (pp) relative to cash-dominant *woredas* ($C\hat{a}sh - F\hat{o}od$) with a *p*-value of 0.02. Similarly to cash-dominant *woredas*, this effect does not differ across transfer time. Figure B.11 provides the average effect across regions, varying from -0.03 in Afar to 0.14 in Tigray. Lastly, I conduct the same analysis excluding pastoralist areas (i.e., Afar and Somali regions) and show in Table A.3 that these regions do not drive the previous results.[26]

Next, I rely on Callaway and Sant'Anna (2021)'s estimator to estimate whether the estimated effects vary across treated "cohorts". Panel A of Figure B.13 shows that except for the effects outside of transfer time where cash-dominant *woredas* treated earlier drive the effects, price effects are similar across cohorts. The null price effect observed for food-dominant *woredas* is homogenous across cohorts (Panel B of Figure B.13).

I also investigate which food groups drive these effects. Table 2 shows the result by food groups: Panel A focuses on the entire year, Panel B on months without transfers, and Panel C on months during transfer. For food-dominant *woredas,* I detect significant negative impacts on cereal (-30%) and legumes (-7%) prices, smaller negative ones for vitamin A-rich fruits and vegetables (-3%) prices, and significant positive effects on dairy prices (19%). These absolute effects are even larger for grains (-32%) and legumes (-10%) relative to *cash* woredas.

Within *woreda* effect. Using annual variation in the share of food and cash transfers in annual total transfers a *woreda* receives, I can estimate the effects of switching from a transfer type dominant regime to another on prices with equation 4. I restrict the sample to treated *woreda* and use *woredas* that never switch from a dominant regime to another as a control group. Figure B.15 provides evidence that a parallel trend holds. Table 3 shows the results of switching from a transfer type dominance to another. I find that, on average, while switching from a food-dominant to a cash-dominant regime yields an 8% price increase, the opposite does not significantly affect prices.

[25] Figure B.14 shows the full dynamic event-study results by transfer time.

[26] Because the program has components specific to pastoralist areas (i.e., Afar and Somali regions), this tests for the sensitivity of my main results. If anything, the magnitude of the coefficients is slightly larger, suggesting that pastoralist areas do not experience price variations.

While there is mixed evidence regarding general equilibrium effects (Attanasio and Pastorino, 2020; Beegle et al., 2017; Egger et al., 2022), these findings provide additional evidence supporting the indirect effects of cash and food transfers on local markets (Cunha et al., 2019; Filmer et al., 2021; Hoddinott et al., 2018). Cunha et al. (2019) show that prices are 4% lower under in-kind transfers than cash transfers in the most isolated villages in rural Mexico. In the Philippines, Filmer et al. (2021) shows that a cash transfer program raises local prices of protein-rich perishable foods, such as eggs and fresh fish, by 6 to 8 percent while keeping staples' prices unchanged. In work closely related to this paper, Hoddinott et al. (2018) investigate the PSNP effects on local grain prices using observational data. They find that only food transfers reduce grain prices. However, these studies only consider treatment effects at the extensive margin for a unique transfer type, or compare treatment effects at the intensive margin between transfer types. I go further and conciliate these two approaches in the following paragraphs.

6.1.2. Treatment intensity effect

Beyond a transfer's type, its intensity could play a greater role in the market responses. I first analyze whether price affects proportionally the *woreda*'s population covered by the PSNP. Table 4 shows results from equation (6) estimations explaining variation in market prices by intensity quartile of the *woreda*'s share of the population covered and main transfer type.[27] While I find a negative correlation between price effects and the share of the population receiving PSNP transfers in food-dominant *woredas*, there is a positive correlation in cash-dominant *woredas*. Column (1) in table 4 shows that prices in the top 25% intensity cash-dominant *woredas* increase by 7 pp ($Q4 \times \widehat{cash} - Q1 \times \widehat{cash}$) relative to prices in the bottom 25% (p-value=0.11). Column (2) shows a similar seven ppt price difference between the bottom and top 25% in food-dominant *woredas* (p-value=0.09). In addition, these effects are mainly concentrated during transfer time (columns 5 and 6).

Next, I estimate the heterogeneous price effects according to the transfer's share in *woreda* economies. To do so, I use the 2005 round (i.e., the last round before the first treatment period) of the Household Income, Consumption, and Expenditures to calculate the share food and cash transfers represented in *woreda* total expenditures and classify *woredas* in

[27] I calculate the share of pre-PSNP *woreda*'s population covered by the program and construct quartile based on its distribution. Treatment intensity quartiles are as follow: Q1 $\in$ [0.01;0.09]; Q2 $\in$]0.09;0.18]; Q3 $\in$]0.18;0.38]; Q4 $\in$]0.38;1].

quantile according to this distribution.[28] Odd (even) columns of Table 5 shows the results for cash (food) dominant *woredas*. Results provide evidence of a correlation between price effects and the transfer share in *woreda* expenditures. More specifically, the price effect is 15 ppt higher in the top 20% intensity cash-dominant *woreda* relative to prices in the bottom 20% (*p*-value=0). Similarly, the price effect is 20 ppt higher in the top 20% intensity food-dominant *woreda* relative to prices in the bottom 20% (*p*-value=0). To derive an elasticity of the transfer share intensity, I use the variation in the average share of the transfers in *woredas* expenditures between bottom and top 25% and the differences in the estimated effects between these groups. Hence, the estimated elasticities for cash and food transfers are about 1.02 and 0.82. In other words, when the transfers share in *woreda* expenditures increases by 1% in cash (food) dominant *woredas*, it leads to an increase (decrease) by about 1.02 % (0.82%) of the price.

These results provide evidence that price effect responses vary proportionally to treatment intensity. Filmer et al. (2021) identified price increases from a cash transfer program on nutritious foods when the proportion of eligible households in the local population is high. In contrast, Egger et al. (2022) find limited price effects from a cash transfer at the intensive margin without considering the extensive one in rural Kenya. In contrast, program population coverage and the transfer's share in local economies are important determinants of price effects (Walker et al., 2024).

6.1.3. Spillover effects

The extent to which transfer effects in one locality can impact neighboring areas remains uncertain, as transfer shocks may extend beyond *woreda* borders. In my baseline specification, *woredas* without transfers are included in the control group, though these untreated areas might still be affected if adjacent *woredas* received transfers. Similarly, *woredas* directly receiving PSNP benefits could experience amplified effects if surrounded by other treated woredas. To investigate these spatial dynamics, I construct buffers of varying radii around each *woreda*'s centroid to identify potential "spillover *woredas*" —those with at least one treated *woreda* falling within the specified buffer distance.[29] This classification

[28] I calculate *woreda* i transfer share in aggregated *woreda* expenditure for each transfer type in 2005 q: $ST_{it}^{q} = \frac{\%\text{transfer}q_{it}}{\text{Total expenditures}_{i,2005}}$; and construct quartiles based on each distribution. Cash intensity quartiles are as follow: Q1 ∈ [0.03;0.28]; Q2 ∈]0.28;0.46]; Q3 ∈]0.46;0.64]; Q4 ∈]0.64;0.90]. Food intensity quartiles are as follow: Q1 ∈ [0.10;0.27]; Q2 ∈]0.27;0.43]; Q3 ∈]0.43;0.62]; Q4 ∈]0.62;0.78].

[29] The average size of a *woreda* is 1,659 square kilometers. Figure B.23 shows the construction of a 10km buffer.

exercise yields to four groups: (i) pure control (i.e., not treated without a nearby treated *woreda*); (ii) control spillover (i.e., not treated with a nearby treated *woreda*); (iii) treated only (i.e., treated without a nearby treated *woreda*); and (iv) treated spillover (i.e., treated with a nearby treated *woreda*).

I estimate a modified version of Equation 3 to measure the effects of being exposed directly or indirectly to the PSNP relative to never being exposed (i.e., pure control group). Table 6 shows the results for 10km to 50km buffer with a 10km steps. Overall, I find limited spillover effects on local market prices, if anything these effects are spatially concentrated and becomes null starting from 20km buffer. In addition, these effects are stronger in pure treated than treated spillover *woreda*, even though these can be highly correlated with remoteness and market access.

6.2. Mechanisms

6.2.1. Supply-side

How could transfers affect local prices? There are several supply-side mechanisms through which transfers may affect local prices. First, competition among suppliers can impact price responses. Attanasio and Pastorino (2020) theoretically shows that price discrimination should yield a negative within-village price-quantity correlation when suppliers have market power.[30] Second, when market integration increases, better access to supply outside the community relaxes constraints to satisfy local demand. Third, treatment effects can vary across pre-treatment *woreda* agricultural production levels.

Suppliers market power. I investigate how the price effects vary with local suppliers' market power. To measure market power, I would ideally use data on the number of suppliers and their market share. For lack of such data, I follow Attanasio and Pastorino (2020)'s approach as a second-best solution to quantify local suppliers' market power which links the existence of bulk price discounts in Mexico. Using 2005 Household Income, Consumption, and Expenditures survey data (pre-PSNP) I compute within *woreda*'s correlation between prices (unit values) and quantity purchased. Then, I classify a *woreda* as experi-

[30]This negative within district/village prices-quantity correlation result also applies to the East Africa context. Dillon et al. (2021) document additional evidence supporting price discrimination and negative within-village correlation between prices and quantities. I show the distribution of this correlation in figure B.16

encing suppliers market power if the correlation coefficient is negative, which is the case in 85% of the *woredas*. Table 7 tests the hypothesis that the price effect is higher in *woredas* with more supply-side market power. While I find that price effects are higher in cash-dominant *woredas* where suppliers have market power, it is not the case in food-dominant *woredas*.

Market access. Next, I assess the differential effects of the transfers by *woreda* market access quantile and present the results in Table 8.[31] The price effect is negatively correlated with market access level; the less integrated into the local economy, the higher the price effect. In column (1), I find that prices in the bottom 20% market access rise by 13 pp ($\hat{Q5} - \hat{Q1}$) relative to prices in the top 20% (p-value=0.01). In addition, price responses during transfer time (column 3) are 3% higher in the least integrated market than outside transfer time. These results suggest that less integrated *woreda*s are likelier to be close to small-autarkic economies outlined in section 4 and experience larger price responses.

These results provide evidence that price effects are larger in more isolated *woredas*, suggesting that trade may attenuate this adverse effect. Better access to national or regional markets can relax constraints to satisfy local demand. Figure B.17 provides additional evidence supporting this assumption: there is a positive correlation between *woreda*'s market access and *woreda*'s aggregated consumption in 2005 (pre-PSNP). In addition, higher integration may facilitate input market and public services access, raising agricultural productivity (Gebresilasse, 2023). Table A.4 supports this assumption and shows that agricultural production responses vary by market access level. While less integrated *woredas* tend to diversify their production after being integrated into the PSNP (column 1), more integrated *woredas* experience larger productivity gains (column 3). Column 3 shows that agricultural productivity in treated *woredas* in the top 20% market access rises by 16 pp ($\hat{Q5} - \hat{Q1}$) relative to productivity in the bottom 20% (p-value=0.10). Overall, market access relax constraints on the supply and demand sides, mitigating price effects following transfers.

Agricultural production. In addition to market access, pre-treatment agricultural production level can also affect the magnitude of the PSNP effects on prices. Using the 2005

[31] I follow Donaldson and Hornbeck (2016)'s methodology to estimate *woreda*'s market access. Using 2005 road network data and *woreda*'s population in 2000, I compute market access in *woreda* o in year t(=2005) as follows: $MA_{ot} = \sum_d \tau_{odt}^{-\theta} Pop2000_d$ with $Pop2000_d$ destination *woreda* population in 2000. See section C for more details.

Agricultural Sample Survey round (i.e., last year before PSNP), I calculate the *woreda* agricultural production level and create two groups based on the median value. Table 9 provides the differential effects based on this classification for cash and food dominant *woredas* in odd and even columns. The first result is that the positive price effect observed in cash-dominant *woredas* is orthogonal to the production level. Next, even columns provide evidence that the negative price effect observed in food-dominant *woredas* is restricted to the least productive *woreda*. This result suggests that food transfers have more significant effects in *woredas* where they represent a largest share of the initial production.

6.2.2. Implementation

There is a rising interest regarding implementation issues in at-scale policies that can explain the results observed previously (Angrist and Dercon, 2024; Mobarak, 2022). While the PSNP has been quickly scaled up, implementing institutions have faced some difficulties in providing timely transfers in the first years of the program (Sabates-Wheeler and Devereux, 2010). I investigate whether the implementing institution matters. I measure whether price effects differ in *woredas* having NGO (mainly the World Food Program) or the government as the primary implementing institution. Table 10 shows the average treatment effect of the implementing institution on local prices. Column (1) provides results for cash-dominant *woredas* and Column (2) results for food-dominant *woredas*. While the result in Column (1) suggests that prices in cash-dominant *woredas* are 7ppt higher when an NGO is the main implementing institution relative to the government, such difference does not exist in food-dominant *woredas* (Column 2). In addition, this result is concentrated during the transfer period (p-value=0.1 in Column (5)). Lastly, I show in Table A.5 that these results do not arise from differences in market access between NGO and Government *woredas*.

These results suggest that implementing actors have a comparative advantage policymakers should rely on when designing social protection transfer programs. Indeed, NGOs such as the World Food Program have been providing food aid for many years in Ethiopia using a specific operational logistic (e.g., warehouse network) and might be more efficient in delivering food in these locations. These results are consistent with studies analyzing the unintended consequences of NGO-provided aid on government services and differential effects of project implementers (Barr and Fafchamps, 2006; Deserranno et al., 2024; Wolfram et al., 2023).

6.3. Effects on Production

Through its impact on prices, the program could indirectly affect the agricultural production beneficiaries and non beneficiaries households through changes in crop choices. PSNP transfers may reduce risk aversion, incentivizing them to diversify their production (Gazeaud et al., 2023; Merfeld, 2020). Gilligan et al. (2009) show that PSNP transfers have an income effect, which raises farm investment and production. This channel would cause an increase in supply (unless investments yield positive returns only in the long run) for both the cash and in-kind treatments. PSNP is a productive workfare with infrastructure provision (e.g., watershed, irrigation) aiming to increase agricultural productivity during the lean season. Increasing productivity during the lean season can increase local supply, which may in turn mitigate the price effects estimated before.

The form of transfers may affect beneficiaries' usage, yielding different production responses. Because food transfers are not procured locally, they are unlikely to stimulate local markets and incentivize local suppliers to increase their production. Conversely, cash transfers can stimulate local supply directly through price effects (i.e., increase in local supply) or indirectly through income effects (i.e., beneficiaries' investment in agriculture). Indeed, beneficiaries can use transfers to increase agricultural investments (Gilligan et al., 2009). For instance, households can enhance their farm productivity or diversify their production.

Table 11 shows the effects of PSNP exposure by transfers type on agricultural production outcomes.[32] PSNP has a strong positive effect on both production diversification (column 1) and total production (column 3) at the *woreda* level.[33] These effects are similar for both transfer types (columns 2 and 4). Similar to Gazeaud and Stephane (2022)'s results, there are no discernible effects on agricultural productivity (column 5). Yet, there are differential effects on agricultural productivity between *woredas* receiving mostly cash or food transfers (column 6). Agricultural productivity in cash dominated *woredas* increases by 14 pp ($F\hat{o}od - C\hat{a}sh$) relative to productivity in food dominated *woredas* (p-value=0.09).

Next, I investigate whether PSNP's public work component or individual behavior drives this effect. The public work component focuses on developing productive community

[32] Figures B.18, B.19, and B.20 show that parallel trends assumption hold when investigating PSNP effects on these outcomes.

[33] I use the Simpson index as a measure of production diversity. It is define as follows $D_{jt} = 1 - \sum_{k=1}^{k=K} p_{jt}^2$, in which K is the number of crops cultivated in *woreda* j at time t, and p, is the relative share of each crop in *woreda* annual total production. Note that D increases in diversity, with 0 representing no diversity.

assets such as water conservation structures and roads (Hoddinott et al., 2015). Due to data scarcity in the AgSS, I focus only on the irrigation coverage. I capture individual behavior through input intensity usage. Table A.6 reports the effect of PSNP exposure by transfer type on agricultural investments.[34] While there are no discernible effects of receiving a PSNP transfer on fertilizer intensity usage (column 1), the effect differs between cash and food-dominant *woredas* (column 2). *Woredas* receiving mostly cash transfers have a 23 pp higher fertilizer usage rate than those mainly receiving food transfers. I do not detect any effect on irrigation usage (columns 3 and 4). These results suggest that individual behaviors trigger agricultural productivity changes, with the effects concentrated in *woredas* receiving essentially cash transfers. Accordingly, the insight nature of with cash transfers give farmers the opportunity to invest in input leading to productivity gains.

6.4. Effects on demand

Having demonstrated that the PSNP affected local market prices, I next investigate whether these effects represent merely nominal shocks or translate into real welfare impacts for the local population. Given limitations in consumption data precision, I employ anthropometric measures as a second-best approach, drawing on the established finding that consumption shocks disproportionately affect children's anthropometric status in sustainable ways (Carter and Maluccio, 2003; Galasso et al., 2016).

Using DHS survey data on children under five years old, I estimate equation 1 to compare acute malnutrition outcomes between children of the same age in control and treated *woredas*. Table 12 presents these results, first confirming that nutrition status trends between control and treated *woredas* did not significantly differ prior to PSNP implementation.

The findings reveal substantial nutritional disparities: children in cash-dominant *woredas* are 15 percentage points more likely to be underweight and 10 percentage points more likely to experience wasting compared to those in food-dominant *woredas*. However, I detect no significant effect on childhood stunting. The exclusive impact on short-term anthropometric measures (underweight and wasting) suggests that children in cash-dominant *woredas* experienced acute periods of undernutrition rather than chronic malnutrition. The price effects documented in Table 1 provide a plausible mechanism for this increased malnutrition among children in cash-dominant *woredas*.

[34]Figures B.21 and B.22 report parallel trend estimates when measuring the effects of PSNP on fertilizer intensity and irrigation.

An important limitation of this analysis is the partial geographic mismatch between the *woredas* covered in the DHS data and those in the retail price dataset. This discrepancy may partially account for the substantial magnitude of the estimated effects and limits direct comparability between the analyses. The geographic mismatch could introduce selection biases if DHS-sampled *woredas* systematically differ from those in the price analysis in unobserved ways that affect both treatment assignment and nutritional outcomes. Another limitation is the lack of information about individual treatment status. A solution could be to rely on recent machine learning advances to predict treatment status using alternative source of data. These models require large datasets containing granular information, yet the datasets I have in hand are insufficient to predict accurately individual treatment status. Appendix D provides detail on an attempt in predicting individual treatment status using eXtrem gradient boosting model, but performs poorly with a 67% accuracy rate (Figure D.1). Despite these limitations, the results highlight important research directions for understanding how social protection programs' effects on local prices ultimately influence household consumption and welfare outcomes.

7. Conclusion

As part of social protection program, governments often provide goods or cash through transfers to local community. These transfers yields supply and demand shifts, which could have quantitatively important effects on local market. This study tests for price effects of food transfers versus cash transfers using the progressive roll-out of the Ethiopia's Productive Safety Net Program, the largest public workfare in Africa, and a newly available set of data covering retail market price, program implementation, agricultural production, and children nutritional outcomes between 2001 and 2015.

My findings provide novel evidence that social transfers impact local market prices. I test for three main predictions. First, cash transfers should yield to price increase through an income effect, with the effect being larger for higher amounts transferred locally. Second, food transfers should have lower price effects than cash transfers, with the difference being larger for higher amount transferred. Third, the greater the market integration is, the smaller the magnitude of the price effects should be. I find strong evidence supporting the first hypothesis: prices are 5% higher in cash dominated districts and lasts even after 7 years. Prices in cash dominant *woredas* increase by 6% relative to food dominant *woredas*, supporting the second prediction. Lastly, in line with the third prediction, I show that price effects are concentrated in less integrated *woredas*.

In line with previous studies (Egger et al., 2022; Franklin et al., 2024), my result provide additional evidence that social transfer programs that simply compare outcomes in treatment versus control communities may understate true overall impacts by ignoring the general equilibrium effects over time that I measure. Indeed, the estimated price effects translate into real-world impacts with cash transfers relax supply constraints by improving agricultural productivity. However, these productivity gains are accompanied by meaningful welfare trade-offs in children's malnutrition outcomes.

An important limitation of the analysis is that I do not directly observe individual treatment status limiting my ability to disentangle effects on beneficiaries and non beneficiaries within a given district. I am constrained to rely on treatment status at the district level, which may differs from the individual ones in districts where only a subsample of the population is covered by the program.

To conclude, the findings of this paper suggest that greater attention should be paid to the context and the modalities in which social transfers program takes place to ensure that it yields to positive welfare results. Given the price elasticity estimated, policymakers should carefully calibrate transfer sizes relative to local market capacity to avoid excessive price distortions. In addition, considering mixed transfer portfolios rather than relying exclusively on one modality can limit adverse effects. Therefore, designing context-specific targeting should includes timely price monitoring to account for price effects in at-scale evaluation of these policies.

Looking ahead, social protection programs should be included in a larger perspective and implemented along with complementary policies strengthening their positive effects and preventing the adverse ones. For instance, combining transfers with agricultural extension services could help local supply adjust to increased demand, or regular adjustment of transfer amounts based on local price changes to mitigate price effects. An evaluation of combine effects of such policies would provide a valuable experimental test to improve social protection transfer implementation.

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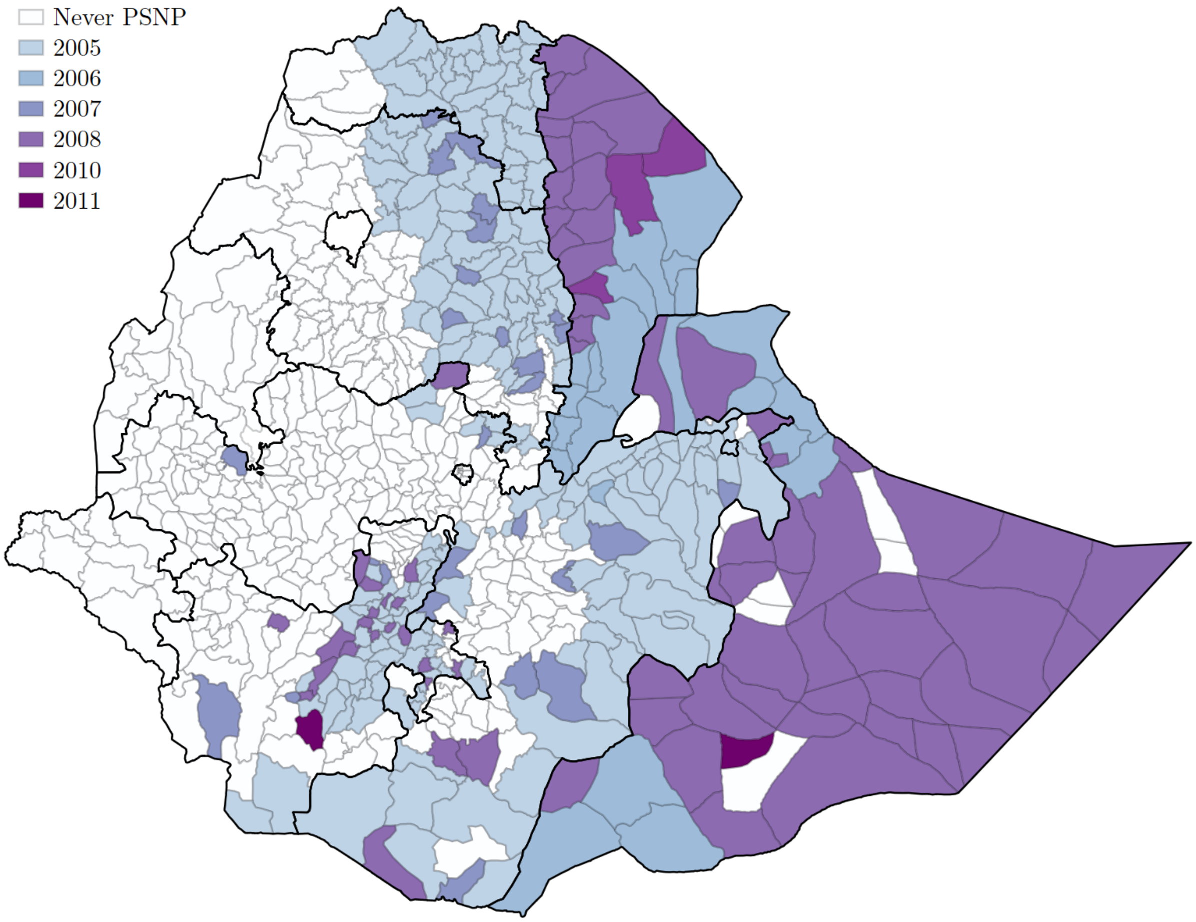
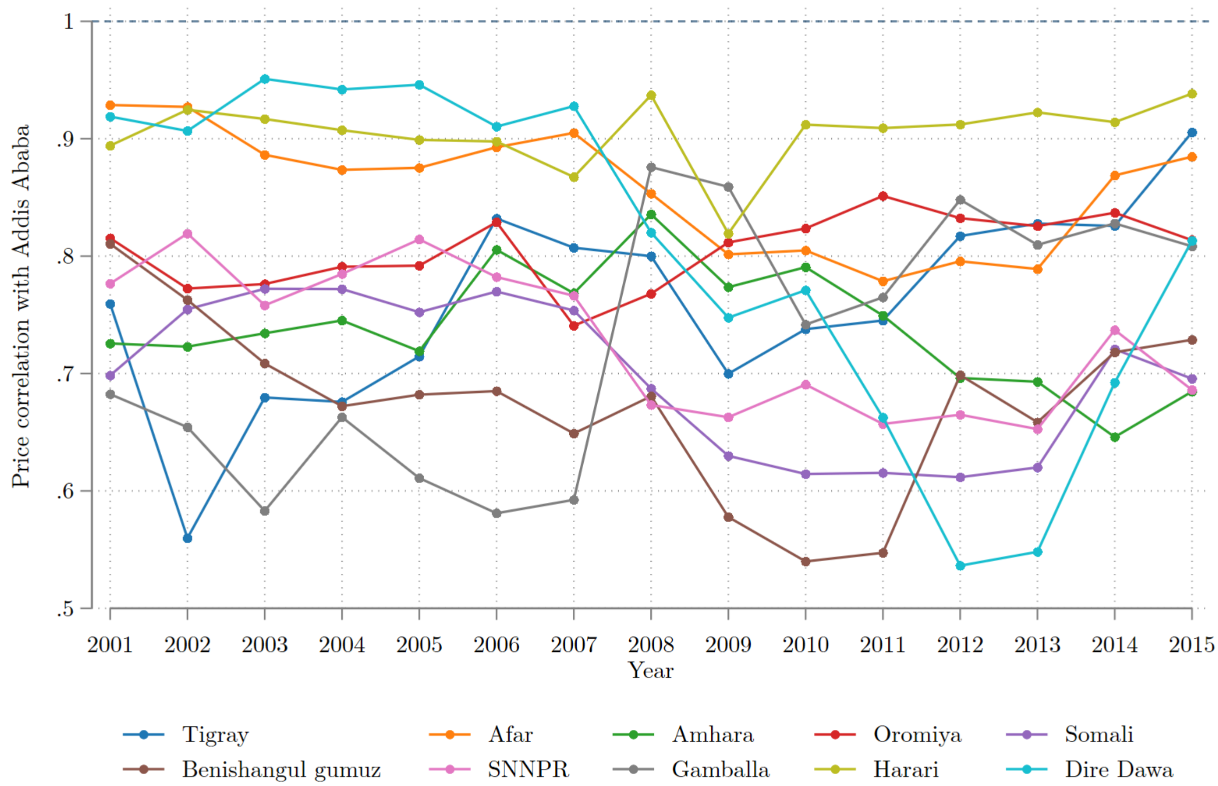
Figure 1. PSNP coverage and roll-out



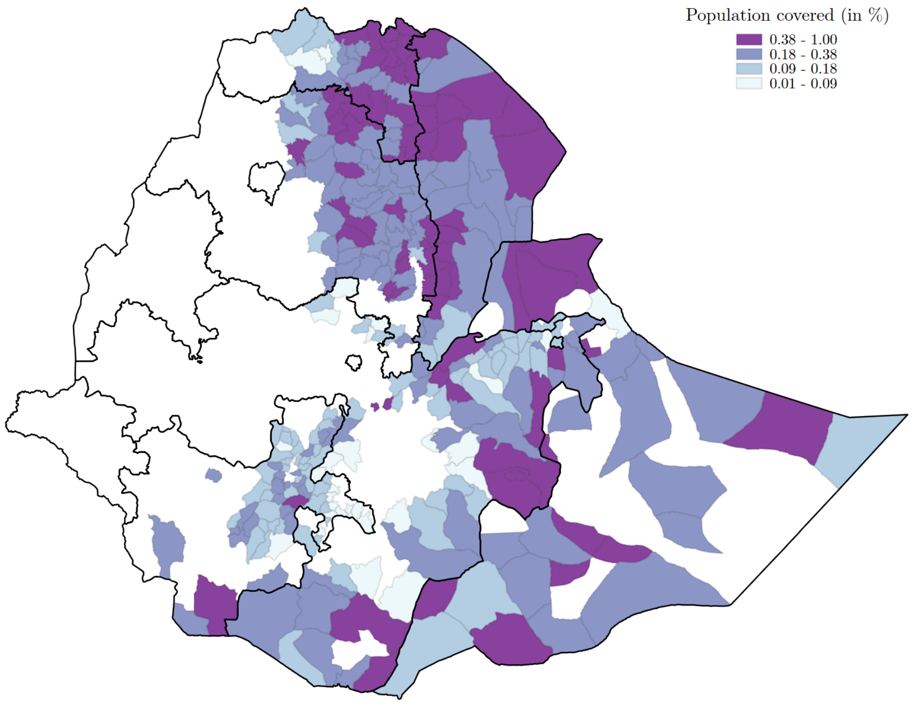
Notes. This figure shows *woreda's* first year of the Productive Safety Net Program implementation.

Figure 2. Price correlation with past month Addis Ababa price, by region

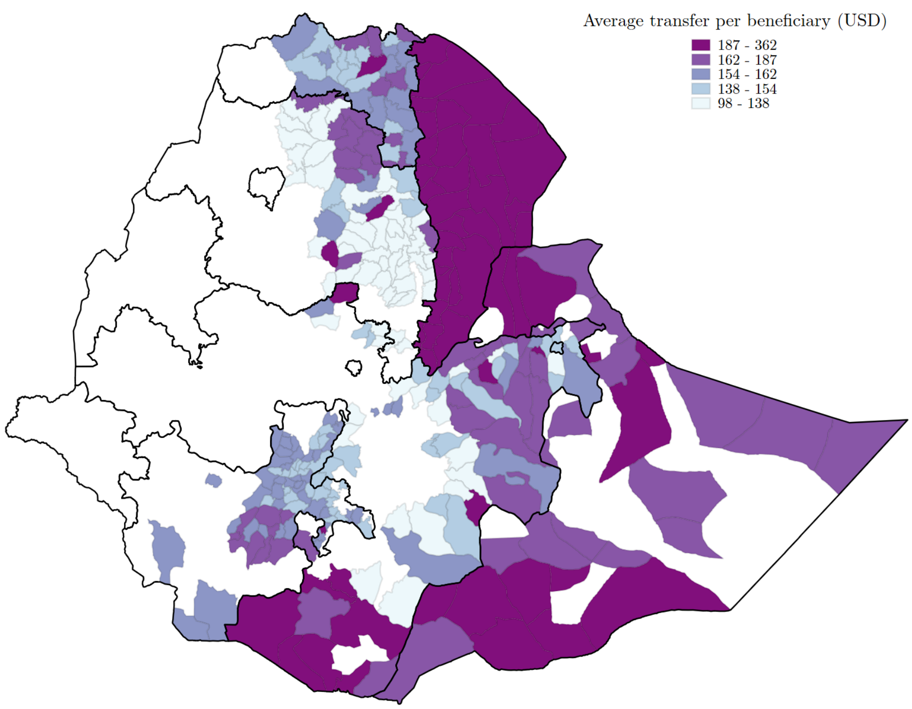


Notes. This figure shows the annual average Pearson correlation between monthly regional prices and past-month prices in Addis Ababa. Price is a (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market month and create my market price indices as an expenditure-weighted average of these median price quotes across all food groups in that market month.

Figure 3. Spatial coverage of treatment intensity



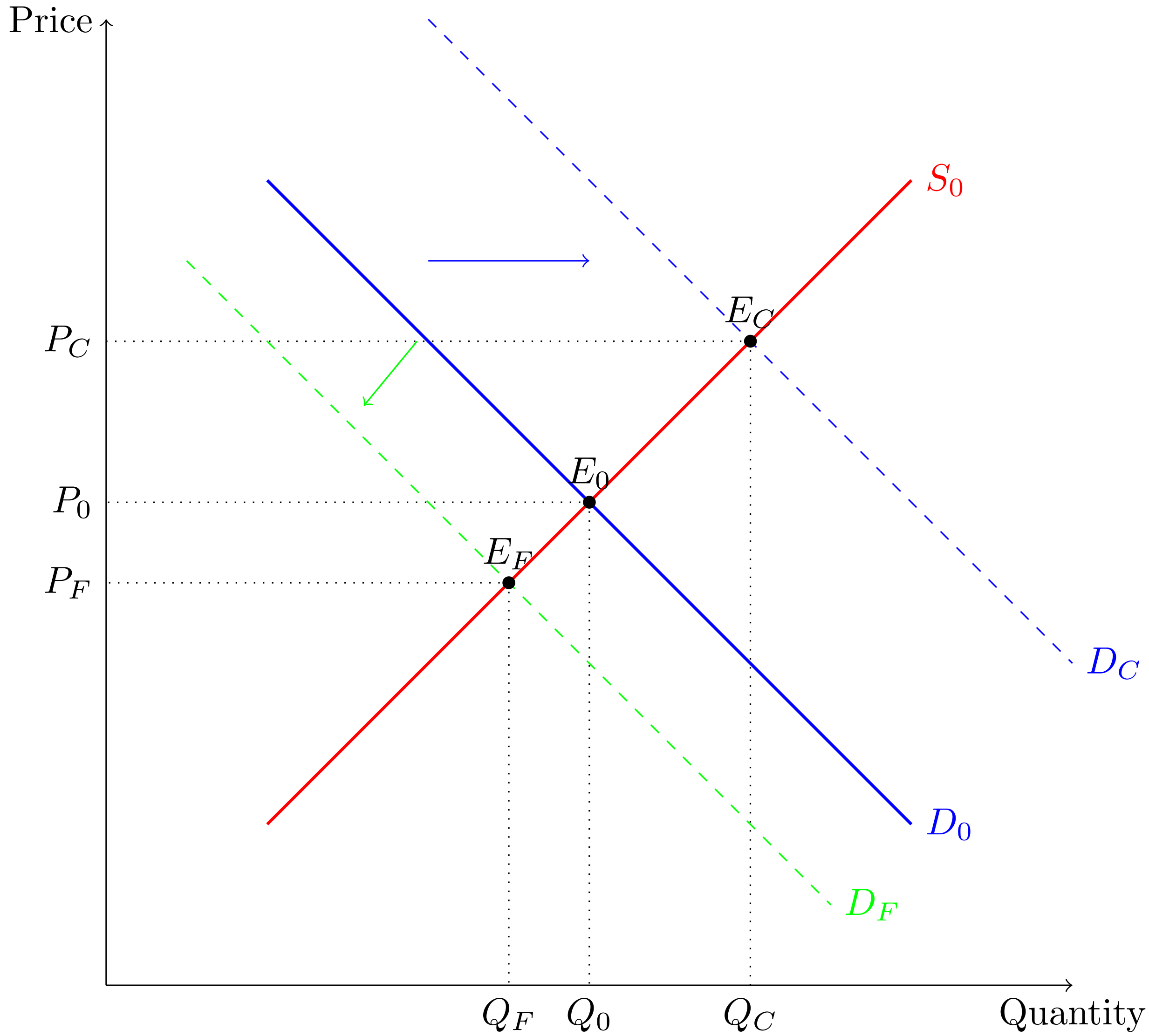
A. Proportion of the population treated per *woreda*



B. Average transfer per beneficiary

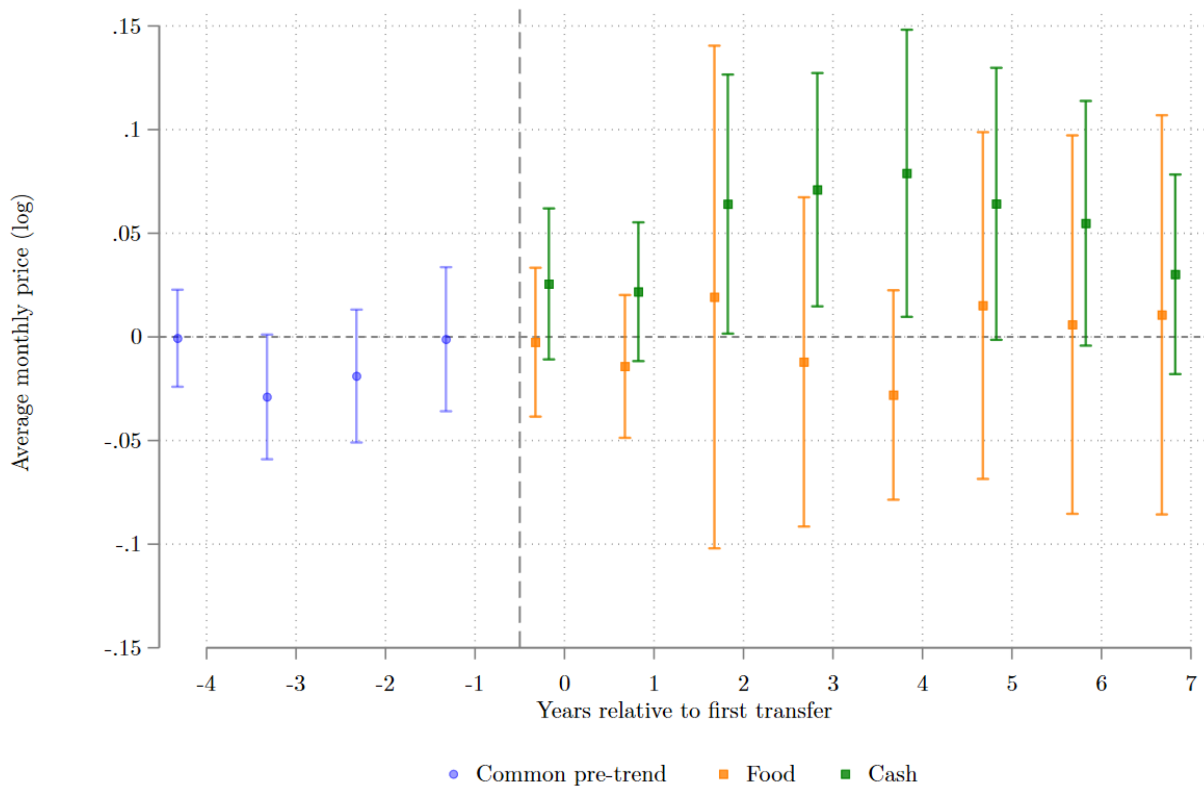
Notes. This figure shows the geoical variation of treatment intensity over the treatment period (2005-2015). Panel A displays the proportion of the population the PSNP covers in a *woreda* (i.e., district). Panel B shows the average transfer per beneficiary (in 2005 US Dollars) at the *woreda* level. Darker colors indicate higher intensity.

Figure 4. Theoretical effect of cash and food transfers on local prices



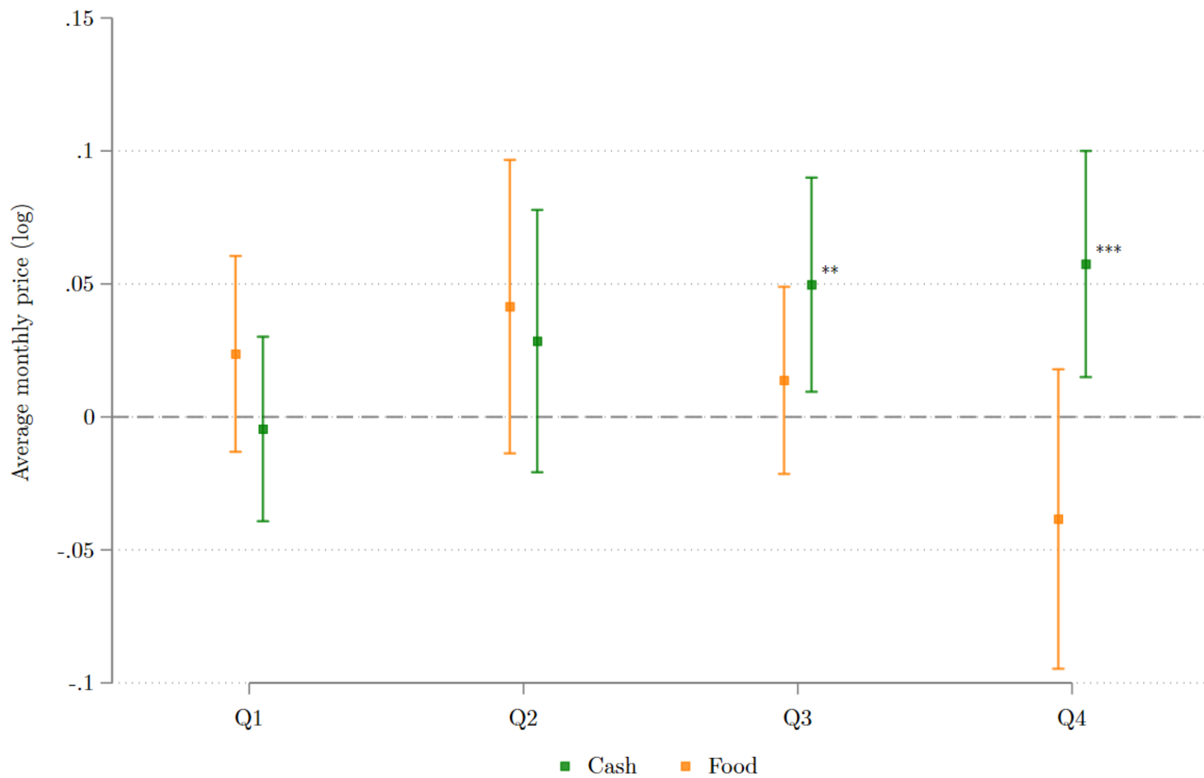
Notes. This figure presents the theoretical effects of cash and food transfers on a local market. D and S lines represent demand and supply. E points represent market equilibrium for price P and quantity Q. Subscript 0, C, and F are for initial equilibrium, post-cash transfers equilibrium, post-food cash transfers equilibrium.

Figure 5. Event study coefficient estimates of the Productive Safety Net Program's effects on market prices, by transfer type



Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) price index in Birr per calorie. It shows heterogeneity treatment effects by main transfer type (food or cash). Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Coefficient estimates are presented for market-by-month cohorts with 95% confidence intervals (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes market, month-year, and region-year fixed effects.

Figure 6. Effect by intensity quantile using share of population treated



Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) price index in Birr per calorie. It shows heterogeneity treatment effects by quantile of population covered by the PSNP for each transfer type. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Coefficient estimates are presented for market-by-month cohorts with 95% confidence intervals (standard errors are clustered at the *woreda* level). The specification includes market, month-year, and region-year fixed effects.

Table 1. Transfer type heterogeneous effect of the Productive Safety Net Program on market prices —DID imputation estimates

	Overall period (1)	Out transfer (2)	During transfer (3)
Food	-0.00	0.01	-0.01
	(0.04)	(0.04)	(0.04)
Cash	0.05*	0.04*	0.05**
	(0.02)	(0.02)	(0.02)
F-test (Cash = Food) p-value	0.29	0.35	0.24
N	20126	10185	9941

Notes. This table reports transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Column (1) reports results using all months. Columns (2) and (3) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2. Transfer type heterogeneous effect of the Productive Safety Net Program on market prices by food group—DID imputation estimates

	Wheat	Grains	Vit.A Fr. and Veg.	Other Fr. and Veg.	Flesh Foods	Eggs	Legumes	Dairy	Others	Spices	Cereal Processed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Overall Period											
Food	-0.24***	-0.25***	-0.03***	-0.01***	-0.00	0.00	-0.07***	0.16***	0.01	0.02	0.00
	(-3.47)	(-2.95)	(-6.68)	(-2.93)	(-0.23)	(0.68)	(-6.70)	(3.03)	(0.08)	(0.74)	(1.62)
Cash	0.05	0.07	0.01	0.00	-0.00	-0.00	0.03	0.01	-0.09**	-0.02	0.00
	(0.69)	(0.85)	(0.57)	(0.85)	(-0.08)	(-0.78)	(1.31)	(0.86)	(-2.16)	(-0.66)	(0.74)
F-test (Cash = Food) p-value	0.00	0.00	0.00	0.00	0.89	0.29	0.00	0.00	0.09	0.27	0.46
N	17571	20126	19957	20118	18040	19716	20117	19448	20120	20112	20119
Panel B: Out Transfer Time											
Food	-0.25***	-0.25***	-0.03***	-0.01***	-0.00	0.00	-0.07***	0.17***	0.00	0.02	0.00
	(-3.39)	(-2.90)	(-6.70)	(-2.71)	(-0.27)	(0.65)	(-6.62)	(2.96)	(0.06)	(0.66)	(1.60)
Cash	0.06	0.06	0.01	0.00	-0.00	-0.00	0.03	0.01	-0.10**	-0.02	0.00
	(0.73)	(0.78)	(0.62)	(0.91)	(-0.12)	(-0.75)	(1.33)	(0.84)	(-2.17)	(-0.65)	(0.74)
F-test (Cash = Food) p-value	0.00	0.00	0.00	0.00	0.89	0.31	0.00	0.01	0.07	0.30	0.47
N	8853	10185	10090	10179	9489	9937	10179	9868	10181	10176	10179
Panel C: During Transfer Time											
Food	-0.19***	-0.25***	-0.03***	-0.01***	-0.00	0.00	-0.07***	0.15***	0.01	0.03	0.00
	(-2.88)	(-3.02)	(-6.65)	(-3.20)	(-0.17)	(0.70)	(-6.78)	(3.10)	(0.12)	(0.80)	(1.63)
Cash	0.05	0.07	0.00	0.00	-0.00	-0.00	0.02	0.01	-0.09**	-0.02	0.00
	(0.65)	(0.92)	(0.51)	(0.76)	(-0.04)	(-0.82)	(1.27)	(0.90)	(-2.15)	(-0.67)	(0.75)
F-test (Cash = Food) p-value	0.00	0.00	0.00	0.00	0.91	0.27	0.00	0.00	0.11	0.25	0.45
N	8665	9941	9867	9939	8483	9736	9938	9549	9939	9936	9940

Notes. This table reports overall treatment effects across all relative time periods estimated using Borusyak et al. (2024)'s imputation estimator for each food group. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Each column reports results for a specific food group (see table A.1 for food group composition). Panel A shows results using all months. Panel B and C report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Within *woreda* effect of the Productive Safety Net Program on market prices —DID imputation estimates

	Overall period (1)	Out transfer (2)	During transfer (3)
Switch to food	-0.03	0.00	-0.06
	(0.04)	(0.03)	(0.05)
Switch to cash	0.08*	0.09**	0.07
	(0.05)	(0.05)	(0.05)
F-test: (Switch to food = Switch to cash) p-value	0.02	0.06	0.01
N	1029	514	515

Notes. This table reports within-*woreda* treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Switch to food (cash) is a dummy equal to 1 the year when a *woreda* switches from receiving more than 50% of PSNP transfers in cash (food) to food (cash). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that switch to food coefficient equals switch to cash coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Effect of the share of the local population treated on the Productive Safety Net Program on market prices —DID imputation estimates

	Overall period		Out transfer		During transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Food	Cash	Food	Cash	Food
Q1 Transfers intensity	0.02	0.04*	0.02	0.04*	0.02	0.04*
	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)
Q2 Transfers intensity	0.04	0.00	0.05	0.00	0.04	-0.00
	(0.03)	(0.01)	(0.04)	(0.01)	(0.03)	(0.02)
Q3 Transfers intensity	0.06***	0.01	0.06***	0.02	0.07***	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Q4 Transfers intensity	0.09***	-0.03	0.08***	-0.01	0.09***	-0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
F-test (Q1 = Q4) p-value	0.11	0.09	0.15	0.17	0.08	0.05
N	17465	19719	8855	9982	8610	9737

Notes. This table reports transfer intensity heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. For treatment intensity, I calculate the share of *woreda*'s population covered by the program and construct quartiles based on its distribution. Treatment intensity quartiles are as follow: Q1 $\in$ [0.01;0.09]; Q2 $\in$]0.09;0.18]; Q3 $\in$]0.18;0.38]; Q4 $\in$]0.38;1]. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Each column reports results for a specific food group (see Table A.1 for food group composition). Coefficient estimates are presented for market-by-month cohorts. Food (cash) *p*-value corresponds to the joint hypothesis test *p*-value that Q1 coefficient equals Q4 coefficient in food (cash) dominant *woredas*. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Effect of the transfers share in local expenditures on the Productive Safety Net Program on market prices —DID imputation estimates

	Overall period		Out transfer		During transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Food	Cash	Food	Cash	Food
Q1 Transfers intensity	-0.02	0.08***	-0.02	0.08***	-0.01	0.08***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.01)	(0.03)
Q2 Transfers intensity	0.07***	-0.02	0.07***	-0.02	0.08***	-0.03*
	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)
Q3 Transfers intensity	0.03	-0.05***	0.03	-0.05***	0.03	-0.06***
	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)
Q4 Transfers intensity	0.12***	-0.13***	0.12***	-0.11***	0.12***	-0.15***
	(0.04)	(0.01)	(0.04)	(0.01)	(0.04)	(0.01)
F-test (Q1 = Q4) p-value	0.00	0.00	0.00	0.00	0.00	0.00
N	16611	15456	8416	7825	8195	7631

Notes. This table reports transfer intensity heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. For treatment intensity, I calculate the average annual share transfers represent in 2005 *woreda* aggregated expenditure (data from 2005 HICES round) and construct quartiles based on its distribution. Treatment intensity quartiles are as follow: Q1 ∈ [0.03;0.28]; Q2 ∈]0.28;0.46]; Q3 ∈]0.46;0.64]; Q4 ∈]0.64;91]. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that Q1 coefficient equals Q4 coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Heterogeneous effect of the Productive Safety Net Program on market prices by treatment intensity exposure—DID imputation estimates

	10km buffer		20km buffer		30km buffer		40km buffer		50km buffer	
	(1) Cash	(2) Food	(3) Cash	(4) Food	(5) Cash	(6) Food	(7) Cash	(8) Food	(9) Cash	(10) Food
Control spillover (CS)	0.01	0.01**	0.01	-0.01	0.00	-0.01	0.00	-0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Treated spillover (TS)	0.05**	0.01*	0.05**	-0.01	0.05**	-0.03	0.04**	-0.04	0.04**	-0.04
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Pure Treated (PT)	0.06***	-0.05	0.07***	-0.07***	0.07***	-0.06***	0.06***	0.00	0.06***	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.00)	(0.02)	(.)	(0.02)	(.)
F-test (CS = TS) p-value	0.07	0.48	0.02	0.96	0.02	0.43	0.04	0.29	0.04	0.29
F-test (TS = PT) p-value	0.02	0.09	0.00	0.02	0.00	0.01	0.01	0.47	0.01	0.49
F-test (CS = PT) p-value	0.62	0.11	0.35	0.01	0.35	0.48	0.48	0.24	0.48	0.24
N	16043	10885	16334	8550	16214	8651	16309	8882	16340	8412

Notes. This table reports spillover effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month. I constructed a buffer surrounding *woreda i* centroid and classified it as spillover if any *woreda j* within this buffer was treated. I use a 10 km buffer in columns (1) and (2); 20km in columns (3) and (4); 30 km in columns (5) and (6); 40km in columns (7) and (8); and 50 km in columns (9) to (10). Control spillover (CS) *woredas* are control *woredas* for which a treated *woreda* falls into the given buffer. Treated spillover (TS) *woredas* are treated *woredas* for which a treated *woreda* falls into the given buffer. Pure treated (PT) *woredas* are treated *woredas* for which not any treated *woreda* falls into the given buffer. The year of treatment considered is the earliest to which a *woreda* is exposed to the PSNP. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Coefficient estimates are presented for market-by-month cohorts. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Heterogeneous effect of the Productive Safety Net Program on market prices by local suppliers' market power —DID imputation estimates

	Overall period (1)	Out transfer (2)	During transfer (3)
No power × Food	-0.00	0.01	-0.01
	(0.04)	(0.04)	(0.04)
Power × Food	0.02	0.02	0.01
	(0.04)	(0.04)	(0.05)
No power × Cash	0.05**	0.04*	0.05**
	(0.02)	(0.02)	(0.02)
Power × Cash	0.08**	0.09**	0.07*
	(0.04)	(0.04)	(0.04)
F-test: Food (No power = Power) p-value	0.22	0.29	0.24
F-test: Cash (No power = Power) p-value	0.12	0.03	0.36
N	20126	10185	9941

Notes. This table reports PSNP heterogeneous treatment effects by local suppliers' market power across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month, and create my market price indices as an expenditure weighted average of these quotes across all food groups in that market month. I follow Attanasio and Pastorino (2020)'s methodology to estimate *woreda*'s market power. Using 2005 Household Income, Consumption, and Expenditures survey data I compute within *woreda*'s correlation between prices (unit values) and quantity purchased. Then, I classify a *woreda* as having market power if the correlation coefficient is negative. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Column (1) reports results using all months. Columns (2) and (3) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. Food (cash) p-value corresponds to the joint hypothesis test p-value that food (cash) *woreda* without market power coefficient equals food (cash) *woreda* with market power coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Heterogeneous effect of the Productive Safety Net Program on market prices by market access intensity—DID imputation estimates

	Overall period (1)	Out transfer (2)	During transfer (3)
Q1 market access	0.11***	0.10**	0.13***
	(0.04)	(0.05)	(0.04)
Q2 market access	0.04	0.04	0.04
	(0.03)	(0.03)	(0.03)
Q3 market access	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)
Q4 market access	0.07***	0.06**	0.07***
	(0.02)	(0.03)	(0.02)
Q5 market access	-0.02	-0.01	-0.02
	(0.02)	(0.02)	(0.02)
F-test (Q1 = Q5) p-value	0.01	0.03	0.00
N	18579	9412	9167

Notes. This table reports PSNP heterogeneous treatment effects by market access quintiles across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month, and create my market price indices as an expenditure weighted average of these quotes across all food groups in that market month. I follow Donaldson and Hornbeck (2016)'s methodology to estimate *woreda*'s market access. Using 2005 road network data and *woreda*'s population in 2000, I compute market access in *woreda* o in year t (=2005) as follows: $MA_{ot} = \sum_d \tau_{odt}^{-\theta} Pop2000_d$ with $Pop2000_d$ is destination *woreda* population in 2000. See section C for more details. Then, I classify *woredas* in quintile. Column (1) reports results using all months. Columns (2) and (3) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that Q1 coefficient equals Q4 coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Average yearly effect of the Productive Safety Net Program on market prices, by initial agricultural production level —DID imputation estimates

	Overall period		Out transfer		During transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Food	Cash	Food	Cash	Food
Below median Agricultural Prod.	0.04	-0.07***	0.03	-0.09***	0.04	-0.06***
	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)
Above median Agricultural Prod.	0.04	0.04	0.04	0.04	0.04	0.05
	(0.03)	(0.05)	(0.03)	(0.06)	(0.03)	(0.05)
F-test (Below = Above) p-value	0.98	0.04	0.95	0.04	0.98	0.05
N	14269	12898	7047	6375	7222	6523

Notes. This table reports average and transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month, and create my market price indices as an expenditure weighted average of these quotes across all food groups in that market month. Below (Above) Agricultural prod. median includes *woredas* with agircultural production level below (above) the median value in 2005. Cash (food) at the top of each column characterize *woredas* for which cash (food) represents more than 50% of total transfer during the period exposed to PSNP. Columns (1-2) reports results using all months. Columns (3-4) and (5-6) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that below coefficient equals above coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 10. Transfer type heterogeneous effect of the Productive Safety Net Program on market prices by implementing institution—DID imputation estimates

	Overall period		Out transfer		During transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Food	Cash	Food	Cash	Food
NGO	0.09**	0.01	0.09**	0.00	0.09**	0.01
	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Government	0.02	-0.02***	0.02	-0.03***	0.01	-0.02*
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
F-test (NGO = Government) p-value	0.12	0.50	0.14	0.55	0.10	0.47
N	17821	15959	8800	7883	9021	8076

Notes. This table reports average and transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price in Birr per calorie. For each food group, I take the logarithm of the median price quotes in a market-month, and create my market price indices as an expenditure weighted average of these quotes across all food groups in that market month. NGO (Government) includes *woredas* where the implementing institution is an NGO (Goverment). Cash (food) at the top of each column characterize *woredas* for which cash (food) represents more than 50% of total transfer during the period exposed to PSNP. Columns (1-2) reports results using all months. Columns (3-4) and (5-6) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that NGO coefficient equals Government coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 11. Average yearly effect of the Productive Safety Net Program on agricultural production —DID imputation estimates

	Production Diversification		Total Production		Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
Exposed to PSNP	0.02*		0.15**		0.04	
	(0.01)		(0.06)		(0.04)	
Cash		0.02		0.15*		0.09*
		(0.01)		(0.08)		(0.05)
Food		0.02		0.15*		-0.05
		(0.02)		(0.08)		(0.06)
F-test (Cash = Food) p-value		0.95		0.97		0.09
N	5792	5783	5779	5770	5790	5781

Notes. This table reports average and transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable in columns (1-2) is the crop production diversification index, (log) total agricultural production in quintals in columns (3-4), and (log) agricultural productivity in quintals per hectare in columns (5-6). All dependent variables are at *woreda* level. Crop production diversity equals $D_{jt} = 1 - \sum_{k=1}^{k=K} p_{jt}^2$, in which K is the number of crops cultivated in *woreda* j at time t, and p, is the relative share of each crop in *woreda* annual total production. D increases in diversity, with 0 representing no diversity. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Columns (1), (3), and (5) report average results result. Columns (2), (4), and (6) report results by transfer types. Coefficient estimates are presented for *woreda*-by-year cohorts. P-value corresponds to the joint hypothesis test p-value that food coefficient equals cash coefficient. All specifications include *woreda*, year, region-year fixed effects, and agricultural production composition. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Average yearly effect of the Productive Safety Net Program on malnutrition —DID imputation estimates

	Underweight (0/1) (1)	Wasting (0/1) (2)	Stunting (0/1) (3)
Food	-0.05	-0.04*	-0.04
	(0.03)	(0.02)	(0.04)
Cash	0.10***	0.06**	0.05
	(0.04)	(0.03)	(0.03)
F-test (Food = Cash) p-value	0.00	0.00	0.01
F-test pre-treatment p-value	0.59	0.17	0.16
N	4600	4766	4600

Notes. This table reports transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable in column (1) is a dummy for being underweighted (weight for age z-score lower than 2 standard deviations for the reference value), a dummy for being wasted (weight for height z-score lower than 2 standard deviations for the reference value) in column (2), and stunted (height for age z-score lower than 2 standard deviations for the reference value) in column (3). Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Coefficient estimates are presented for *woreda*-by-year cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient and that all pre-treatment coefficients are null. All specifications include *woreda*, year, and cash-dominant status-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

A. Additional Tables

Table A.1. Mapping of food items to food groups

Food group	CSA food item
Grains, roots and tubers	Barley white milled kg
Grains, roots and tubers	Maize (white) kg
Grains, roots and tubers	Teff black (red) milled kg
Grains, roots and tubers	Barley black kg
Grains, roots and tubers	Sorghum milled kg
Grains, roots and tubers	Wheat mixed milled kg
Grains, roots and tubers	Wheat white kg
Grains, roots and tubers	Potato kg
Grains, roots and tubers	Wheat black (red) kg
Grains, roots and tubers	Sweet potato kg
Grains, roots and tubers	Hulled barley kg
Grains, roots and tubers	Maize(white) milled
Grains, roots and tubers	Teff mixed milled kg
Grains, roots and tubers	Durra kg
Grains, roots and tubers	Oats milled kg
Grains, roots and tubers	Oats kg
Grains, roots and tubers	Sorghum white kg
Grains, roots and tubers	Barley white kg
Grains, roots and tubers	Rice (imported) kg
Grains, roots and tubers	Teff white milled kg
Grains, roots and tubers	Wheat white milled kg
Vitamin A-rich fruits and vegetables	Ethiopian kale kg
Vitamin A-rich fruits and vegetables	Beet root kg
Vitamin A-rich fruits and vegetables	Carrot kg
Vitamin A-rich fruits and vegetables	Spinach kg
Vitamin A-rich fruits and vegetables	Papaya kg
Vitamin A-rich fruits and vegetables	Pumpkin kg
Vitamin A-rich fruits and vegetables	Mango kg
Other fruits and vegetables	Cabbage kg
Other fruits and vegetables	Tomatoes kg
Other fruits and vegetables	Pepper green kg

Continued on next page

Table A.1 – *Continued from previous page*

Food group	**CSA food item**
Other fruits and vegetables	Onions kg
Other fruits and vegetables	Ginger dry(local) kg
Other fruits and vegetables	Avocado kg
Other fruits and vegetables	Cauliflower kg
Other fruits and vegetables	Leaks kg
Other fruits and vegetables	Garlics kg
Other fruits and vegetables	Mandarin kg
Other fruits and vegetables	Lemon kg
Other fruits and vegetables	Ginger wet(local) kg
Other fruits and vegetables	Grapes kg
Other fruits and vegetables	Lettuce kg
Other fruits and vegetables	Orange kg
Other fruits and vegetables	Green peas kg
Other fruits and vegetables	Banana kg
Other fruits and vegetables	Cactus kg
Flesh foods	Beef kg
Flesh foods	Fish fresh kg
Eggs	Egg (traditional) dozen
Legumes and nuts	Sunflower kg
Legumes and nuts	Ground nut shelled kg
Legumes and nuts	Fenugreek kg
Legumes and nuts	Sesame seed kg
Legumes and nuts	Lentils kg
Legumes and nuts	Haricot beans kg
Legumes and nuts	Soya beans kg
Legumes and nuts	Peas green(dry) kg
Legumes and nuts	Linseed white kg
Legumes and nuts	Peas split kg
Legumes and nuts	Chick peas kg
Legumes and nuts	Linseed red kg
Legumes and nuts	Horse beans kg
Legumes and nuts	Lima beans kg
Dairy products	Powdered milk 450gm
Dairy products	Yoghurt (traditional) lit
Dairy products	Cow milk (unpasteurized) lit
Dairy products	Cheese cottage kg

Continued on next page

Table A.1 – *Continued from previous page*

Food group	**CSA food item**
Dairy products	Cow milk (pasteurized) lit
Dairy products	Goat milk lit
Others	Cooking oil (imported) lit
Others	Cooking oil (local) lit
Others	Butter unrefined kg
Others	Sugar kg
Others	Honey kg
Others	Vegetable butter(imported) kg
Others	Coca cola/Fanta 33cl
Others	Pepsi/Miranda 33cl
Spices	Pepper whole kg
Spices	Black pepper (local) kg
Spices	White cumin bishop
Spices	Cloves (imported) kg
Spices	Cinnamon (imported) kg
Spices	Cardamon (local) kg
Spices	Turmeric flour (local) kg
Spices	Chillies whole kg
Spices	Basil dry kg
Spices	Tea leaves (local) 100g
Spices	Coffee beans kg
Processed cereal-based	Spaghetti without eggs (local) kg
Processed cereal-based	Macaroni without eggs (local) kg
Processed cereal-based	Enjera unit
Processed cereal-based	Bread wheat (bakery) 350gm
Processed cereal-based	Biscuits 150gm
Temptation goods	Chat kg
Temptation goods	Beer (bedele) 33cl
Temptation goods	Beer (harar) 33cl
Temptation goods	Beer (meta abo) 33cl
Big livestock	Heifer
Big livestock	Cow
Big livestock	Bull
Big livestock	Ox
Big livestock	Donkey
Small livestock	Sheep

Continued on next page

Table A.1 – *Continued from previous page*

Food group	**CSA food item**
Small livestock	Goat
Small livestock	Hen
Small livestock	Cock
Non food non durable	Netela
Non food non durable	Gabi
Non food non durable	Fire wood
Non food non durable	Charcoal
Non food non durable	Kerosene
Non food non durable	Diesel
Non food non durable	Dry cell
Non food non durable	Hard Soap (local)
Non food non durable	Hard soap (imported)
Non food non durable	Detergent
Non food non durable	Aspirin (local)
Non food non durable	Toilet paper
Durable	Cement (50 kg bag)
Durable	Cooking pan
Durable	Gas Stove
Durable	Kuraz
Durable	Flash Light

Notes. This table presents the classification of the 108 food products used.

Table A.2. Balance and summary statistics between food and cash *woredas*

	N	Cash-dominant (1)	Food-dominant (2)	P-value Diff (3)	Normalized diff. (4)
Suppliers market power (0/1)	209	0.30	0.31	0.13	0.02
		[0.46]	[0.46]		
Distance to Addis Ababa (km)	186	328.03	363.62	0.66	0.32
		[93.53]	[128.81]		
Distance to regional capital (km)	186	115.25	150.73	0.27	0.36
		[69.73]	[120.16]		
Distance to zone capital (km)	186	38.26	57.51	0.72	0.60
		[22.57]	[39.12]		
Market access	186	0.57	0.66	0.83	0.16
		[0.66]	[0.46]		
District population	187	12.13	11.99	0.23	-0.21
		[0.59]	[0.73]		
Ag. diversification index	69	0.35	0.32	0.19	-0.15
		[0.19]	[0.21]		
Cereal Production land (Ha)	69	7.12	6.48	0.99	-0.37
		[1.32]	[2.04]		
Highland (0/1)	186	0.62	0.33	0.02	-0.60
		[0.49]	[0.47]		

Notes. This table reports balance tests between cash and food dominant *woredas*. Baseline means and standard deviations [in brackets] by *woreda* groups. *P*-values reported in column 3 for food-dominant *woredas* relative to the cash-dominant group mean. Standard errors clustered at the *woreda* level. The normalized differences in column 4 are computed as the difference in means in food and cash *woreda,* divided by the square root of the sum of the variances in both groups. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfers during the period exposed to PSNP. Suppliers' market power equals one if within *woreda*'s average correlation between prices and quantity is negative. Market access in *woreda* o in year t=2005 as follows: $MA_{ot} = \sum_d \tau_{odt}^{-\theta} Pop2000_d$ with $Pop2000_d$ is destination *woreda* population in 2000. See section C for more details. Crop production diversity equals $D_{jt} = 1 - \sum_{k=1}^{k=K} p_{jt}^2$, in which K is the number of crops cultivated in *woreda* j at time t, and p, is the relative frequency of each crop in *woreda* annual total production. D increases in diversity, with 0 representing no diversity.

Table A.3. Transfer type heterogeneous effect of the Productive Safety Net Program on market price without pastoralist regions —DID imputation estimates

	Overall period (1)	Out transfer (2)	During transfer (3)
Food	-0.03***	-0.03***	-0.04***
	(0.01)	(0.01)	(0.01)
Cash	0.08**	0.07*	0.08**
	(0.04)	(0.04)	(0.04)
F-test (Cash = Food) p-value	0.00	0.01	0.00
N	13699	6933	6766

This table reports transfer type heterogeneous treatment effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimator. Pasoralist regions of Afar and Somali are excluded from the sample. Each column reports the coefficient of interest from a separate imputation. The dependent variable is the (log) price index in Birr per calorie. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Column (1) reports results using all months. Columns (2) and (3) report results on samples restricted to months without any transfer (August-January) and with transfers (February-July). Coefficient estimates are presented for market-by-month cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient. All specifications include market, month-year, and region-year fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4. Average yearly effect of Productive Safety Net Program on agricultural production by market access—DID imputation estimates

	Production Diversification (1)	Total Production (2)	Productivity (3)
Q1 market access	0.01	0.14	-0.07
	(0.01)	(0.12)	(0.06)
Q2 market access	0.06***	0.05	-0.10
	(0.02)	(0.12)	(0.09)
Q3 market access	0.06***	0.37***	0.22***
	(0.02)	(0.13)	(0.08)
Q4 market access	-0.05**	-0.02	0.03
	(0.03)	(0.16)	(0.10)
Q5 market access	0.01	0.11	0.09
	(0.02)	(0.15)	(0.08)
F-test (Q1 = Q5) p-value	0.89	0.84	0.10
N	5753	5742	5753

Notes. This table reports market access heterogeneous treatment effects across all relative time periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable in column (1) is the crop production diversification index, (log) total agricultural production in quintals in column (2), and (log) agricultural productivity in quintals per hectare in column (3). I follow Donaldson and Hornbeck (2016)'s methodology to estimate *woreda*'s market access. Using 2005 road network data and *woreda*'s population in 2000, I compute market access in *woreda* o in year t=2005 as follows: $MA_{ot} = \sum_d \tau_{odt}^{-\theta} Pop2000_d$ with $Pop2000_d$ is destination *woreda* population in 2000. See section C for more details. Then, I classify *woredas* in quintiles. Crop production diversity equals $D_{jt} = 1 - \sum_{k=1}^{k=K} p_{jt}^2$, in which K is the number of crops cultivated in *woreda* j at time t, and p, is the relative frequency of each crop in *woreda* annual total production. D increases in diversity, with 0 representing no diversity. All variables are at *woreda* level. Coefficient estimates are presented for *woreda*-by-year cohorts. P-value corresponds to the joint hypothesis test p-value that Q1 coefficient equals Q5 coefficient. All specifications include *woreda*, year, and region-year fixed effects and agricultural production composition. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5. Relationship between market access and implementing institution.

	(1) MA 2002	(2) MA 2004	(3) MA 2006
Market Access	-0.02 (0.02)	-0.03 (0.04)	-0.02 (0.02)
N	40	38	40

Notes. This table shows the relationship between market access and the institutions in charge of implementing the Productive Safety Net at the *woreda* level. The dependent variable is a dummy equal 1 if the Government is in charge of implementing the PSNP, 0 if it is a NGO. Market access value is computed using the existing road network at the year specified at the top of the column. All specifications include zone fixed effects. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6. Average yearly effect of Productive Safety Net Program on agricultural investment —DID imputation estimates

	Fertilizer		Irrigation	
	(1)	(2)	(3)	(4)
Exposed to PSNP	0.00		-0.00	
	(0.06)		(0.00)	
Cash		0.08		-0.00
		(0.07)		(0.01)
Food		-0.15*		-0.01
		(0.09)		(0.01)
F-test (Cash = Food) p-value		0.03		0.52
N	5789	5780	5789	5780

Notes. This table reports average and transfer type heterogeneous treatment effects across all relative time periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable in columns (1-2) is the (log) fertilizer usage in quintals per hectare in columns (1-2) and the share of agricultural land under irrigation in columns (3-4). Both dependent variables are at *woreda* level. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Columns (1) and (3) report average results result. Columns (2) and (4) report results by transfer types. Coefficient estimates are presented for *woreda*-by-year cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient. All specifications include *woreda*, year, and region-year fixed effects and agricultural production composition. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7. Average yearly effect of Productive Safety Net Program on agricultural investment —DID imputation estimates

	Overall period		Out transfer		During transfer	
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Food	Cash	Food	Cash	Food
Below median Agricultural Prod.	0.04	-0.07***	0.03	-0.09***	0.04	-0.06***
	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)
Above median Agricultural Prod.	0.04	0.04	0.04	0.04	0.04	0.05
	(0.03)	(0.05)	(0.03)	(0.06)	(0.03)	(0.05)
F-test (Below = Above) p-value	0.98	0.04	0.95	0.04	0.98	0.05
N	14269	12898	7047	6375	7222	6523

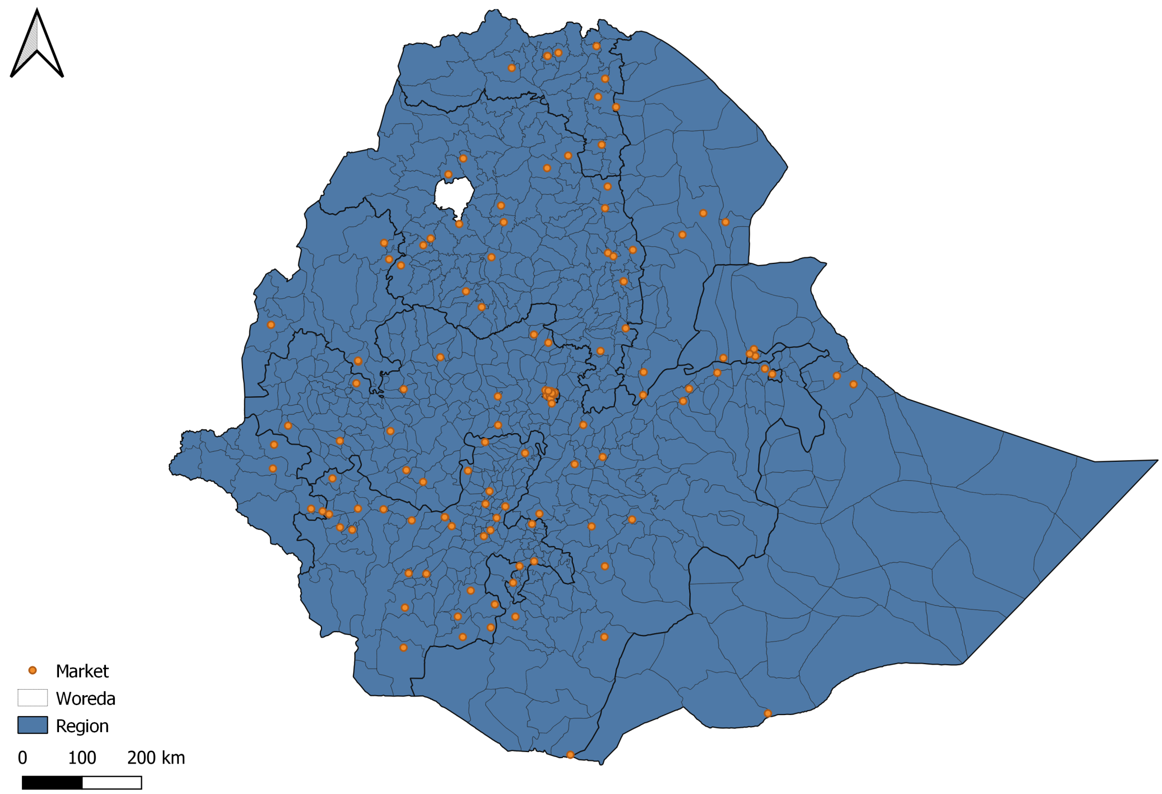
Notes. This table reports average and transfer type heterogeneous treatment effects across all relative time periods estimated using Borusyak et al. (2024)'s imputation estimator. Each column reports the coefficient of interest from a separate imputation. The dependent variable in columns (1-2) is the (log) fertilizer usage in quintals per hectare in columns (1-2) and the share of agricultural land under irrigation in columns (3-4). Both dependent variables are at *woreda* level. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. Columns (1) and (3) report average results result. Columns (2) and (4) report results by transfer types. Coefficient estimates are presented for *woreda*-by-year cohorts. *P*-value corresponds to the joint hypothesis test *p*-value that food coefficient equals cash coefficient. All specifications include *woreda*, year, and region-year fixed effects and agricultural production composition. Standard errors (in parentheses) are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

B. Additional Figures

Figure B.1. Example of PSNP infrastructure construction

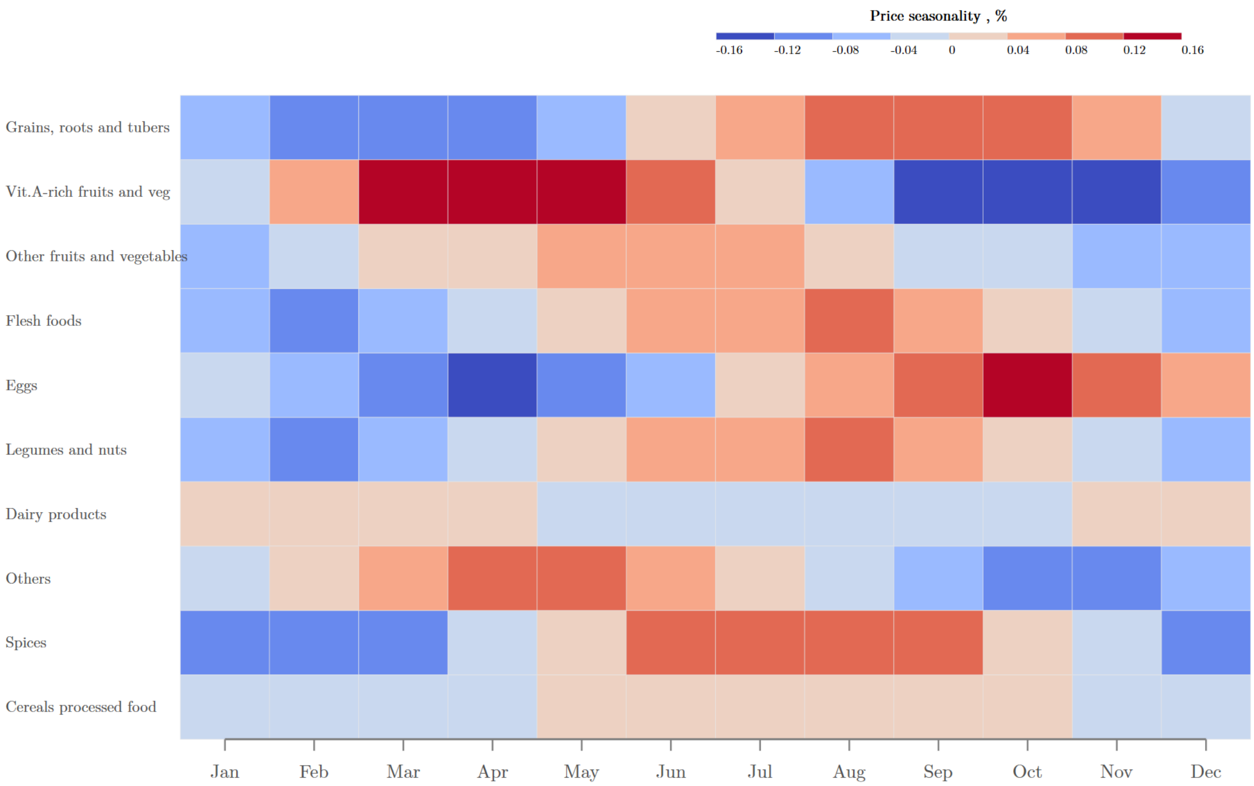
Notes. This figure shows a dam built for water harvesting near Aksoum in the Tigray regional state.

Figure B.2. Sampled markets in the CSA monthly retail price survey



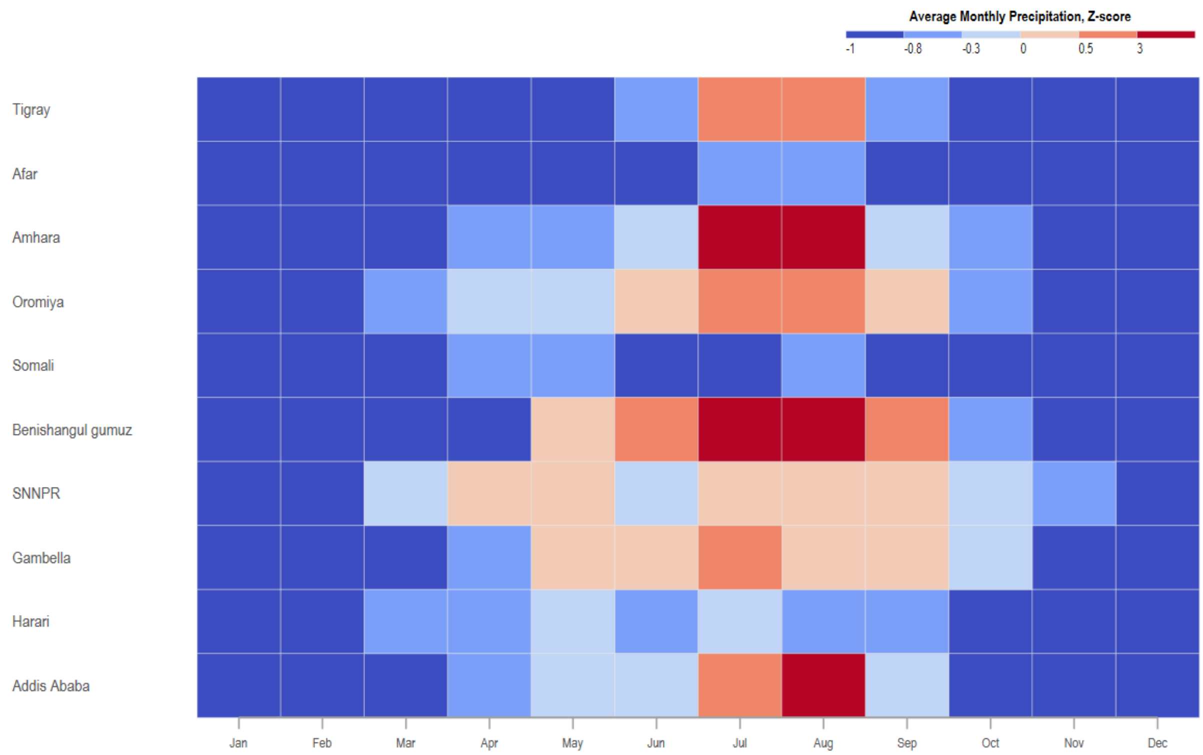
Notes. This figure shows the location of the retail markets included in the Central Statistical Agency data.

Figure B.3. Monthly Price seasonality across food group: 2001-2016 period



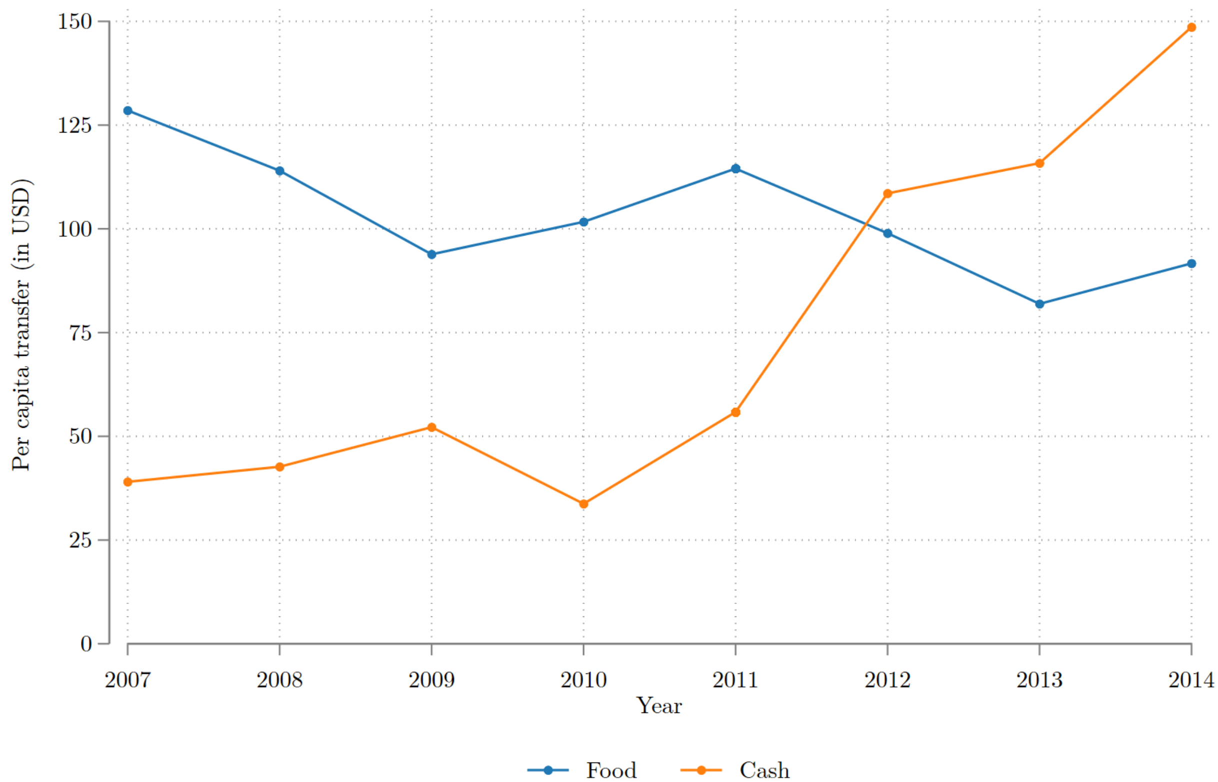
Notes. This figure shows the average monthly price gap to the annual median price in percentage for each group, with warmer colors indicating a larger positive price gap. See table A.1 for details about food groups classification.

Figure B.4. Regional monthly rainfall pattern



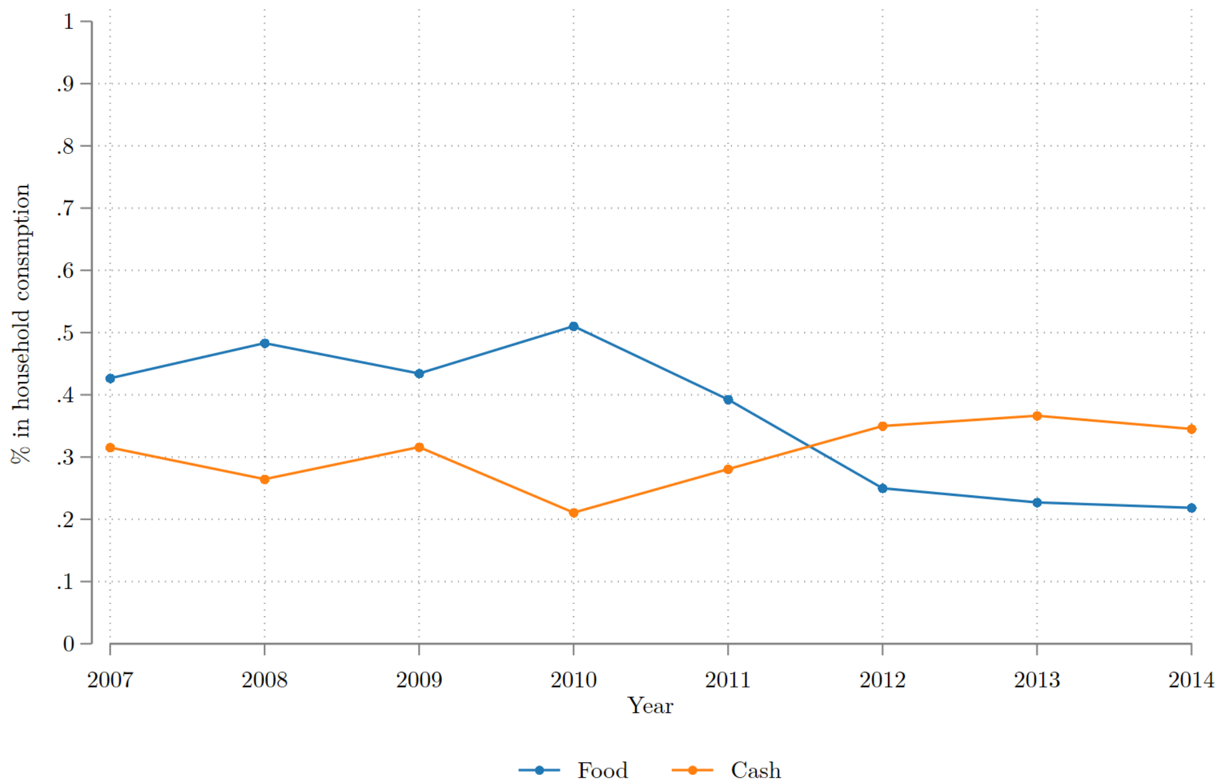
Notes. This figure shows the standardized rainfall monthly deviation from regional means across regions between 2000 and 2015, with warmer colors indicating a larger positive rainfall deviation from the annual mean.

Figure B.5. Transfer per beneficiary (in US Dollars)



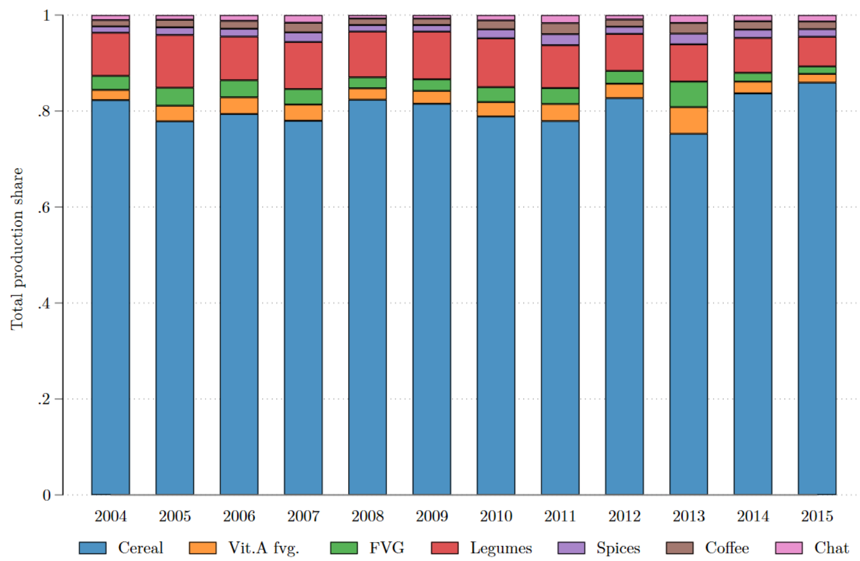
Notes. This figure shows transfer values (in 2005 US Dollars) per beneficiary. The orange line corresponds to cash transfer expressed in 2005 US Dollars, and the blue line corresponds to food transfer monetary equivalent expressed in 2005 US Dollars. Food transfer is converted using the equivalent market price for 3kg of cereals and 0.8 kg pulses from the previous season on the nearest market.

Figure B.6. Transfer share in household expenditures

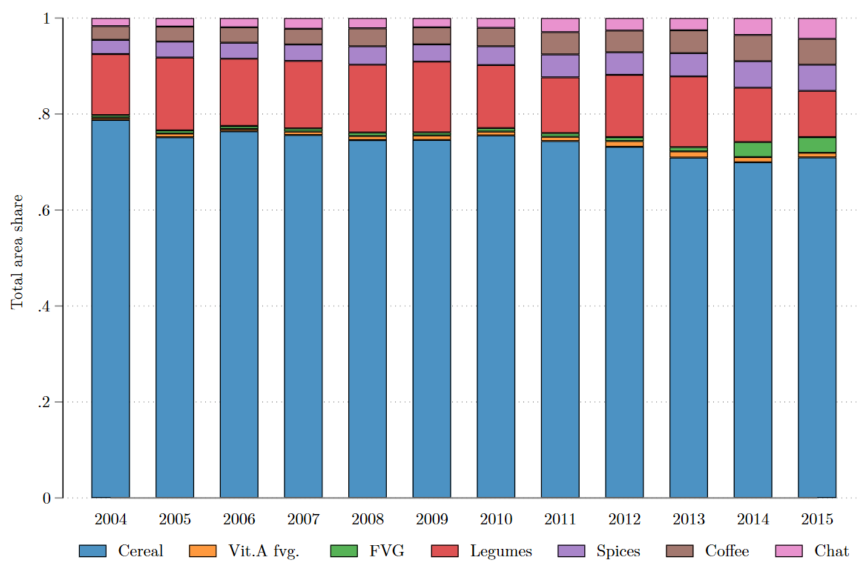


Notes. This figure shows the transfer share in household expenditures. The orange line corresponds to the cash transfer share in annual household expenditures in 2005 US Dollars. The blue line corresponds to the food transfer monetary equivalent share in annual household expenditures expressed in 2005 US Dollars. Food transfer is converted using the equivalent market price for 3kg of cereals and 0.8 kg pulses from the previous season on the nearest market. The expenditures data for this figure come from the Household Income, Consumption, and Expenditures surveys: 2004/5 wave for 2007-2009 years, 2010/11 wave for 2010-2013 years, and 2014/5 for 2014.

Figure B.7. Evolution in production and land occupation



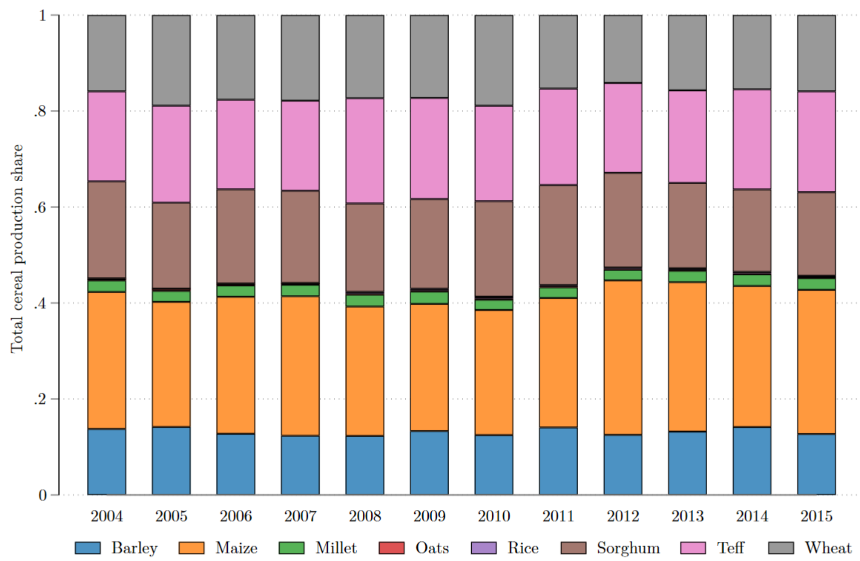
A. Production



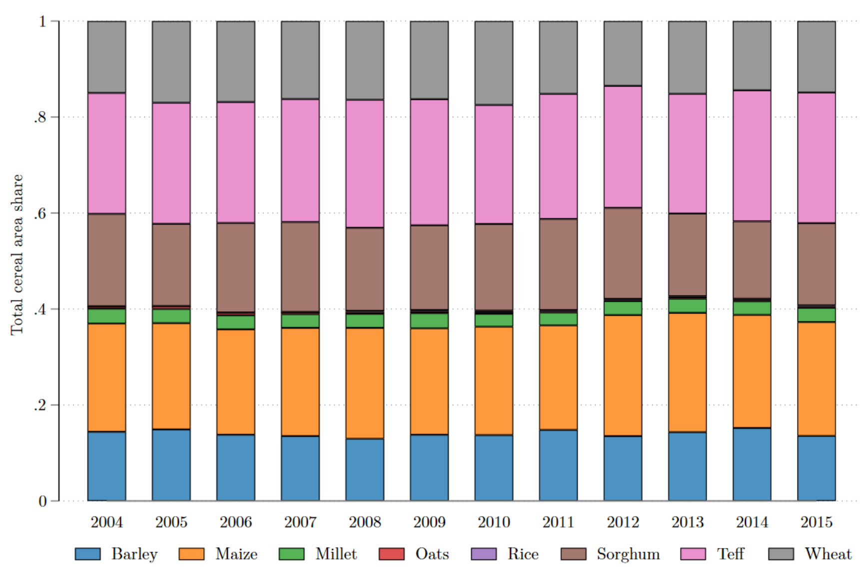
B. Land occupation

Notes. This figure shows the evolution of national representative crop production and land occupation shares between 2004 and 2015. Panel A displays crop production share in total production. Panel B displays land crop occupation share in total land under cultivation. Cereal includes barley, maize, millet, sorghum, wheat, sorghum, teff, oats, and rice. Vit. A. fvg corresponds to vitamin-A-rich fruits and vegetables and includes mango, papaya, beetroot, carrot, Ethiopian kale, pumpkins, and spinach. FVG corresponds to other fruits and vegetables, including haricot beans, grapes, lemons, mandarins, oranges, cabbages, cauliflowers, lettuces, onions, green peppers, tomatoes, green beans, and avocado. Legumes include chickpeas, white haricot beans, horse beans, lentils, peas, soybeans, linseeds, groundnuts, sunflowers, and fenugreeks. Spices include black cumin, black pepper, cardamom, cinnamon, and turmeric.

Figure B.8. Evolution in cereal production and land occupation



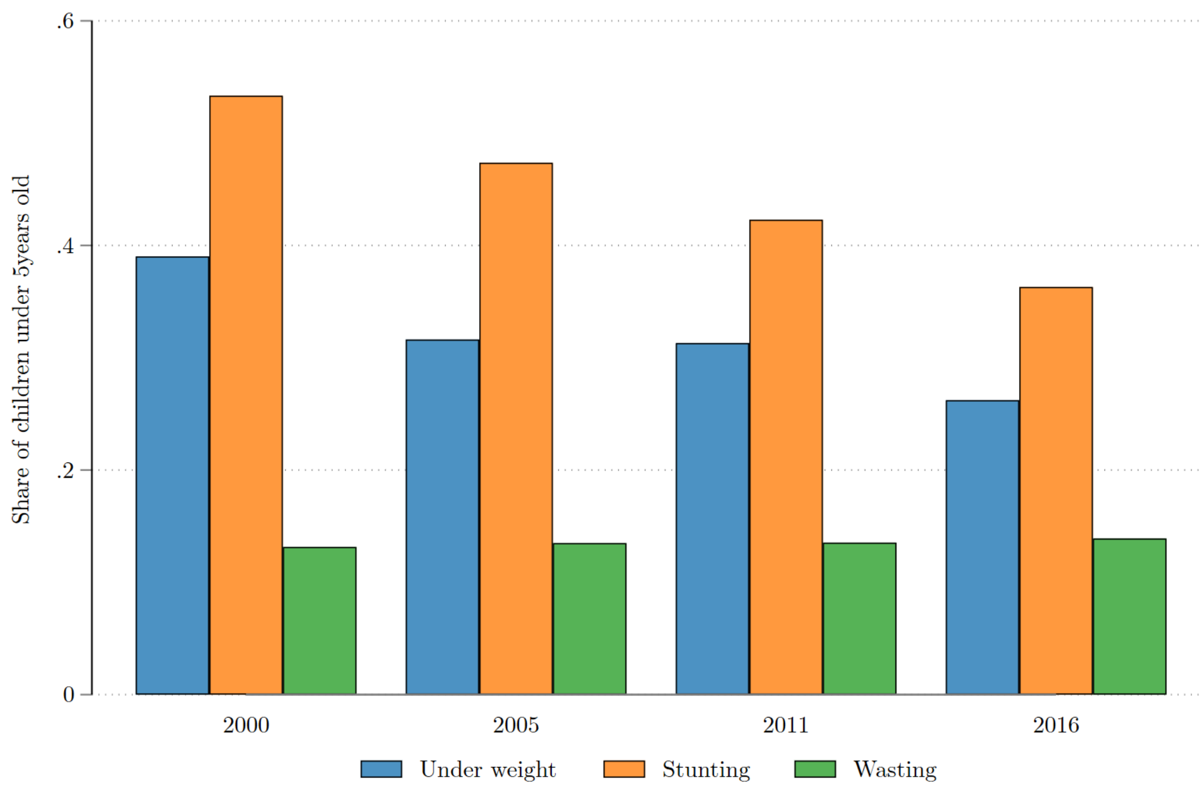
A. Production



B. Land occupation

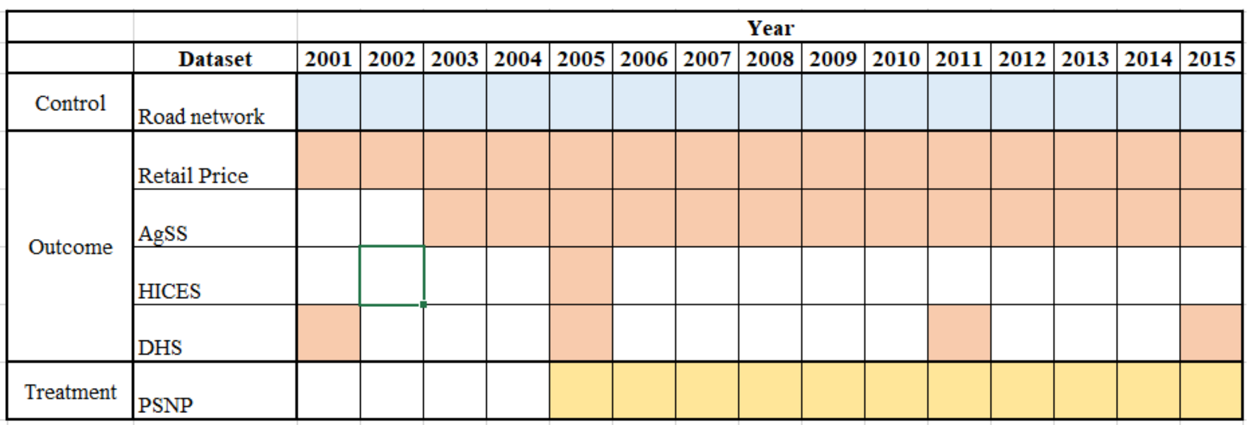
Notes. This figure shows the evolution of national representative cereal production and land occupation shares between 2004 and 2015. Panel A displays the share of cereal production in total cereal production. Panel B displays land crop occupation share in total cereal land under cultivation.

Figure B.9. Evolution in acute malnutrition status



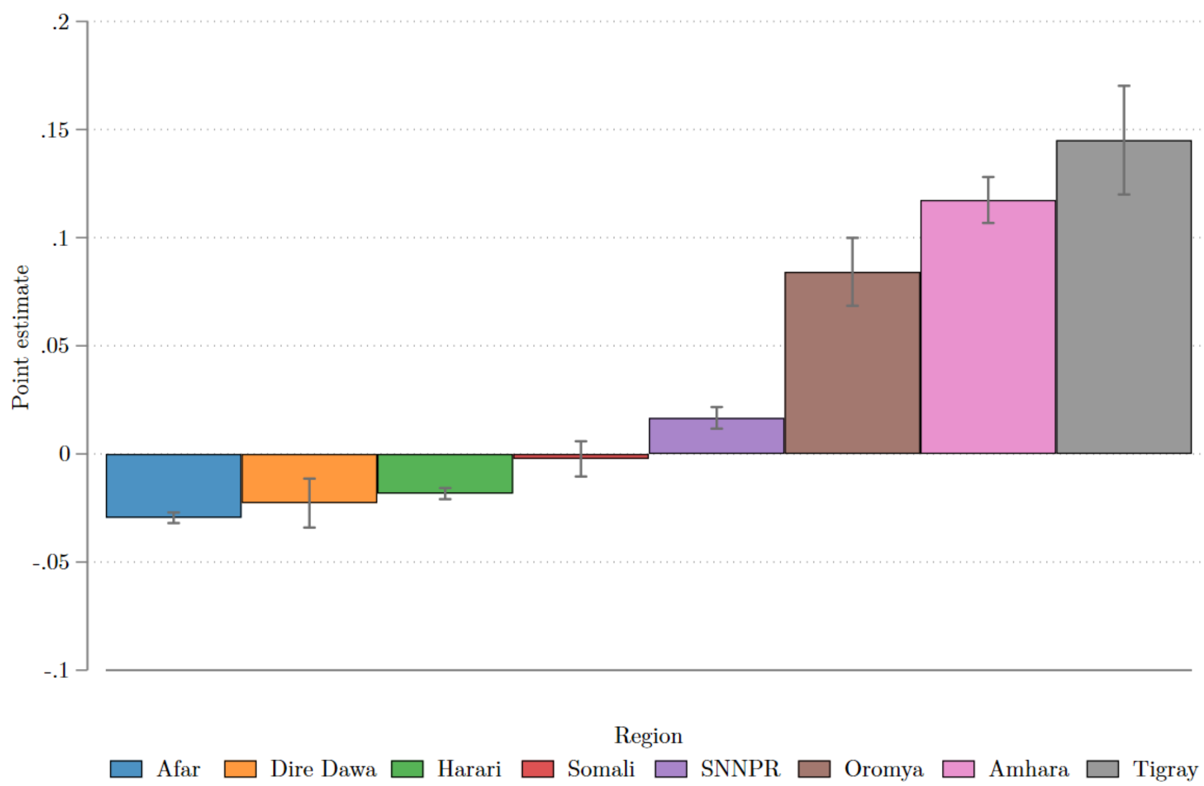
Notes. This figure shows the evolution of the proportion of children under 5 years old that are under weighted, stunted, and wasted using the Demographic and Health Survey data. An individual is under weighted when their weight for age z-score is lower than 2 standard deviations the reference median. An individual is under stunted when their height for age z-score is lower than 2 standard deviations the reference median. Lastly, an individual is wasted when their weight for height z-score is lower than 2 standard deviations the reference median.

Figure B.10. Data coverage



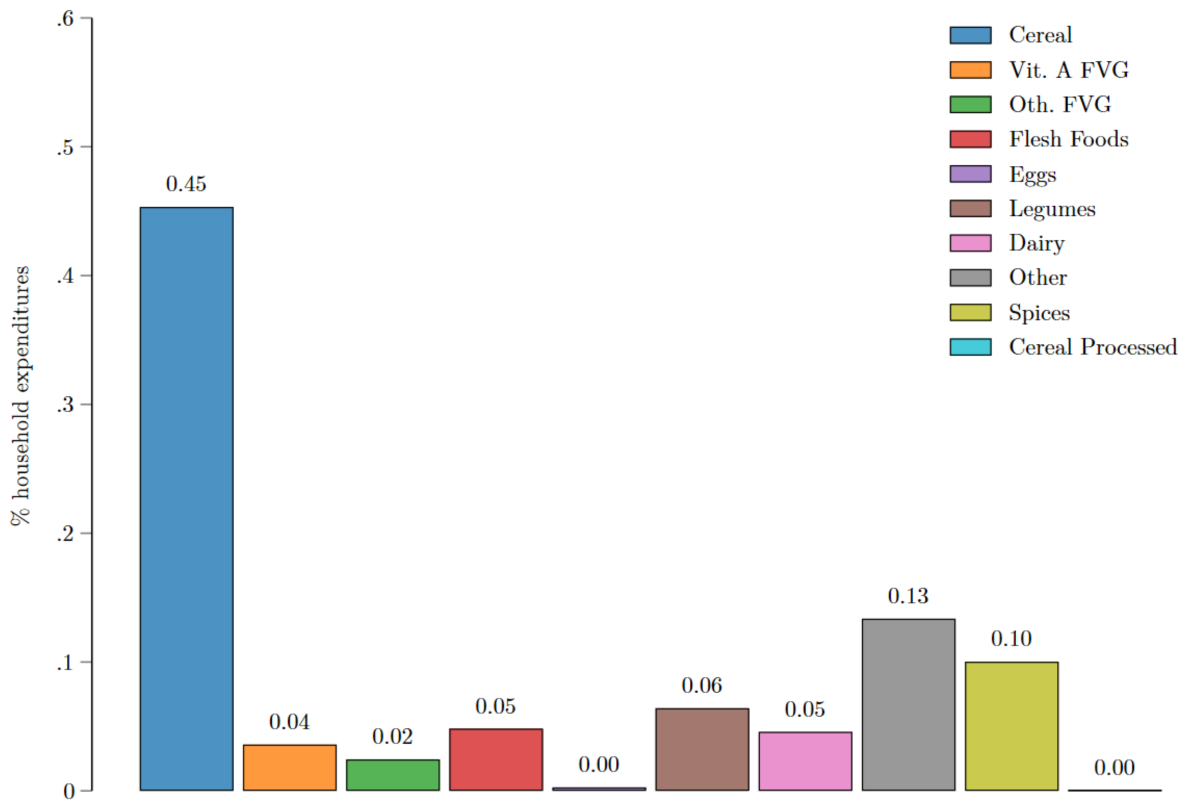
Notes. This figure shows data sources and temporal coverage. AgSS is for Agricultural Sample Survey. HICES is for Household Income, Consumption, and Expenditures Survey. Retail Price is monthly panel retail prices data. DHS is for Demographic and Health Survey. AgSS, DHS, and HICES are nationally representative repeated cross-section surveys.

Figure B.11. Average yearly effects of the Productive Safety Net Program on market prices



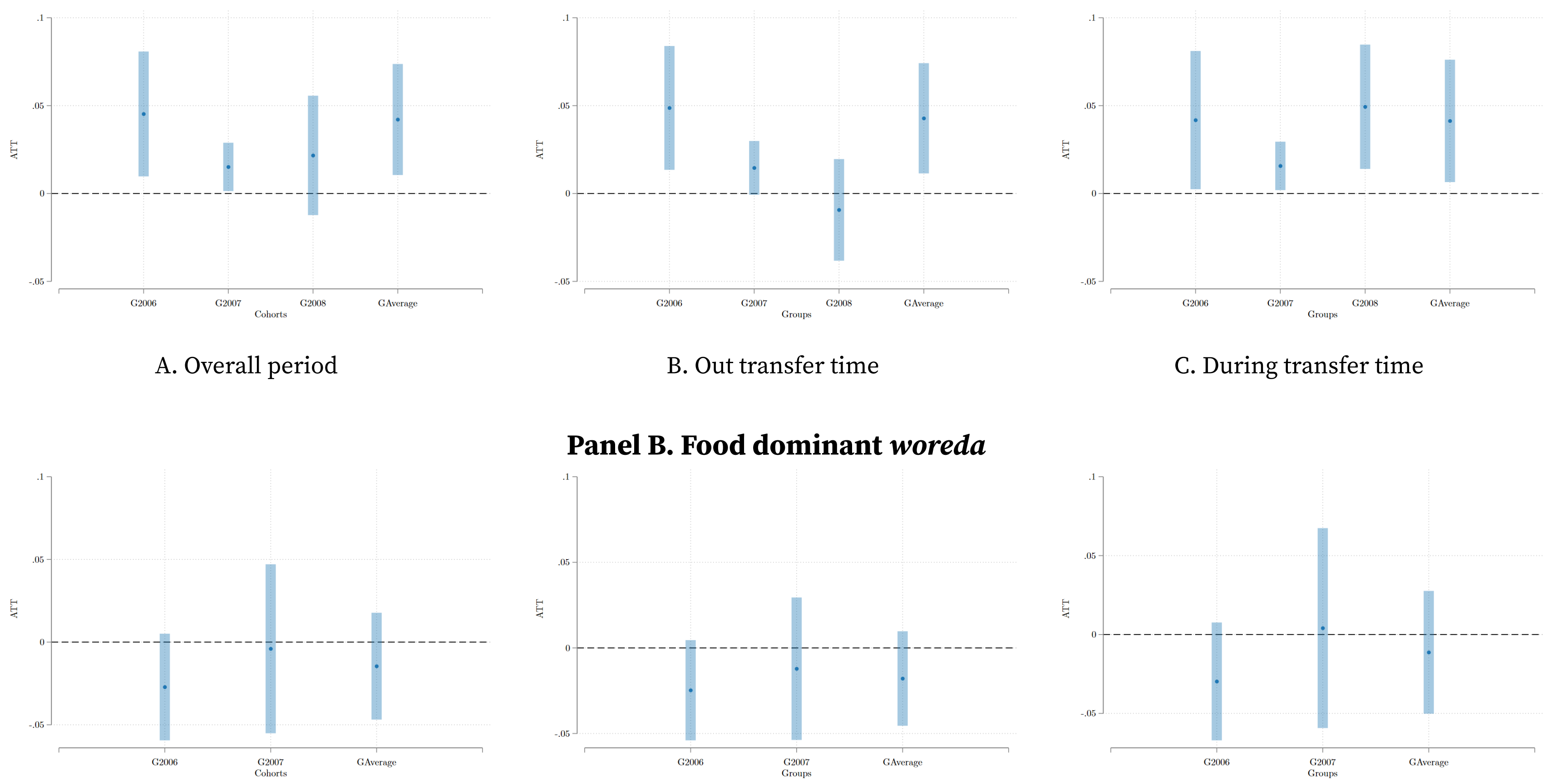
Notes. This figure shows the estimated regional average effects using equation 3 and displayed in Table 1. Each bar represents the average effects across all relative periods estimated using Borusyak et al. (2024)'s imputation estimation where the dependent variable is the (log) price index in Birr per calorie. 95% confidence intervals are also reported.

Figure B.12. Expenditure shares 2005



Notes. This figure shows national representative expenditure shares across food groups in 2005. Vit. A. fvg corresponds to vitamin-A rich fruits and vegetables, Oth. FVG corresponds to other fruits and vegetables. See table A.1 for food group composition.

Figure B.13. Average treatment effect estimates of the Productive Safety Net Program on local prices, by first year of exposure and transfers type



Panel A. Cash dominant *woredas*

A. Overall period

B. Out transfer time

C. During transfer time

Panel B. Food dominant *woreda*

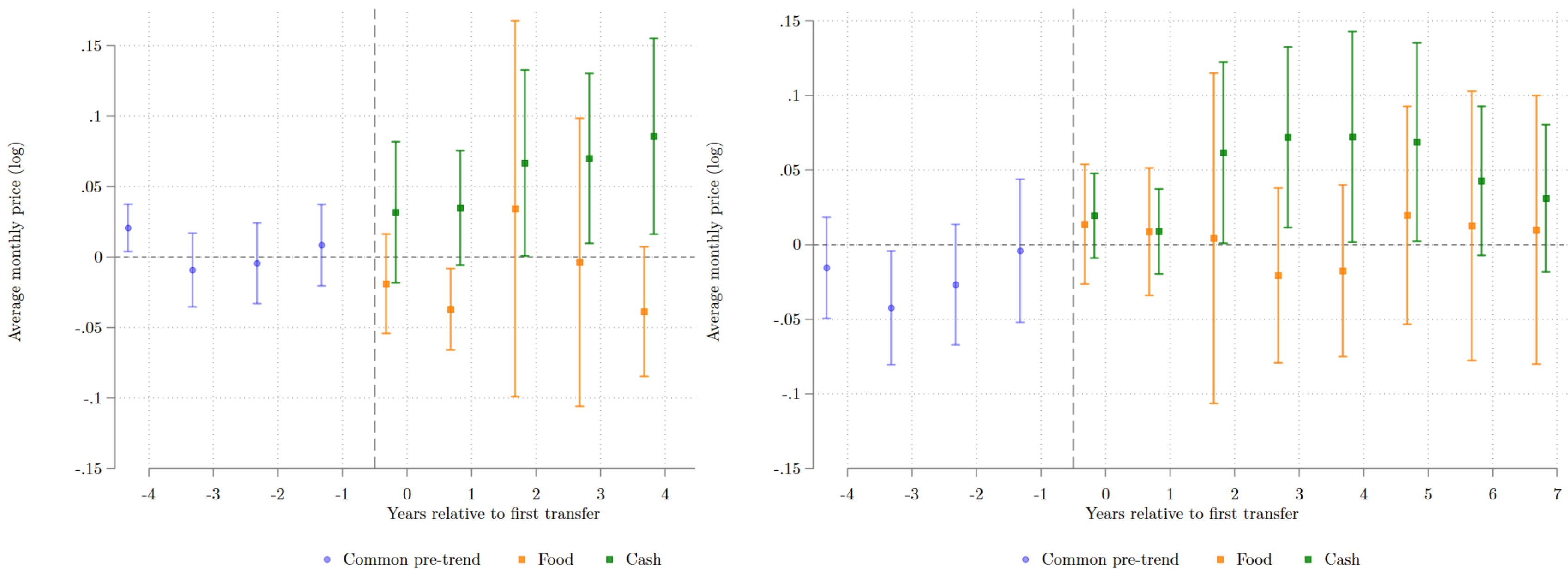
D. Overall Period

E. Out transfer time

F. During transfer time

Notes. This figure plots coefficient estimates from event study specification using Callaway and Sant'Anna (2021)'s estimator where the dependent variable is the (log) price index in Birr per calorie. It shows heterogeneity treatment effects by treated cohort. Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. The dependent variable is constructed as follows. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Coefficient estimates are presented for market-by-month cohorts with 95% confidence intervals (standard errors are clustered at the *woreda* level). Leftest graphics show coefficient estimates for the overall period. Central graphics show coefficient estimates for months when transfers are not offered (August-January). Rightest graphics show coefficient estimates for months when transfers are provided (February-July). The specification includes market, month-year, and region-year fixed effects.

Figure B.14. Event study coefficient estimates of the Productive Safety Net Program's effects on market prices, by transfer type and period

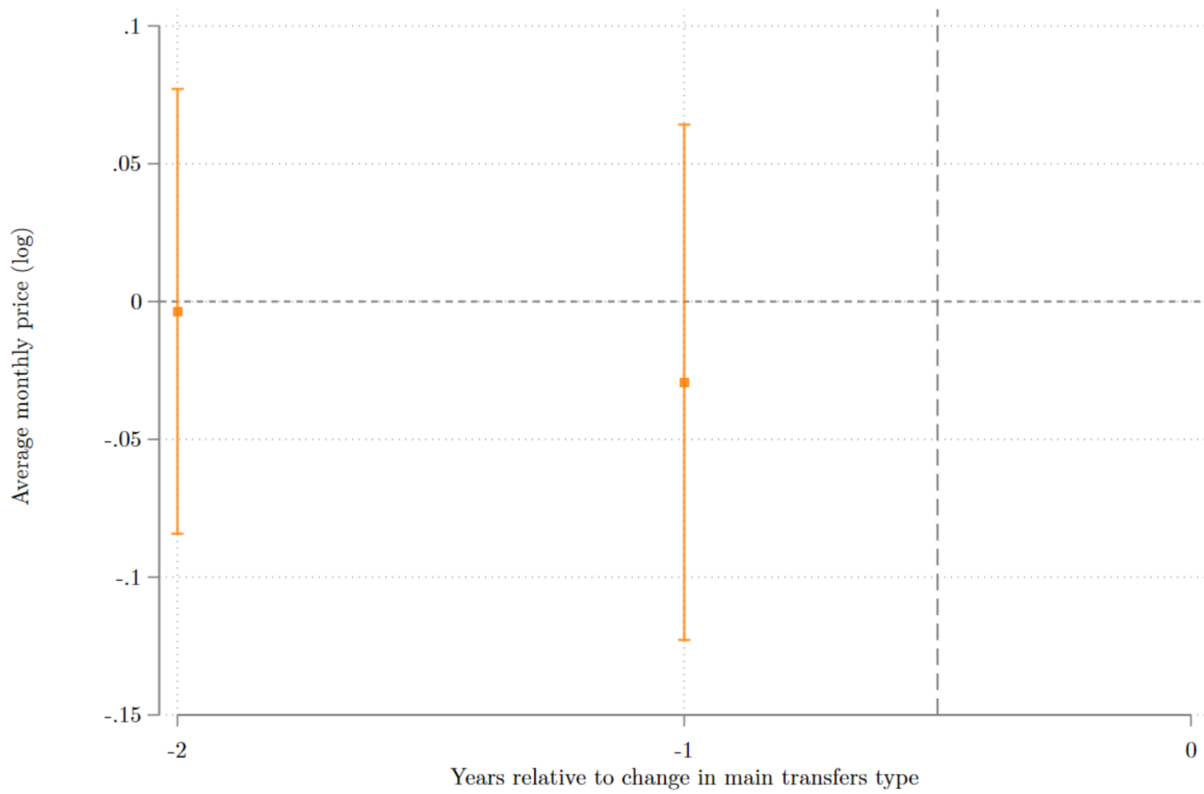


A. During transfer

B. Outside transfer

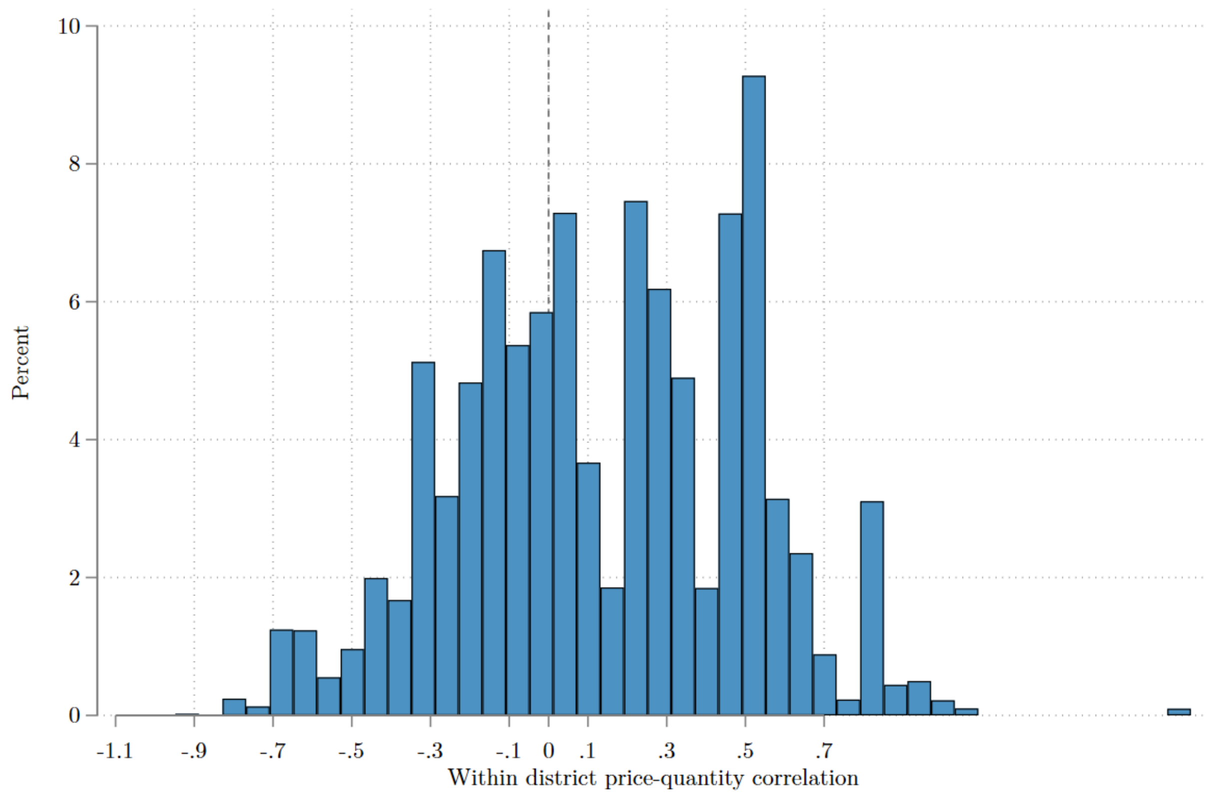
Notes. This figure plots coefficient estimates from event study specifications using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) price index in Birr per calorie. Panel A shows coefficient estimates for months when transfers are provided (February-July). Panel B shows coefficient estimates for months when transfers are not offered (August-January). It shows heterogeneity treatment effects by primary transfer type (food or cash). Food (cash) *woredas* characterize *woredas* for which food (cash) represents more than 50% of total transfer during the period exposed to PSNP. For each food group, I take the logarithm of the median price quote in a market-month, and create my market price indices as an expenditure weighted average of these median price quotes across all food groups in that market month. Coefficient estimates are presented for market-by-month cohorts with 95% confidence intervals (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes market, month-year, and region-year fixed effects.

Figure B.15. Parallel Trend estimates for transfers regime switch



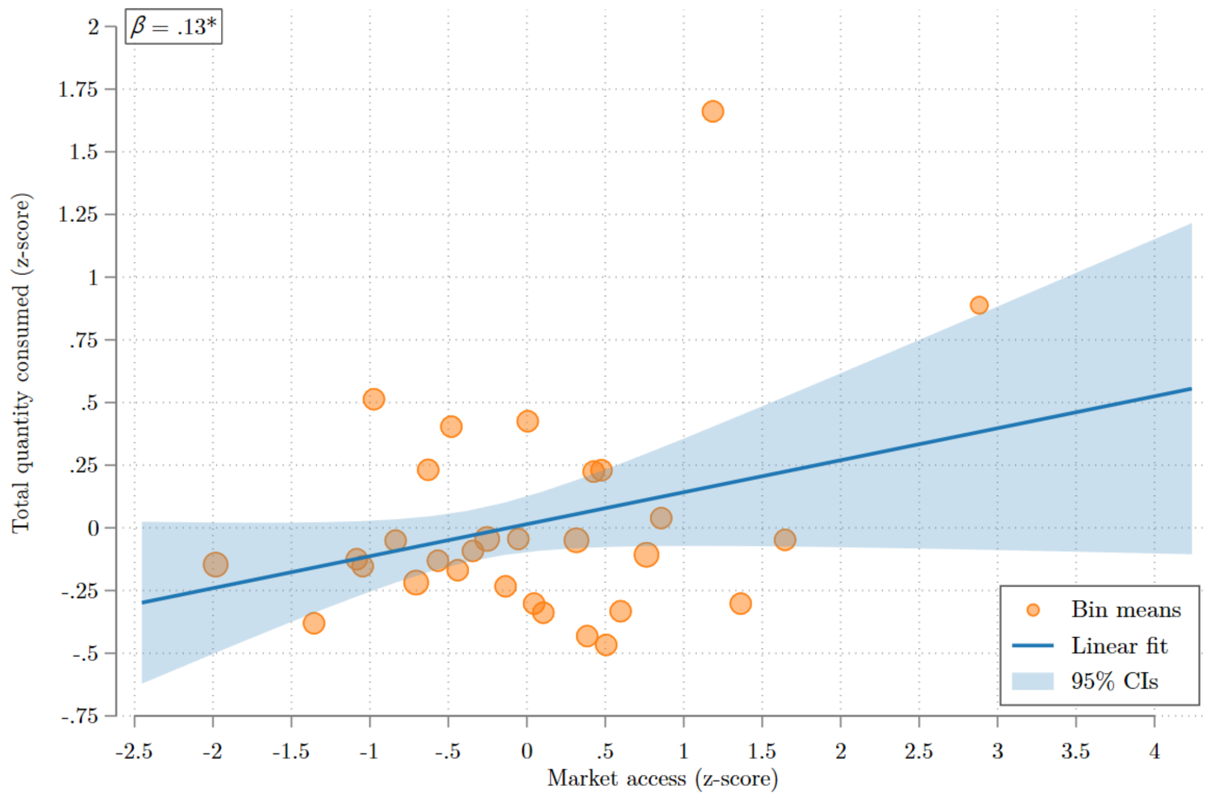
Notes. This figure plots parallel trend estimates from event study specification using Borusyak et al. (2024)'s estimator to estimate equation (4) where the dependent variable is the (log) price in Birr per calorie. The sample is restricted to treated *woredas*. For each food group, I take the logarithm of the median price quotes in a market-month, and create my market price index as an expenditure weighted average of these quotes across all food groups in that market-month. See Table 3 for the post-treatment coefficients. Coefficient estimates are presented for market-by-month cohorts with 95% confidence intervals (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the switch from a transfer-dominant regime to another. The specification includes market, month-year, and region-year fixed effects.

Figure B.16. Within *woreda* price-quantity correlation in 2005



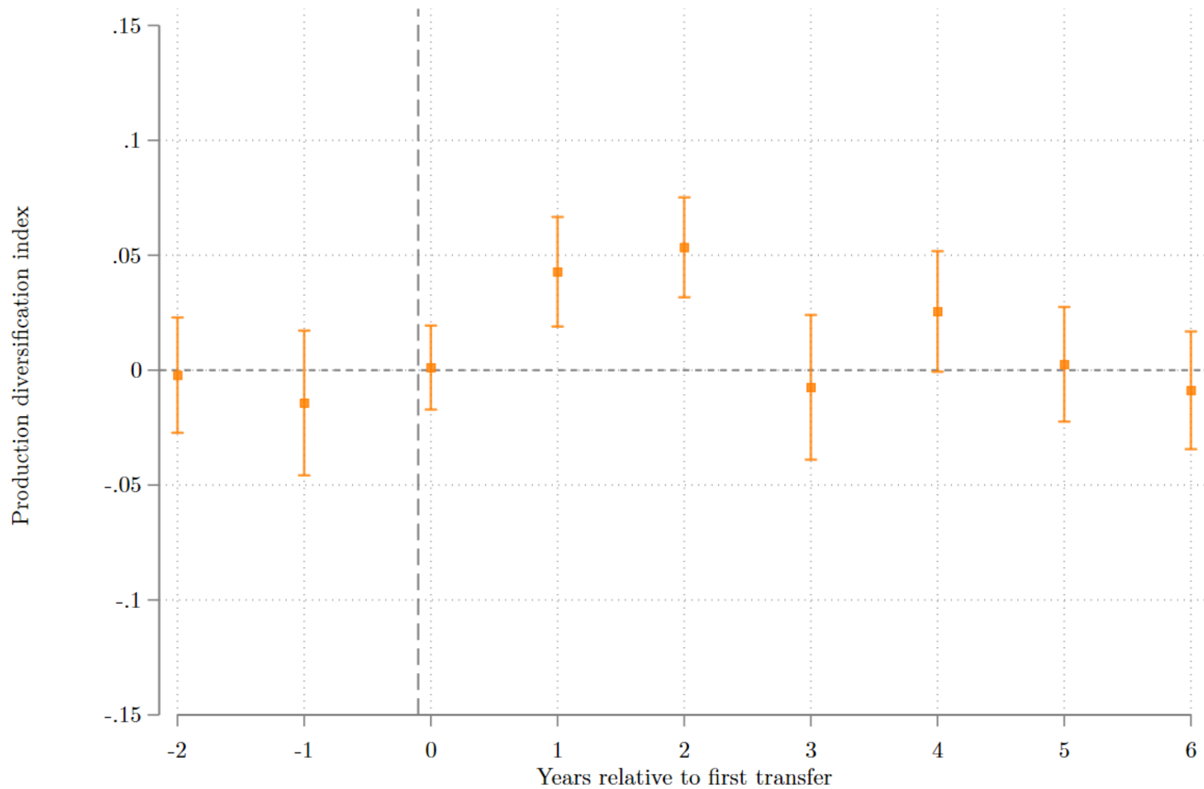
Notes. This figure shows within *woreda* price-quantity correlation in 2005 (pre-PSNP). I follow Attanasio and Pastorino (2020)'s methodology to estimate *woreda*'s market power. Using 2005 Household Income, Consumption, and Expenditures survey data, I compute within *woreda*'s correlation between prices (unit values) and quantity purchased. Then, I classify a *woreda* as having market power if the correlation coefficient is negative (i.e., on the right of the gray dashed line).

Figure B.17. Relationship between *woreda* aggregated consumption and market access in 2005



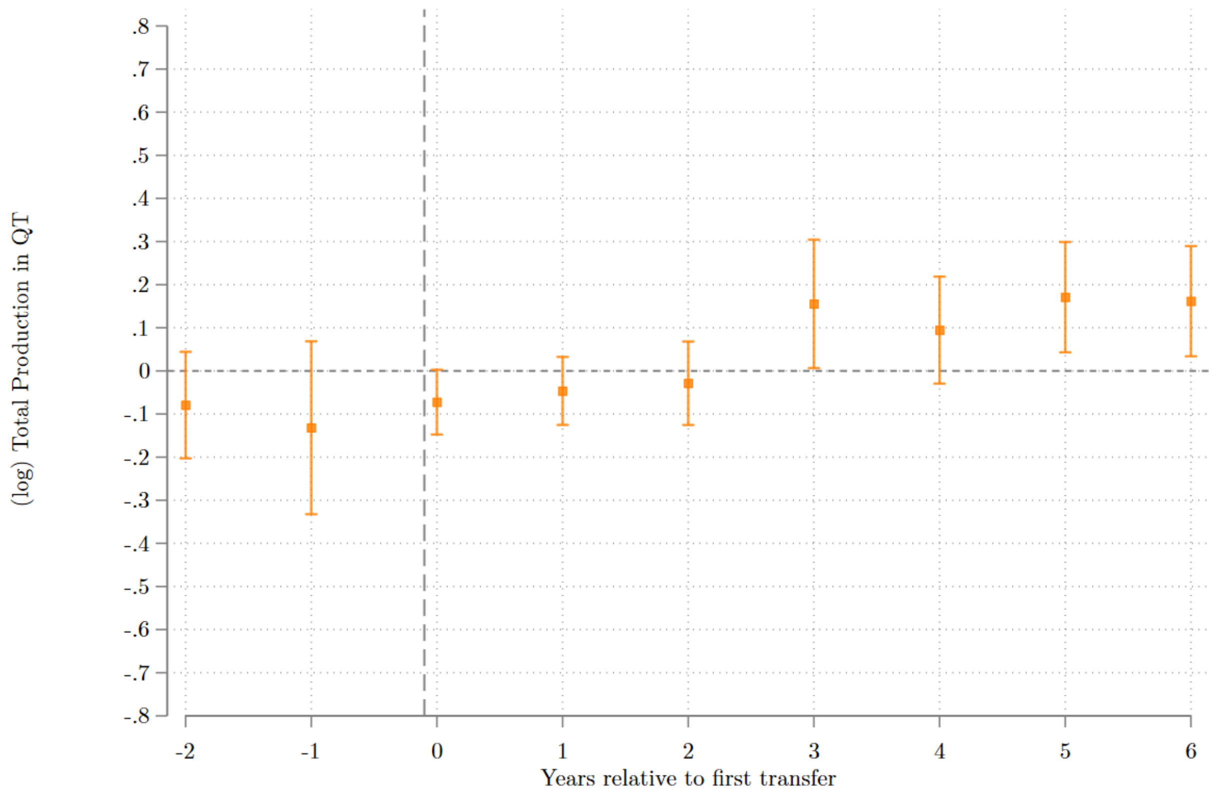
Notes. This figure shows the relationship between market access and *woreda* aggregated food consumption in 2005 (pre-PSNP). Figure shows weighted binned mean scatter plots (in orange) with a linear fit along its 95% confidence intervals (in blue) between market access and aggregated food consumption. β is the estimated coefficient from regressing market access on aggregated food consumption. All estimates include region-fixed effects. Standard errors are clustered at the *woreda* level. *** p<0.01, ** p<0.05, * p<0.1.

Figure B.18. Event study coefficient estimates of the Productive Safety Net Program's effects on production diversification index



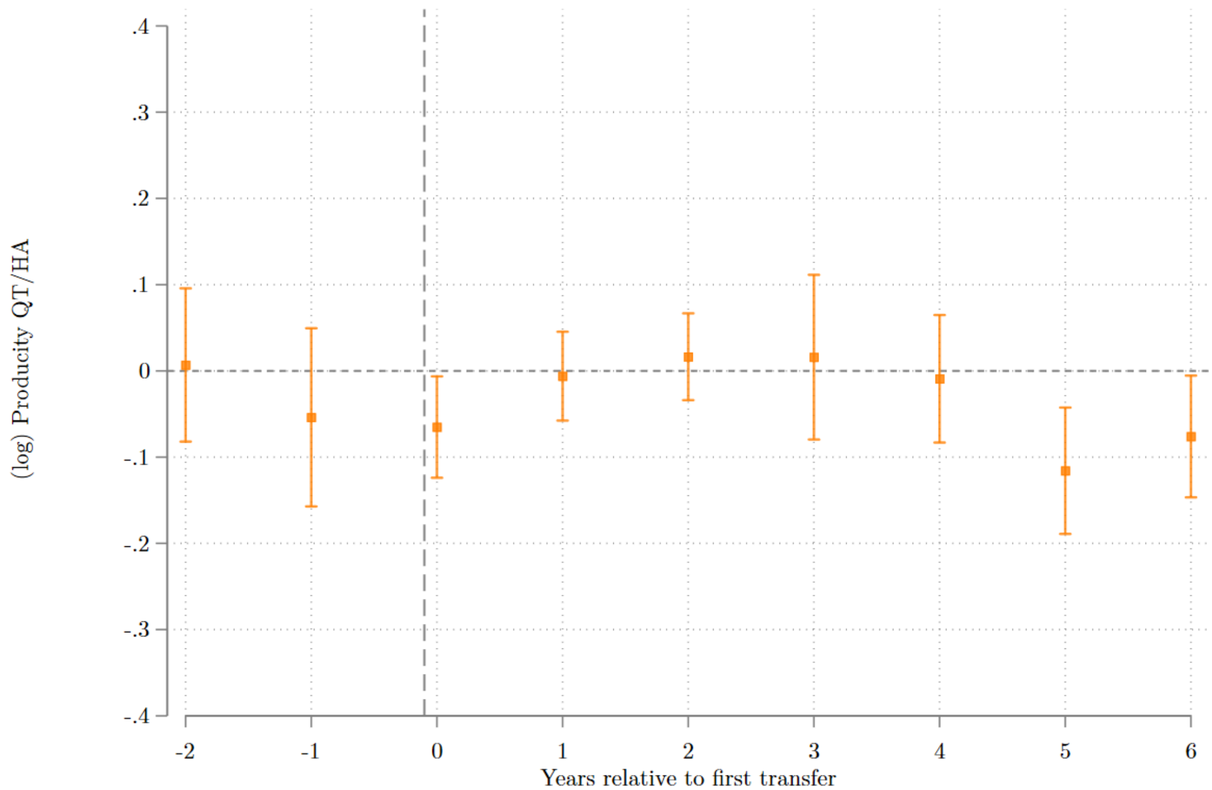
Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator, where the dependent variable is the crop production diversification index. Crop production diversity equals $D_{jt} = 1 - \sum_{k=1}^{k=K} p_{jt}^2$, in which K is the number of crops cultivated in *woreda* j at time t, and p, is the relative frequency of each crop in *woreda* annual total production. D increases in diversity, with 0 representing no diversity. Coefficient estimates are presented for *woreda*-by-year cohorts with 95% confidence interval (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes *woreda*, year, and region-year fixed effects.

Figure B.19. Event study coefficient estimates of the Productive Safety Net Program's effects on agricultural production



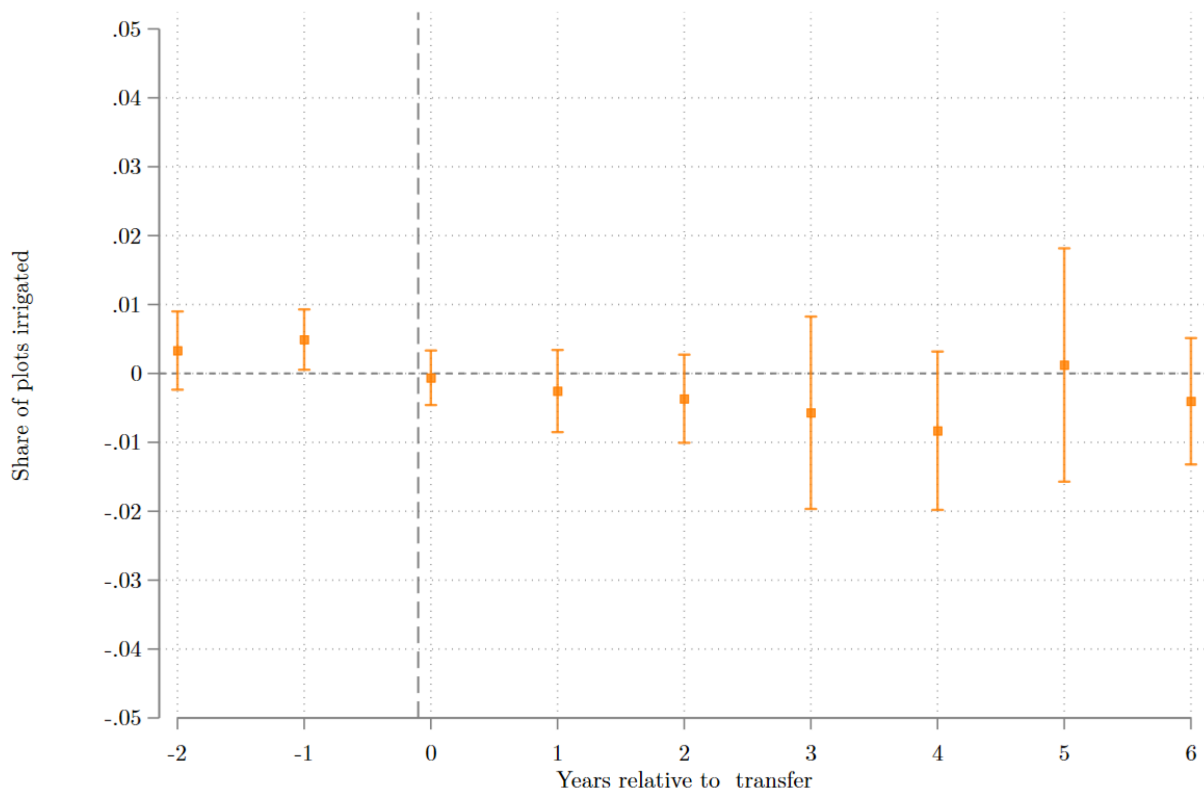
Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) of agricultural production. Coefficient estimates are presented for *woreda*-by-year cohorts with 95% confidence interval (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes *woreda*, year, and region-year fixed effects.

Figure B.20. Event study coefficient estimates of the Productive Safety Net Program's effects on agricultural productivity



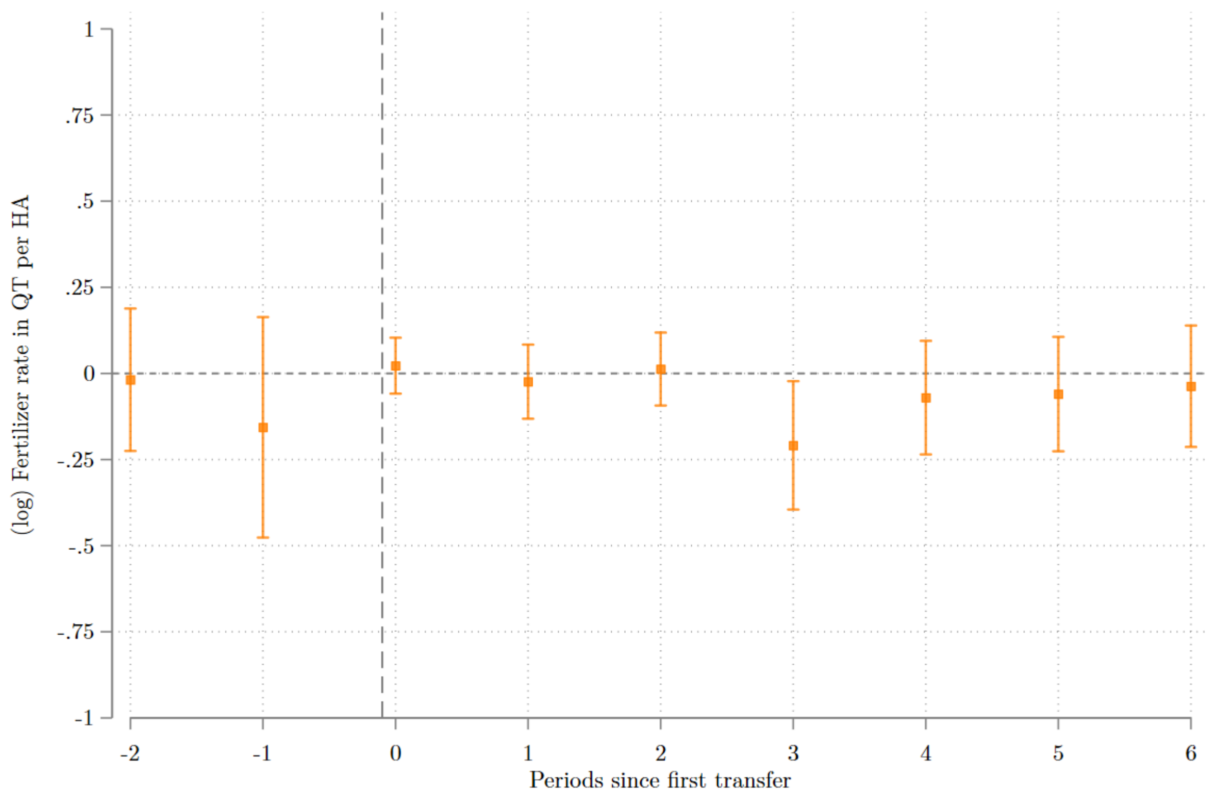
Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) of agricultural productivity. Coefficient estimates are presented for *woreda*-by-year cohorts with 95% confidence interval (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes *woreda*, year, and region-year fixed effects.

Figure B.21. Event study coefficient estimates of the Productive Safety Net Program's effects on irrigation coverage



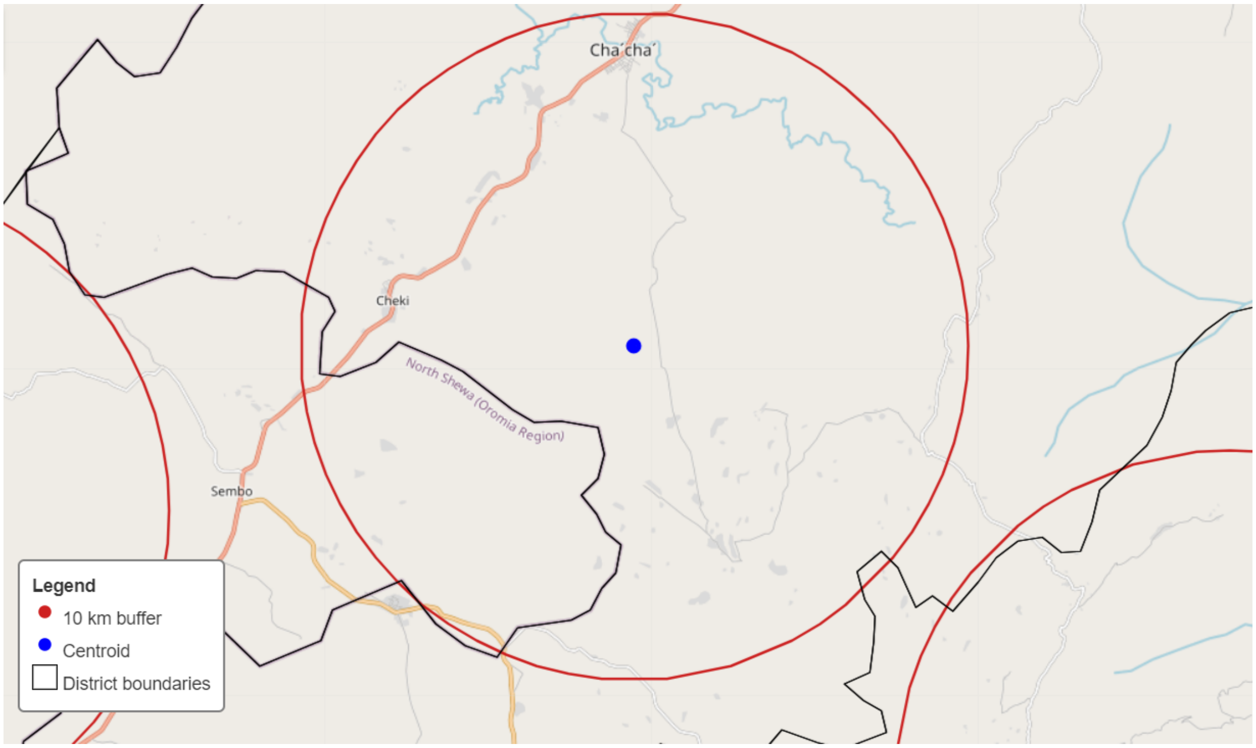
Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the share of agricultural land under irrigation. Coefficient estimates are presented for *woreda*-by-year cohorts with 95% confidence interval (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes *woreda*, year, and region-year fixed effects.

Figure B.22. Event study coefficient estimates of the Productive Safety Net Program's effects on fertilizer usage



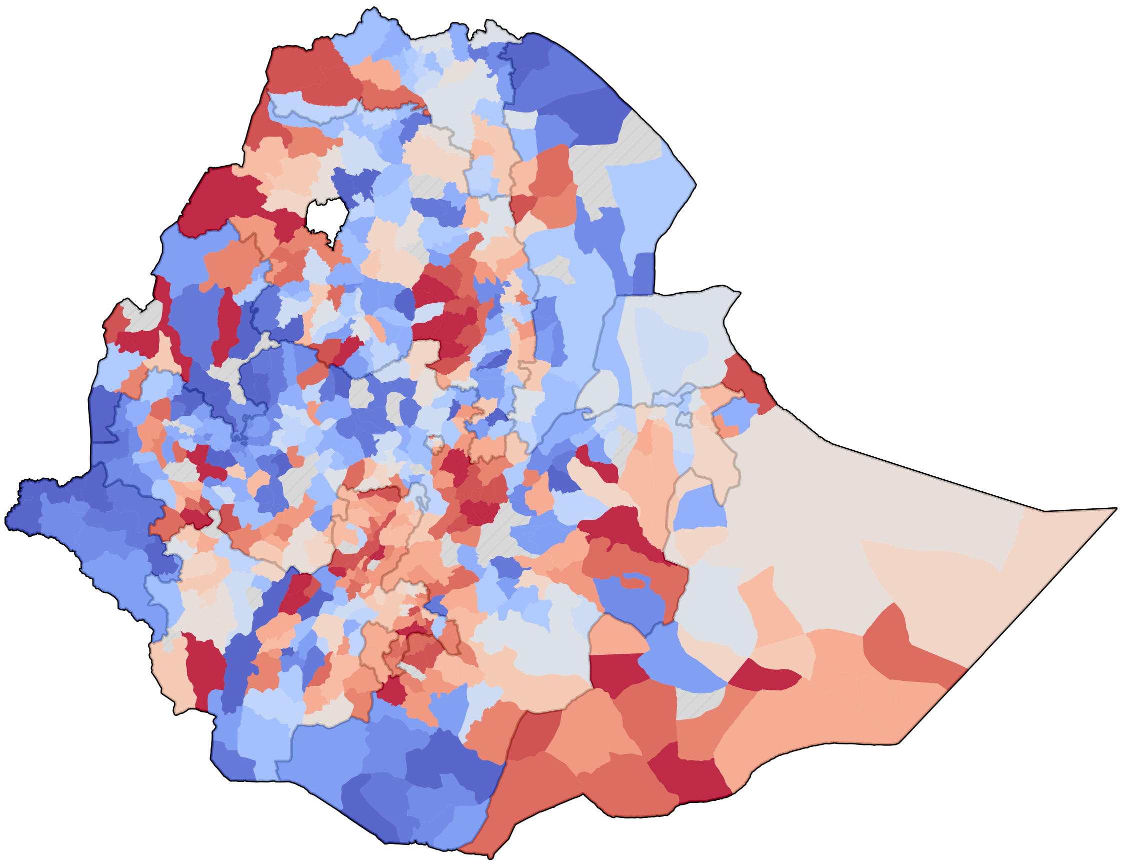
Notes. This figure plots coefficient estimates from event study specification using Borusyak et al. (2024)'s estimator where the dependent variable is the (log) fertilizer usage in quintals per hectare. Coefficient estimates are presented for *woreda*-by-year cohorts with 95% confidence interval (standard errors are clustered at the *woreda* level). The vertical dashed line indicates the first year before the inclusion in the Productive Safety Net Program. The specification includes *woreda*, year, and region-year fixed effects.

Figure B.23. Construction of a 10 km buffer



Notes. This figure shows buffer construction. The blue dot is a *woreda* centroid. The red circle corresponds to a 10km buffer around the *woreda* centroid. Black lines correspond to *woreda* boundaries.

Figure B.24. Change in market access between pre-PSNP period and 2016



Notes. This figure shows the change in market access from the pre-PSNP period (i.e., last wave was conducted in 2004). The population is fixed at its initial pre-PSNP level, and only travel time is changing using the 2016 road network. *Woredas* are grouped into vigintiles based on the change in market access, with warmer colors indicating a larger increase in market access. The changes are normalized to have a mean of zero. For the change in market access, the min is -4.52, the max is 2.23, and the standard deviation is 0.95. See Appendix C for more details.

C. Market access construction

I use a market access measure derived from general equilibrium trade models to take into account changes in market access from both direct and indirect connectivity and the density of the network to which a *woreda* gets connected (Donaldson and Hornbeck, 2016). To this end, I am using the panel road network data and the distribution of population across *woredas* in Ethiopia in 2000:

$$MA_{ot} = \sum_{d} \tau_{odt}^{-\theta} Pop2000_{d} \tag{7}$$

where $Pop2000_d$ is destination *woreda* population derived from 2000 SEDAC estimates (Ciesin, 2016). Using pre-PSNP population distribution is necessary because population distribution could respond to road infrastructure improvement. θ is the trade elasticity parameter, which equals 2.7, taken from Kebede (2024)'s estimation in rural Ethiopia. τ_{odt} is the cost of transporting one ton of cargo from origin *woreda* to destination *woreda* along the least cost path during year t. I use the following procedure to estimate each year's τ_{odt}. First, I connect each *woreda* to the existing road network. Then, I measure the average travel distance between *woredas* by calculating the distance using the road network between the geographical center (or centroid) of each pair of *woredas*. Next, I create routes from each *woreda* centroid to each nearby road in each relevant direction. I use the complete network database and apply Dijkstra's algorithm to calculate the lowest-cost route between each pair of *woredas* every two years from 2004 to 2016 (i.e., 474,721 calculations per year).

D. Predicting treatment status using machine learning

The main limitation of the DHS data I use is the lack of information regarding individual treatment status, preventing me to estimate treatment on the treated effects. Recent advances in machine learning allows potentially to alleviate this constraint and have been use to improve cash transfers and humanitarian aid targeting (Aiken et al., 2025; 2022). Using household panel survey data collected by the Ethiopia's Central Statistical Agency in localities in which the PSNP operates since 2006, I predict individual treatment status in the DHS dataset. In this panel dataset, districts (woredas) were randomly selected proportional to their size from a list of chronically food-insecure woredas stratified by region where the PSNP was operating in 2006. Within each *woreda*, enumeration areas (EAs) were randomly selected from subdistricts (*kebeles*) where the PSNP was operating. Within each EA, 15 beneficiary and 10 nonbeneficiary households were sampled resulting in 25 households per EA. This generated a sample of 146 EAs and 3,688 households followed biannually until 2014 (Hirvonen and Hoddinott, 2021).

I use a set of 18 individual characteristics, Z_i, that I can observe in both datasets (e.g., wealth index, plot size, household size) and express the treatment status as:

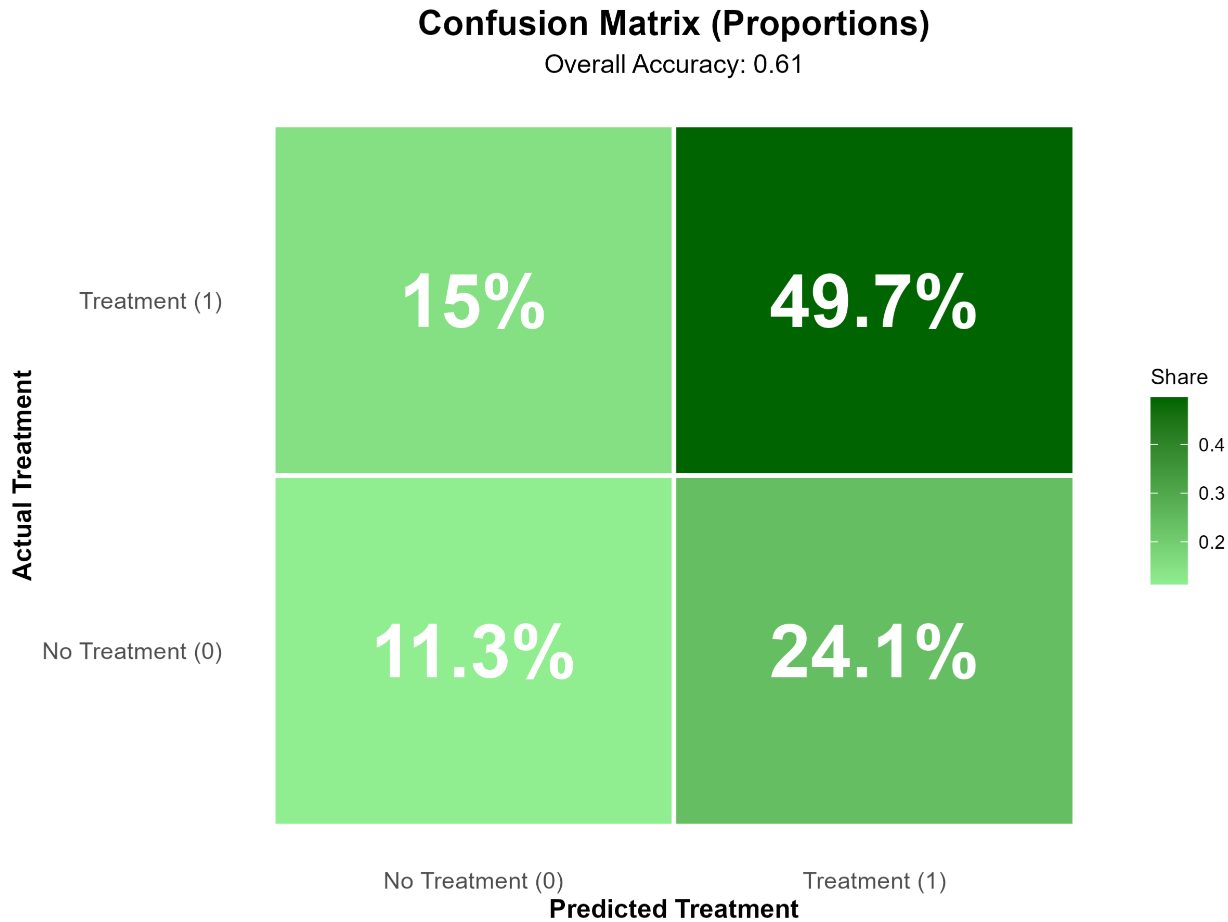
$$T_i = \beta Z_i + \epsilon_i \tag{8}$$

where ϵ_i is the treatment status component not captured by the set of predictors. I estimate β from equation (8) using the sample where individual treatment status is available, and then estimate the missing treatment status using $\hat{\beta}$ as:

$$\hat{T}_i = \hat{\beta} Z_i \tag{9}$$

I rely on eXtrem gradient boosting algorithm to perform this prediction task. The set of predictors include *kebele* and year fixed effects, wealth index (i.e., following DHS method), total land size, tropical livestock unit, total area and production of cereals (i.e., teff, maize, wheat, sorghum, barley), total farm production, and respondent age and gender. The model is trained on training sample representing 70% of the panel dataset and tested on the 30% remaining. The accuracy of the prediction on my out-of-sample fit (computed with my test sample) is 61%. Figure D.1 shows the confusion matrix and the accuracy of the predictions.

Figure D.1. Quality of the prediction of treatment status



Notes. This figure shows the confusion matrix showing the accuracy of the eXtrem gradient boosting algorithm in predicting individual treatment status. The sample is randomly selected by drawing 30% of the individual from the panel dataset for which I have individual treatment status information.