WORKING PAPER

N° 2026-7

CAUSAL IMPACT OF THE HEALTH EXTENSION PROGRAM ON CHILD IMMUNIZATION AND NUTRITION IN RURAL ETHIOPIA: EVIDENCE FROM A RETROSPECTIVE ANALYSIS

GEREMEW KASSIE, NICOLAS MOREAU

www.tepp.eu

TEPP – Theory and Evaluation of Public Policies - FR CNRS 2042

Causal impact of the Health Extension Program on child immunization and nutrition in rural Ethiopia: Evidence from a retrospective analysis

Geremew Kassie and Nicolas Moreau*

Abstract

Ethiopia launched the Health Extension Program (HEP) in 2003 to improve the health of children and women in the targeted rural states of Tigray, Amhara, Oromia, and Southern Nations, Nationalities, and Peoples' Region. Here we conduct a retrospective analysis of the HEP's causal effects on child health before the nationwide scaling-up of the program starting in 2010. We apply the doubly robust difference-in-differences estimator developed by Sant'Anna and Zhao (2020) using two waves of the Ethiopian Demographic Health Survey.
Our findings show that the HEP had a limited effect on children's vaccination uptake, as only the coverage for poliomyelitis vaccines 1 and 2 significantly improved. The program's impact on anthropometric scores proved more conclusive but masked significant disparities. Regarding vaccination uptake, the HEP's impact was more pronounced for girls and limited exclusively to children from poor families. Conversely, positive effects on anthropometric variables were primarily observed among boys and those from non-poor households.

Keywords: Vaccination uptake, Anthropometric scores, Impact evaluation, Children's health, Health program, Child development

JEL codes: I1, I3, O1, O2

* Geremew Kassie, Bahir Dar University (Geremew.Worku@bdu.edu.et). Nicolas Moreau, University of Réunion (nicolas.moreau@univ-reunion.fr).

1. **Introduction**

While Ethiopia is the second most populous country in Africa, with an estimated population of 132 million inhabitants in 2024, it remains one of the world's poorest nations, with a gross national income of $1,020 per capita. This economic context is characterized by significant barriers to healthcare access. For instance, healthcare system densities indicate a ratio of one specialized hospital per 3.5 million inhabitants, one general hospital per 1 to 1.5 million inhabitants, one primary hospital per 60,000 to 100,000 inhabitants, and one health center per 15,000 to 25,000 inhabitants. Furthermore, the surgical workforce ratios per 100,000 inhabitants for specialized, general, and primary hospitals are only 1.32, 1.15, and 7.5, respectively (Meshesha et al., 2022).

These challenges in accessing healthcare are particularly acute in rural areas. For instance, urban areas have three times more physicians and four times more nurses than rural areas (Larson and Desie, 1994; Hierink et al., 2023). Additionally, persistent and significant barriers remain in reaching vulnerable groups such as children and women (Tiruneh et al., 2024). Ethiopia is also characterized by a very high percentage of children suffering from malnutrition: approximately 36.6% suffer from stunting, 12.2% from wasting, and 25.2% are underweight (Gagabo et al., 2023).

In response to these large-scale health challenges, the Ethiopian government launched a Health Sector Development Program (HSDP) from 1997/98 to 2014/15. This initiative aimed to address chronic health issues in rural areas—with a primary focus on women and children—by improving the healthcare system, increasing the accessibility of essential care, and elevating service quality (Teshome and Hoebink, 2018). In line with this national policy, the Health Extension Program (HEP) was launched in 2003 to enhance community involvement in comprehensive healthcare in selected rural areas (Tefera, 2022; Workie and Ramana, 2023).

In this article, we propose a retrospective analysis of the HEP's effects on child health before the nationwide scaling-up of the program starting in 2010. We examine the impact of its implementation in 2003 on the evolution of child health anthropometric outcomes and vaccination uptake between 2000 and 2005.

To assess the causal effect of the program, we apply the doubly robust difference-in-differences estimator developed by Sant'Anna and Zhao (2020) using two waves of the Ethiopian Demographic Health Survey (EDHS). Sant'Anna and Zhao's (2020) estimator combines the inverse probability weighting estimator (Abadie, 2005) with the outcome regression approach (Heckman et al., 1997), thus providing a more robust inference against model misspecification.

Two studies conducted in other countries are relevant to our own. Herrera-Almanza and Rosales-Rueda (2023) employed repeated cross-sectional data from the Demographic Health Survey in a triple difference framework, concluding that a community-based health worker program in Madagascar did not significantly enhance vaccination coverage among beneficiary children in remote areas. Another study by Le and Nguyen (2020) using Demographic Health Survey data from 68 countries indicated that interventions promoting women's health care use, access to information, health knowledge, and fertility behaviors were associated with improvements in child height-for-age, weight-for-height, and weight-for-age.

Our contribution to the literature is threefold. To our knowledge, this is the first study to estimate the causal effect of the HEP on individual children's malnutrition levels and vaccination access in Ethiopia. Second, we accurately assess the program's effects by sex and family wealth. Third, we provide several robustness checks, including placebo analysis.

Our findings indicate that the HEP moderately improved vaccination uptake. A significant effect is observed only for poliomyelitis vaccines 1 and 2, which were already the most widely distributed. Nonetheless, this effect remains modest, with the probability of being vaccinated increasing by nearly 9 to 11 percentage points over the study period. The program benefited girls more than boys, as well as children from poor households. The program had a more pronounced impact on anthropometric variables, specifically the weight-for-age and weight-for-height z-scores. However, our estimates suggest that the HEP's benefits were more pronounced for boys than for girls in this regard and were limited to children from non-poor households. The weight-for-height z-score increased by 0.446 standard deviation (SD) units for children from non-poor families compared to a non-significant 0.124 SD units for those from poor families. This paper proceeds as follows. Section 2 presents the Health Extension Program and related literature. Section 3 presents the data and sample selection. Section 4 describes the empirical strategy. Sections 5 and 6 present the empirical results. Finally, section 7 concludes the paper.

2. Background

2.1 Health Extension Program

The HEP targets children, women, and economically disadvantaged groups by delivering essential preventive healthcare to promote equity and improve healthcare accessibility. Concretely, in all designated areas, two HEP workers were assigned to Ethiopia's smallest government administrative unit (called Kebele), which on average covers 33 km² and accommodates between 3,000 and 5,000 residents (Rudgard et al., 2022; Pei, et al., 2013). HEP

workers visit each family once a month, with visits usually taking between 30 and 60 min (Negussie and Girma, 2017). Seventeen health packages are designed to improve the beneficiaries' health outcomes (Admassie et al., 2009). They primarily consist of family health services, including maternity and child health, family planning, immunization, and adolescent reproductive health in addition to hygiene, environmental sanitation, disease control, and preventive strategies for HIV/AIDS, malaria, and tuberculosis. All children in treated regions are eligible for HEP. Overall, this program has trained and deployed over 45,000 HEP workers. After its implementation in 2003, HEP became a comprehensive national health program in 2009, covering all rural and urban areas in Ethiopia (Alemayehu et al., 2023; Gobezie et al., 2023).

The HEP was initially implemented in 2003 in the four rural areas of Tigray, Amhara, Oromia, and Southern Nations, Nationalities, and Peoples' Region (SNNPR) before being extended to the rural areas of Afar, Somalia, Benishangul Gumuz, and Gambella in 2007. Our treatment group consists of children living in Tigray, Amhara, Oromia, and SNNPR between 2000 and 2005. Our comparison group comprises children residing in Afar, Somalia, Benishangul Gumuz, and Gambella between 2000 and 2005.

The criteria for selecting the regional states that initially participated in the HEP include cost-effectiveness, population density, and health outcomes to ensure the equitable delivery of community healthcare services (Assebe et al., 2021). Rural areas that joined the program from 2007 onwards have a lower population density, with their villages being scattered. For instance, in Afar and Somali rural regions, the nomadic lifestyle of the communities who lack a fixed settlement made the cost of delivering the HEP expensive during the commencement period. Similarly, the selection criteria of rural (instead of urban) inhabitants aim to narrow the rural-urban gaps in children's health outcomes and access to essential health services (Gebrehiwot et al., 2015; Negussie and Girma, 2017).

2.2 Related literature

Cummins et al. (2024) and Grossman (2017) model children's health outcomes as a function of their health endowment at birth and subsequent streams of health investments. Usual proxies for health endowment at birth are related to birth weight, birth length, and other very early life health measurements. Usual determinants of health endowment at birth in the literature include maternal height, maternal weight, maternal age, and birth order (Aiyar and Cummins, 2021; Beltran-Silva, 2023; Cummins et al., 2024; Dang, 2025; Grossman, 2017; Quintana-Domeque and Ródenas-Serrano, 2017; von Grafenstein et al., 2023).

Following Cummins et al. (2024) and Grossman (2017), health investment flows can be split into three categories: private investments made by households, public investments affecting the availability of public health services, and policy interventions. Private investments are usually approximated by household wealth or assets (Cummins et al., 2024; Liu et al., 2024; Wang et al., 2024). Examples of public investments in public health services include a better clean water supply, improved sanitation, and availability of healthcare centers. All these investments have a positive impact on the health outcomes of children and infants (Adams et al., 2018; Behrman and Deolalikar, 1988; Cummins et al., 2024; Ding et al., 2025; Doyle et al., 2022; Manley et al., 2013; Spears, 2020).

In the literature, most studies document the positive impact of policy interventions on children's health outcomes. Using data from Malawi, Durevall and Isaksson (2024) find that children under 2 years living within 10 km of an active aid project had a better height-for-age z-score.[1] They were also less likely to suffer from stunting. Using other data from Malawi, Mwale et al. (2022) and Khonje et al. (2022) respectively document the positive effects of nutrition programs on children's height-for-age and weight-for-height z-scores and legume input subsidy programs on weight-for-age z-score. In Ethiopia, a study by Han et al. (2021) uses a cluster randomized control trial to randomly implement a 4-month behavior change program with food vouchers, which improved child-feeding practices and helped reduce chronic child undernutrition. Also with Ethiopian data, Tesfaye (2022) analyzes the impact of crop diversification on child nutrition and documents a positive but small effect on child growth. A similar study by Kandpal (2011) on the impact of the Indian Integrated Child Development Services finds that the program significantly reduced malnutrition. Likewise, Patwardhan (2023) analyzes the impacts of the Mamata cash transfer program implemented in India, concluding that the intervention reduced child wasting by 7 percentage points. Himaz (2008) analyzes the effect of the Sri Lankan Samurdhi Program, which aims to raise family income, and finds that the program increased children's height-for-age and weight-for-height z-scores. Using English data at the school level, Holton and Fabe (2024) document that exposure to universal free lunches reduced the prevalence of obesity and BMI among young children.

Holland and Rammohan (2019) find that empowered women in Bangladesh, via decision-making about resource access and mobility, reduced child malnutrition and increased child dietary diversity, specifically in rural areas. Similarly, Imai et al. (2014a), using data from three

[1] A height (weight)-for-age z-score is the number of standard deviations of the actual height (weight) of a child from the median of a child of the same age and sex in a reference population (see Section 3.2 for a detailed presentation). Low height (weight)-for-age z-score indicates malnutrition.

rounds of the National Family Health Survey (NFHS) in India, found that healthcare schemes, health insurance, and women's empowerment improve height-for-age, weight-for-age, and weight-for-height z-scores. Also using Indian data, Augsburg and Rodríguez-Lesmes (2018) study the effects of a sanitation-focused health package on children's health, observing that a 10 percentage point increase in sanitation usage coverage increased child height-per-age by 0.17 SD of the z-score. Finally, using data from the 2018 wave of China's Family Panel Studies and adopting a DID approach to explore the effects of the Student Nutrition Improvement Program in rural China, Fang and Zhu (2022) conclude that it significantly improved children's health outcomes in the long run, increasing the probability of reporting excellent health status by 7.2 percentage points.

Concerning childhood vaccination coverage, Hirani and Wüst (2024) find that vaccination reminders aimed at Danish families led to an increase in childhood vaccinations. Similarly, a subsidy program in Japan against infectious diseases improved vaccination rates among the beneficiaries' children (Ibuka and Bessho, 2015). De and Timilsina (2020) analyze the impact of a maternal protection scheme implemented in India, showing that it increased the probability of tuberculosis (BCG) and diphtheria, pertussis, and tetanus toxoid (DPT) vaccinations among newborns and infants. However, it did not significantly affect the measles vaccine rate. Using a DID technique in Indonesia with the Program Keluarga Harapan, Kusuma et al. (2017) show that 2 years after the intervention, the program significantly increased child vaccination rates for all basic vaccine types by up to 30 percent compared to the control group means among children under 12 months. However, the program had modest effects among children aged 12–23 months.

Some empirical studies show little to no positive effect of policy interventions on child health outcomes. For instance, Raghunathan et al. (2023) conclude that a health and nutrition intervention in India had no impact on alleviating the children's underweight and wasting issues. Likewise, de Groot et al. (2022) examine the effect of Ghana's health insurance fee exemption and cash transfer programs by applying double differences to cross-sectional data, finding no reduction in child undernutrition. Using Ethiopian data, Haji (2022) find mixed evidence of the impact of smallholder crop commercialization levels on child undernutrition. Underweight, wasting, and stunting increase with lower and higher intensities of commercialization but decrease with medium commercialization intensities. Using repeated cross-section data in a triple-difference framework, Herrera-Almanza and Rosales-Rueda (2023) conclude that a community-based health worker program in Madagascar did not significantly enhance vaccination coverage among beneficiary children living in remote areas.

Finally, Nyqvist et al. (2024) study whether assertive communication training for women can strengthen their influence over household expenditure choices to shift household spending toward child health and nutrition investments. Their results from a randomized control trial in Uganda show no impact on most child health outcomes.

3. Data

We utilize the Ethiopian Demographic and Health Survey (EDHS), a component of the Demographic and Health Surveys (DHS), which comprises 95 nationally representative household surveys conducted worldwide. The DHS questionnaire maintains consistency across survey rounds and countries, thus facilitating data comparison and analysis between countries (Panda et al., 2020; Islam et al., 2022). The surveys collect comprehensive data from children under 5 years and women aged 15 to 49. The DHS also collects data on household characteristics, family planning, maternal and child nutrition, education, and other related topics.

While the EDHS is not a panel dataset, its structure allows for the construction of repeated cross-sectional surveys. Using data collected approximately every 5 years since 2000, this study employs the pre-treatment (2000) and post-treatment (2005) waves to estimate the impact of the HEP on child immunization access and child anthropometric outcomes. As the EDHS is a repeated cross-sectional survey and our analysis focuses on children under 5 years, it is inherently impossible to resample the same individuals from baseline in the post-intervention wave.

The treatment group comprises children from the rural regions of Tigray, Amhara, Oromia, and SNNPR, while the control group includes those from rural Afar, Somalia, Benishangul-Gumuz, and Gambella. Although the treatment group is larger due to the higher population density of those regions (Headey et al., 2014), the stratified sampling of the EDHS maintains a representative proportion of inhabitants per region.

It is important to note that the EDHS does not contain a variable indicating whether each child in the treatment group actually received the treatment. Consequently, we can only measure an intention-to-treat effect.

3.1 Sample selection

The initial samples for 2000 and 2005 comprised 8,541 and 7,927 children, respectively. We first excluded visiting children and those with inconsistent or unclear residence status, thus reducing the sample to 8,432 and 7,895, respectively. Given that the HEP was implemented in

2003, we further restricted the 2005 cohort to children under 5 years who had resided in their current location for at least 2 years, resulting in 6,693 units. To maintain a comparable age distribution and residential history across periods, the same selection criteria were applied to the pre-treatment (2000) sample, yielding a sample of 7,394 units for that year.

The resulting samples comprise 14,087 observations for the immunization coverage analysis and 9,294 for the anthropometric outcomes. This discrepancy is attributable to the substantial number of missing values for height and weight measurements, as detailed below. Table 1 presents the sample distribution by year and group.

Table 1: Number of observations by year and group

	Vaccination Sample		Anthropometric Sample	
	2000	2005	2000	2005
Treatment	5,312	4,857	4,705	2,137
Control group	2,082	1,836	1,692	760
Total	7,394	6,693	6,393	2,897
	N=14,087		N=9,294	

A substantial decline in observations is evident in the 2005 anthropometric subsample, primarily due to the large number of missing values. The Ethiopian Ministry of Health provides two explanatory elements. First, this shortfall resulted from resource constraints during the 2005 EDHS wave during which enumerators had to prioritize the less time-consuming collection of immunization data over the more intensive and time-consuming measurement of child height and weight. Measuring anthropometric outcomes demands precise physical assessments with equipment like height boards and weight scales as well as trained personnel to minimize errors. This process is more time-, capital-, and labor-intensive than simply surveying vaccination uptake. Second, some social and political unrest occurred during the survey collection period. Consequently, anthropometric data are missing for over 50% of the 2005 sample.

To assess whether missing values were randomly distributed across regions and family types, we regressed a binary indicator ($miss = 1$ if height or weight is missing, 0 otherwise) on regional dummies, child sex, child age in years, and a household wealth indicator. Results are reported in Table 2. Overall, the goodness-of-fit is very low, with the coefficient of determination being nearly zero. Nevertheless, the results suggest that the probability of missing weight or height data decreases very slightly with child age, while missingness remains uncorrelated with sex and household wealth. Consequently, our results may not be perfectly representative of all children under 5 years. It also appears that missingness is related to

geographic location, as the Gambella region exhibits a significantly different rate of missing data compared to other regions. We therefore excluded children from this region from the analysis of anthropometric outcomes, leading us to exclude 514 observations from the corresponding sample and leaving 8,780 observations.

Table 2: Test of missingness at random

	Estimate	SE	*t*-stat	*p*.value
Region of residence				
Tigray	Ref.	Ref.	Ref.	Ref.
Afar	0.047	0.031	1.525	0.127
Amhara	0.035	0.024	1.445	0.149
Oromia	0.014	0.022	0.621	0.535
Somalia	0.045	0.029	1.548	0.122
Benishangul-Gumuz	-0.024	0.029	-0.825	0.409
SNNP	0.029	0.023	1.262	0.207
Gambella	0.090	0.031	2.934	0.003
Child's sex	-0.005	0.012	-0.392	0.695
Non-poor family	-0.017	0.014	-1.144	0.253
Child's age	-0.010	0.004	-2.412	0.016
Intercept	0.588	0.021	27.746	0.000
R^2=0.004				

3.2 Vaccination uptake and child health outcomes

We analyze the impact of the HEP on the uptake of essential childhood vaccinations, specifically: tuberculosis (BCG); diphtheria, pertussis, and tetanus (DPT) doses 1–3; and poliomyelitis (POL) doses 0–3. These represent the main vaccination types provided during the 2000 and 2005 EDHS survey waves. To conduct this analysis, we construct indicator variables for each vaccine type, assigned a value of 1 if administered and 0 otherwise. Following Durevall and Isaksson (2024), our main child health outcome variables are the well-known anthropometric outcome indicators defined by the World Health Organization (WHO): height-for-age z-score ($htaz$), weight-for-age z-score ($wtaz$), and weight-for-height z-score ($wthz$). For each child i in the sample, these indicators are calculated as:

$$htaz_i = \frac{height_i - height_{ref.pop_{sex_i, age_i}}}{sd\left(height_{ref.pop_{sex_i, age_i}}\right)},$$

$$wtaz_i = \frac{weight_i - weight_{ref.pop_{sex_i, age_i}}}{sd\left(weight_{ref.pop_{sex_i, age_i}}\right)},$$

$$wthz_i = \frac{weight_i - weight_{ref.pop_{sex_i, height_i}}}{sd(weight_{ref.pop_{sex_i, height_i}})},$$

where $height_i$ and $weight_i$ are child $i's$ height and weight, respectively; $height_{ref.pop_{sex_i, age_i}}$ is the median height of a child of the same age and sex as child i in the reference population; $weight_{ref.pop_{sex_i, age_i}}$ is the median weight of a child of the same age and sex as child i in the reference population; and $weight_{ref.pop_{sex_i, height_i}}$ is the median weight of a child of the same sex and height as the child i in the reference population. The variables $sd\left(height_{ref.pop_{sex_i, age_i}}\right)$, $sd\left(weight_{ref.pop_{sex_i, age_i}}\right)$, and $sd(weight_{ref.pop_{sex_i, height_i}})$ are the corresponding SD. The medians and SD in the reference population are calculated by the WHO from a representative sample of children from diverse cultures, countries, and living conditions across six countries (see Heymsfield and Stevens, 2017; De Onis et al., 2006). Like Durevall and Isaksson (2024), we use the stata function Zanthro (Vidmar et al., 2013) to calculate *htaz*, *wtaz*, and *wthz* scores. A weight-for-height z-score is the number of SDs of a child's actual weight from the median of the reference population and sex in the reference population.

Table 3 includes descriptive statistics. To compare the distributions of vaccination coverage and child health outcome variables between groups, we compute conventional *t*-statistics for equal means as well as normalized differences.[2] Unlike *t*-statistics, normalized differences are not sensitive to sample size. Regarding vaccination coverage, substantial disparities exist between the treatment and control groups, with children in the treatment group exhibiting higher vaccination rates across the two periods. The *t*-statistics are consistently high, and several normalized differences are large, thus indicating imbalances. POL 1 is the most prevalent vaccine followed by POL 2. Notably, 68.9% of children in the treatment group received the POL 1 vaccine in 2000. By contrast, this percentage was only 40.5% for the control group in 2005, representing a marked decline from 2000 levels. Conversely, POL 0 and measles

[2] Following Imbens and Rubin (2015), normalized differences are defined as $\Delta_{tc} = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{\frac{s_t^2 + s_c^2}{2}}}$, where $\bar{X}_t$ and $\bar{X}_c$ denote the sample averages of the variable in the treatment and comparison groups, respectively. Let s_t^2 and s_c^2 denote the corresponding sample variances of the variable in the two groups. Despite the lack of an established convention, the normalized difference becomes large if it exceeds 0.25 or 0.3.

vaccinations are the least frequent. Only 8.7% of children in the 2005 control group had received the POL 0 dose.

Table 3: Descriptive statistics of vaccination uptake and anthropometric outcomes

	Mean		Mean	Std		*t*-stat	p.value	Norm.
	Treated	Control	diff.	Treated	Control			diff.
Vaccination uptake (2000)								
Vaccine BCG	0.405	0.195	0.210	0.491	0.396	-17.428	0.000	0.471
Vaccine DPT1	0.401	0.183	0.218	0.49	0.387	-18.208	0.000	0.494
Vaccine DPT2	0.293	0.118	0.174	0.455	0.323	-15.983	0.000	0.442
Vaccine DPT3	0.198	0.063	0.135	0.399	0.243	-14.453	0.000	0.409
Vaccine polio 0	0.088	0.068	0.019	0.283	0.252	-2.725	0.006	0.072
Vaccine polio 1	0.689	0.597	0.092	0.463	0.491	-7.577	0.000	0.193
Vaccine polio 2	0.526	0.414	0.112	0.499	0.493	-8.688	0.000	0.225
Vaccine polio 3	0.320	0.180	0.14	0.466	0.384	-12.147	0.000	0.327
Vaccine measles	0.223	0.097	0.126	0.416	0.296	-12.636	0.000	0.349
Anthropometric outcomes (2000)								
Height-for-age z-score	-2.327	-2.104	-0.223	1.579	1.756	4.407	0.000	-0.133
Weight-for-age z-score	-1.846	-1.795	-0.051	1.217	1.339	1.317	0.188	-0.040
Weight-for-height z-score	-0.718	-0.831	0.113	1.226	1.41	-2.86	0.004	0.086
Vaccination uptake (2005)								
Vaccine BCG	0.523	0.260	0.262	0.500	0.439	-19.803	0.000	0.558
Vaccine DPT1	0.501	0.205	0.296	0.500	0.404	-22.745	0.000	0.652
Vaccine DPT2	0.401	0.143	0.258	0.490	0.350	-20.681	0.000	0.607
Vaccine DPT3	0.268	0.085	0.184	0.443	0.279	-16.546	0.000	0.496
Vaccine polio 0	0.157	0.087	0.070	0.364	0.281	-7.477	0.000	0.216
Vaccine polio 1	0.653	0.405	0.248	0.476	0.491	-18.864	0.000	0.513
Vaccine polio 2	0.551	0.314	0.237	0.497	0.464	-17.709	0.000	0.493
Vaccine polio 3	0.386	0.185	0.201	0.487	0.389	-15.854	0.000	0.456
Vaccine measles	0.273	0.116	0.157	0.445	0.320	-13.778	0.000	0.404
Anthropometric outcomes (2005)								
Height-for-age z-score	-1.991	-1.806	-0.185	1.813	2.015	2.188	0.029	-0.097
Weight-for-age z-score	-1.487	-1.611	0.123	1.313	1.465	-2.008	0.045	0.089
Weight-for-height-z-score	-0.480	-0.823	0.343	1.394	1.575	-5.242	0.000	0.231

Source: Ethiopian Demographic Health Survey. Note: authors' calculations.

Differences are less pronounced regarding anthropometric variables. Although the null hypothesis of equal means between treatment and control groups is rejected for height-for-age and weight-for-height z-scores in the pre- and post-treatment periods, the normalized

differences remain relatively small. Both height-for-age and weight-for-age z-scores improved between 2000 and 2005, with average increases observed in both groups. These z-scores are sometimes used to quantify childhood malnutrition. According to the WHO Child Growth Standards, a child is classified as undernourished if their anthropometric z-score falls by more than two SDs below the reference population median. Specifically, a child is classified as stunted if $htaz_i < -2$, wasted if $wtaz_i < -2$, and underweight if $wthz_i < -2$. Applying these thresholds, the treatment group's percentages of stunting, wasting, and underweight in the pre-treatment period were 60.06%, 43.55%, and 13.65%, respectively. By 2005, these figures declined to 52.92% for stunting and 34.44% for wasting, while underweight prevalence showed only a marginal reduction to 11.84%. A similar decreasing pattern was observed in the control group, except for underweight children, which exhibited a slight increase up to 21.06% (see Table A1 in the Appendix).[3]

4.1 Estimation method

In event studies, the identification of treatment effects generally relies on the parallel trend assumption, which states that potential outcomes for the treatment and comparison groups follow a common trend in the absence of treatment. This is a strong assumption, and researchers may prefer to assume a common trend after conditioning on covariates in the regression function. As Sant'Anna and Zhao (2020) point out, this strategy imposes additional restrictions on the data-generating process. It implicitly assumes homogeneity in the covariate treatment effects and rules out covariate-specific trends in the treatment and comparison groups (Sant'Anna and Zhao, 2020, p. 105). Recent contributions that assume a common trend conditional on covariates without imposing these additional restrictions include Borusyak and Hull (2023), Callaway and Sant'Anna (2021), Sant'Anna and Zhao (2020), and Wooldridge (2021). In this study, we apply Sant'Anna and Zhao (2020) whose estimator of the average treatment effect on the treated (ATT) is suited to repeated cross-sections with two periods. They develop a doubly robust DID estimator (DRDID) that combines Heckman et al. (1997)'s outcome regression approach with Abadie (2005)'s inverse probability weighting approach.

Sant'Anna and Zhao (2020)'s estimand for the ATT with repeated cross-sections is computed in three steps. In the first step, the propensity score, that is, the conditional probability of being

[3] The use of fixed thresholds to define malnutrition is certainly debatable, particularly for children near the threshold values. See Durevall and Isaksson (2024) and Perumal et al. (2018) for a critique of these binary variables in the context of the $htaz$ score.

treated given the set of covariates, is estimated using all observations. In the second step, four regressions with the observed outcome variable as the regressand and covariates as regressors are computed on four different subgroups. The first two regressions are weighted least squares computed on the comparison group for the pre-treatment and post-treatment periods, respectively. Weights depend on the estimated propensity score. These two regressions give the vectors of estimated parameters $\hat{\beta}_{0,pre}^{wls,rc}$ for the pre-treatment period and $\hat{\beta}_{0,post}^{wls,rc}$ for the post-treatment period, with $\hat{\beta}_{0,pre}^{wls,rc}$ and $\hat{\beta}_{0,post}^{wls,rc}$ being used to estimate the potential outcome of the units without treatment in both periods, respectively. In the third step, the estimand $\widehat{ATT}^{dr,rc}$ is calculated as a weighted average of the difference between the observed outcome and the estimated potential outcome without treatment, with the weights being based on the estimated propensity score:

$$\widehat{ATT}^{dr,rc} = \frac{1}{N}\sum_{i=1}^{N}(\hat{w}_1^{rc} - \hat{w}_0^{rc}) \cdot \left(Y_i - T_i \cdot X_i\hat{\beta}_{0,post}^{wls,rc} - (1-T_i) \cdot X_i\hat{\beta}_{0,pre}^{wls,rc}\right),$$

where T_i is a dummy variable equal to 1 if unit i belongs to the post-treatment period, Y_i is the outcome variable, and X_i is a vector of covariates. The sample size is N. Let $W_i = 1$ if unit i is treated and 0 otherwise and let $\hat{\pi}(X_i)$ denote the estimated propensity score. Then,

$$\hat{w}_1^{rc} = \frac{W_iT_i}{\frac{1}{N}\sum_{i=1}^{N} W_iT_i} - \frac{W_i(1-T_i)}{\frac{1}{N}\sum_{i=1}^{N} W_i(1-T_i)},$$

and

$$\hat{w}_0^{rc} = \frac{\hat{\pi}(X_i)(1-W_i)T_i}{1-\hat{\pi}(X_i)} \Big/ \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\pi}(X_i)(1-W_i)T_i}{1-\hat{\pi}(X_i)} - \frac{\hat{\pi}(X_i)(1-W_i)(1-T_i)}{1-\hat{\pi}(X_i)} \Big/ \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{\pi}(X_i)(1-W_i)(1-T_i)}{1-\hat{\pi}(X_i)}.$$

We refer the reader to Sant'Anna and Zhao (2020, p. 110) for a detailed presentation and discussion. To compute the estimator of Sant'Anna and Zhao (2020), we use the Stata function developed by Rios-Avila et al. (2022). As already mentioned, in this study, we will be estimating an intent-to-treat (ITT) rather than an ATT.

4.2 Choice of covariates and interaction terms

The EDHS provides information on children, women, households, parents, and area cluster-level characteristics. Following Cummins et al. (2024), we select covariates related to child health endowment, private health inputs, and public health inputs, with the additional constraint that the set of covariates X_i in Sant'Anna and Zhao (2020) must contain only time-invariant variables. Child health endowment variables include a dummy variable equal to 1 if the mother's age at first marriage is at least 15 years, and a dummy variable equal to 1 if the mother's age at first birth is at least 18 years. Private investment variables include a dummy variable equal to 1 if the mother attended at least 1 year of schooling, and a dummy variable

equal to 1 if the father also attended at least 1 year of schooling. Note that for all mothers in our sample, first marriage and first birth occurred before the implementation of the HEP. Public health variables include a dummy variable equal to 1 if the household has access to clean water, and another dummy variable equal to 1 if the household has access to a health card, which is unrelated to the HEP. Since there was no significant expansion of water infrastructure or policy changes during the study period from 2000 to 2005, these variables remained constant because of the time frame and are thus considered time-invariant. Therefore, we control these factors that do not change over time but may affect child health outcomes.

We also include other relevant variables that do not fall within a specific category. We incorporate variables like child sex (Hull and Yan, 2024; Herrera-Almanza and Rosales-Rueda, 2023; Afridi, 2010) and the sex of the household head (Han et al., 2021; Afridi, 2010), because in developing countries, the latter may play a significant role in decision-making such as controlling resources and accessing health services.

To better fit the data and enrich the specification of the propensity score used to calculate individual weights, Sections 5 and 6 present results including selected interaction terms between covariates. These terms were chosen following the stepwise procedure outlined in Imbens (2015, p. 414).

Table 4 presents descriptive statistics for the covariates.[4] The proportion of boys and girls remains balanced and close to 0.5 for each group and year. The proportion of mothers who attended school for at least 1 year is very low in rural areas, particularly for those in the control group, resulting in differences that are significantly different from zero between groups. While the proportion of fathers with at least 1 year of schooling is higher, it remains low, being 0.389 for the treatment group and 0.225 for the control group in 2005. These differences are significant, as fathers in the control group are notably less educated regardless of the year considered. More than half of mothers had their first child before the age of 18, and slightly more than half were married after the age of 15. No significant difference in age at marriage is found between treatment and control groups. Further, the proportion of children living in a family holding a health card differs between groups. In 2005, only 28% of children in the control group lived in a household with a health card versus 51.4% in the treatment group. Finally, high normalized differences are observed for the following covariates: father's education level and living in a family with a health card. Imbens (2015) and Imbens and Rubin (2015) suggest that when including covariates that lead to normalized differences exceeding

[4] Table A2 in the Appendix presents corresponding descriptive statistics for the sub-sample used for the anthropometric analysis and shows similar patterns.

0.25 or 0.3, it is preferable to use alternatives to linear regression methods, as implemented by Sant'Anna and Zhao (2020).

Table 4: Sociodemographic variables – whole sample

	Mean		Mean	Std		*t*-stat	p.value	Norm.
	Treated	Control	diff.	Treated	Control			diff.
Year 2000								
Child's sex	0.515	0.497	0.018	0.500	0.500	-1.359	0.174	0.035
Mother educ	0.123	0.097	0.027	0.329	0.295	-3.237	0.001	0.086
Mother's age 1st birth	0.452	0.495	-0.043	0.498	0.500	3.344	0.001	-0.086
Mother's age marriage	0.479	0.500	-0.021	0.500	0.500	1.603	0.109	-0.041
Father educ	0.300	0.229	0.071	0.458	0.420	-6.158	0.000	0.162
Head sex	0.872	0.875	-0.003	0.334	0.331	0.342	0.732	-0.009
Clean water	0.142	0.172	-0.030	0.349	0.377	3.249	0.001	-0.083
Health card	0.388	0.218	0.170	0.487	0.413	-14.082	0.000	0.377
Year 2005								
Child's sex	0.509	0.509	0.000	0.500	0.500	-0.003	0.998	0.000
Mother educ	0.177	0.120	0.056	0.382	0.325	-5.617	0.000	0.159
Mother's age 1st birth	0.436	0.416	0.020	0.496	0.493	-1.440	0.150	0.040
Mother's age marriage	0.469	0.489	-0.02	0.499	0.500	1.444	0.149	-0.040
Father educ	0.389	0.225	0.164	0.488	0.418	-12.781	0.000	0.362
Head sex	0.905	0.853	0.052	0.293	0.354	-6.118	0.000	0.160
Clean water	0.125	0.117	0.008	0.330	0.321	-0.892	0.373	0.025
Health card	0.514	0.280	0.234	0.500	0.449	-17.585	0.000	0.493

Source: Ethiopian Demographic Health Survey. Notes: authors' calculations.

4.3 Mobility of households between treated and comparison groups

As Abadie (2005, p. 9) points out, "The use of repeated cross sections for DID presents some data availability issues. First, treatment status (in the post-treatment period) must be known for the individuals in the pre-treatment sample." In our data, treatment status is known for every unit in the post-treatment sample as we selected households living in the same place for at least 2 years. They have thus remained in the treatment or control groups since HEP was implemented. However, some households in the pre-treatment period could have moved and lived in another region 5 years later. It is impossible to identify the corresponding households with the available data, although we can still quantify the extent of the phenomenon. In Ethiopia, relocations between rural regions happen to be negligible (Hailemariam et al., 2011;

Schewel, 2019), whereas rural-urban migration is significant for young male adults but not for children and their families (Hailemariam and Adugna, 2011; Eshetu and Beshir, 2017). According to the EDHS data, rural-to-rural migration between treated and control areas in 2000, 2005, 2011, and 2016, was 3.1%, 2.4%, 2.28%, and 2.41%, respectively. Furthermore, if we incorporate the rural and urban areas into the EDHS sample in general, those who moved in the years 2000 and 2005, for instance, only represent 4.3% and 2.7% of all children and their parents, respectively. These results indicate that the proportion of migrants between treated and control groups remains marginal. These patterns indicate that our study data from EDHS is not significantly affected by migration.

Although treatment status in the post-treatment period is not known for households in the pre-treatment sample, we can assume with reasonable confidence that for almost all of them, their treatment status in the post-treatment period is that of the assigned group in the pre-treatment period.

4.4 Common support

Sant'Anna and Zhao (2020) postulate a variant of the traditional common support hypothesis by assuming that at least a small fraction of the population is treated and that, for every value of the covariates, there is at least a small probability that the unit is not treated. The first condition is obviously met in our data. One way to ensure that the second condition is met is to drop from the sample observations with an estimated probability of being treated too close to one. Instead of using an ad hoc threshold, we apply the algorithm outlined in Imbens (2015, p. 394) to determine an optimal cut-off value using the available data and find no need to trim the data.

4.5 Interactions between units

Estimation methods of treatment effects such as that of Sant'Anna and Zhao (2020) rely on the stable unit treatment value assumption (SUTVA), which assumes that there will be no spillover or general equilibrium effects for two distinct units. The outcome of one unit does not depend on the treatment status of the other units (Roth et al., 2023). However, with the HEP, there may be interference between children within the same household. Therefore, in addition to the child-level, we also estimate the causal effect of the HEP at the household level, as there are on average 1.56 children under 5 years per household. We then estimate the impact of the HEP on household averages for both child vaccination uptake and anthropometric outcomes.

4.6 Placebo Analysis

Following Bertrand et al. (2004) and Abadie et al. (2010, 2015), we evaluate the robustness of our results using placebo analysis. This method involves comparing the *t*-statistics for the treatment effects estimated from the real treatment and control groups with the pseudo *t*-statistics from placebo effects (or pseudo effects) based on the assumption that half of the control group participated in the program. These units in the control group thus constitute the pseudo-treatment group. We repeat the analysis for 199,999 possible pseudo-treatment groups created from the initial control group to obtain an accurate approximation of the distribution of the pseudo *t*-statistics under the null hypothesis of no effect. With the robustness analysis of our results, we situate the *t*-statistics calculated from the real treatment and control groups in the distribution of the pseudo *t*-statistics. If the calculated *t*-statistic value is extreme with regard to the distribution of the pseudo *t*-statistic, we may conclude that it is probably due to the program instead of coincidence.

5. Impact of the HEP on vaccination uptake

5.1 Main results

Tables 5 and 6 present the results at the child and family levels, respectively. Each table includes the results with and without the interaction terms. We control for multiple hypothesis testing across the nine vaccination uptakes using Anderson (2008)'s approach. This is based on Benjamini, Krieger, and Yekutieli (2006)'s two-stage procedure to control for the false discovery rate. Our analysis in this section is thus based on adjusted *p*-values, also called *q*-values, defined as the smallest level at which the null hypotheses of no effect would be rejected (Anderson, 2008).[5]

Table 5 shows that estimations performed with and without the interaction terms produce similar results. The HEP significantly increased the probability of being vaccinated only for POL 1 and 2. The probability of receiving these two vaccines increased by approximately 10 and 9 percentage points, respectively. Note that the adjusted *p*-values for these two vaccines increase sharply in comparison with the standard *p*-values. This is due to the large *p*-values for most other vaccines. Still, the adjusted *p*-values for vaccines POL 1 and 2 are small enough to reject the null hypothesis of no effect at conventional levels. For the other vaccines, the estimated ITT is of small magnitude.

[5] For comparison purposes, standard *p*-values are also reported.

Table 5: Effects of HEP on vaccination uptake – Estimations at the child level

	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.032	0.033	0.983	0.325	0.387	0.024	0.033	0.714	0.475	0.642
DPT 1	0.036	0.035	1.032	0.302	0.387	0.029	0.035	0.834	0.404	0.642
DPT 2	0.033	0.031	1.051	0.293	0.387	0.028	0.031	0.904	0.366	0.642
DPT 3	0.019	0.024	0.784	0.433	0.481	0.016	0.024	0.648	0.517	0.642
POL 0	0.045	0.026	1.760	0.078	0.225	0.038	0.025	1.513	0.130	0.437
POL 1	0.104	0.037	2.844	0.004	0.042	0.105	0.036	2.893	0.004	0.036
POL 2	0.087	0.036	2.416	0.016	0.067	0.094	0.036	2.600	0.009	0.039
POL 3	0.039	0.031	1.253	0.210	0.387	0.042	0.031	1.335	0.182	0.467
Measle	0.013	0.028	0.456	0.648	0.720	0.015	0.028	0.527	0.599	0.664

Notes: Number of observations: 14,087. Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

Estimations at the household level give similar results (Table 6). For POL 1 and 2, the hypothesis of no effect of the HEP is rejected at the 5 percent level. The program had no significant effect on other vaccines, with the corresponding estimated ITT being small.

Table 6: Effects of HEP on vaccination uptake – Estimations at the family level

	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.022	0.032	0.693	0.488	0.720	0.012	0.032	0.366	0.715	1
DPT 1	0.039	0.034	1.149	0.251	0.461	0.025	0.034	0.733	0.464	0.865
DPT 2	0.030	0.030	0.989	0.323	0.477	0.023	0.030	0.759	0.448	0.865
DPT 3	0.003	0.025	0.136	0.892	0.898	-0.002	0.025	-0.080	0.936	1
POL 0	0.049	0.025	1.984	0.047	0.125	0.041	0.025	1.670	0.095	0.285
POL 1	0.110	0.036	3.092	0.002	0.019	0.107	0.036	2.967	0.003	0.028
POL 2	0.090	0.036	2.524	0.012	0.049	0.092	0.036	2.56	0.010	0.044
POL 3	0.036	0.032	1.120	0.263	0.461	0.038	0.032	1.169	0.242	0.572
Measle	0.008	0.030	0.260	0.795	0.898	0.005	0.030	0.165	0.869	1

Notes : Number of observations 9,006. Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

Overall, for the period under study, the program had only an impact on POL 1 and 2, which were already the most widely used vaccines before the program started. In 2000, 66.28% of children had received POL 1 and 49.43% POL 2. By comparison, only 8.2% had received POL 0 and 34.6% BCG vaccine. The mixed effects of the HEP on vaccination uptake are somewhat

consistent with the effects reported in the literature for other programs, ranging from no effect to strong positive effects. Herrera-Almanza and Rosales-Rueda (2023) find that the community-based health programs implemented in Madagascar had no impact on the vaccination uptake in treated areas. Kusuma et al. (2017), on the contrary, document a positive and significant effect of the Keluarga Harapan program in Indonesia for all basic vaccine types, up to 30% compared to the control group means for children aged under 12 months. O'Neill et al. (2024) find that a maternal education program implemented in Uttar Pradesh, India, increased 30 months later the uptake of DPT and measles vaccines by 15.2 and 22.2 percentage points, respectively.

One possible explanation why the HEP only had a significant and positive effect on POL 1 and 2 vaccination uptake is the limited access to energy in rural Ethiopia, which creates challenges in maintaining cold chains for vaccine stocks and in training personnel for vaccinations such as DPT and measles, which require injections and stricter temperature control. On the other hand, polio vaccines, specifically the oral polio vaccine, are easy to administer. Further, since polio is a highly visible and feared disease that causes paralysis, vaccination could have greater community acceptance. Finally, the eradication of polio in Ethiopia has been a national priority for several decades. Specifically, in the early 2000s, the Global Polio Eradication Initiative became a high-priority international campaign with strong support from UNICEF and WHO. Ethiopia received substantial technical support and funding for this initiative. Consequently, the positive effects on the uptake of POL 1 and 2 estimated here might not be due to the HEP but rather to its concurrence with this national campaign. However, placebo analysis shows that this is not the case.

5.2 Robustness checks

Table 7 includes the results of the placebo analysis for POL 1 and 2. For each vaccine, Table 7 presents the proportion of pseudo *t*-statistics drawn from the placebo distribution that are greater than the *t*-statistic for the treatment effect calculated from the real treatment and control groups. These proportions are low. Therefore, the *t*-statistics for the treatment effect are unusual with respect to the distribution of placebo *t*-statistics, indicating that the estimated effects are due to the HEP instead of coincidence.

Table 7: Distribution of pseudo *t*-statistics

	Without interaction terms		Without interaction terms	
Estimations at the child level				
	POL 1	POL 2	POL 1	POL 2
Proportion	0.005	0.013	0.005	0.010
Estimations at the family level				
	0.006	0.014		
Proportion	0.003	0.013	0.005	0.014

Note: The proportion of placebo effects for which the *t*-stastitic is higher than the *t*-statistic calculated from real treatment and control groups is 0.005 for POL 1, and 0.013 for POL 2. The placebo distribution is computed for a number of random draws equal to 199,999.

5.3 Heterogeneous effects by sex and family wealth

The effects vary slightly by sex. Table 8 shows that for girls, the program increased the probability of receiving POL 1 by just over 10 percentage points, and the probability of receiving POL 2 by around 10 percentage points. This is 2 to 3 percentage points higher than for boys. While the effects are significant for girls, they are not for boys, unless standard *p*-values are used instead of adjusted ones. Regarding the other vaccines, the program had no effect on boys or girls.

Table 8: Effects of HEP on vaccination uptake by sex – Estimations at the child level

	Boys									
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.022	0.036	0.597	0.550	1	0.008	0.037	0.211	0.833	1
DPT 1	0.022	0.037	0.588	0.556	1	0.013	0.038	0.349	0.727	1
DPT 2	0.017	0.034	0.517	0.605	1	0.016	0.034	0.473	0.636	1
DPT 3	0.028	0.027	1.035	0.301	1	0.029	0.028	1.060	0.289	1
POL 0	0.035	0.030	1.179	0.239	1	0.020	0.030	0.652	0.514	1
POL 1	0.084	0.04	2.103	0.035	0.469	0.084	0.040	2.071	0.038	0.477
POL 2	0.063	0.039	1.608	0.108	0.759	0.070	0.039	1.801	0.072	0.477
POL 3	0.028	0.035	0.800	0.424	1	0.025	0.036	0.702	0.483	1
Measle	-0.002	0.03	-0.082	0.935	1	-0.004	0.031	-0.129	0.897	1
	Girls									
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.028	0.037	0.748	0.455	0.639	0.016	0.038	0.437	0.662	0.897
DPT 1	0.036	0.041	0.866	0.386	0.63	0.026	0.041	0.624	0.533	0.799
DPT 2	0.043	0.038	1.117	0.264	0.572	0.036	0.037	0.971	0.331	0.66
DPT 3	0.003	0.031	0.090	0.928	1	0.001	0.03	0.045	0.964	1
POL 0	0.043	0.028	1.549	0.121	0.395	0.036	0.027	1.359	0.174	0.448
POL 1	0.103	0.039	2.665	0.008	0.072	0.105	0.039	2.698	0.007	0.041
POL 2	0.097	0.040	2.437	0.015	0.072	0.105	0.040	2.626	0.009	0.041
POL 3	0.038	0.035	1.069	0.285	0.572	0.049	0.036	1.351	0.177	0.448
Measle	0.013	0.034	0.382	0.702	1	0.004	0.034	0.133	0.894	1

Notes: Number of observations: 7,174 (boys) and 6,913 (girls). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

Estimations computed at the family level led to estimates of similar magnitude (Table 9). For girls, however, the estimated effect for POL 2 is smaller, resulting in a non-significant effect at the 10 percent threshold.

Table 9: Effects of HEP on vaccination uptake by sex – Estimations at the family level

	Boys									
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.020	0.035	0.559	0.576	0.77	0.006	0.036	0.163	0.871	1
DPT 1	0.032	0.036	0.898	0.369	0.77	0.019	0.036	0.521	0.602	1
DPT 2	0.024	0.033	0.724	0.469	0.77	0.019	0.033	0.591	0.555	1
DPT 3	0.025	0.027	0.948	0.343	0.77	0.023	0.027	0.849	0.396	1
POL 0	0.041	0.028	1.458	0.145	0.631	0.025	0.028	0.875	0.381	1
POL 1	0.083	0.039	2.105	0.035	0.467	0.081	0.040	2.030	0.042	0.533
POL 2	0.061	0.038	1.608	0.108	0.631	0.066	0.038	1.767	0.077	0.533
POL 3	0.021	0.034	0.619	0.536	0.770	0.018	0.034	0.511	0.609	1
Measle	-0.001	0.030	-0.030	0.976	1	-0.005	0.031	-0.178	0.859	1
	Girls									
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.018	0.037	0.482	0.630	1	0.008	0.037	0.229	0.818	1
DPT 1	0.021	0.040	0.524	0.600	1	0.012	0.040	0.309	0.758	1
DPT 2	0.030	0.036	0.831	0.406	0.950	0.023	0.036	0.654	0.513	1
DPT 3	-0.004	0.028	-0.126	0.900	1	-0.006	0.028	-0.206	0.837	1
POL 0	0.044	0.027	1.622	0.105	0.324	0.037	0.027	1.396	0.163	0.612
POL 1	0.102	0.038	2.655	0.008	0.077	0.102	0.038	2.652	0.008	0.078
POL 2	0.086	0.039	2.193	0.028	0.128	0.090	0.040	2.269	0.023	0.103
POL 3	0.030	0.035	0.872	0.383	0.950	0.036	0.035	1.003	0.316	0.953
Measle	0.003	0.033	0.102	0.919	1	0.003	0.033	0.085	0.932	1

Notes: Number of observations: 5,780 (boys) and 5,629 (girls). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

To evaluate whether the program's effects are sensitive to household wealth, we constructed a dummy variable classifying families into two broad categories—poor and non-poor—and estimated the models for each of these two sub-samples. This binary variable is constructed from the quintiles of the EDHS wealth index, which accounts for household assets (primarily land, radios, bicycles, etc.) and livestock (cattle, sheep, horses, camels, and poultry). Households belonging to the bottom three quintiles are classified as poor, while those in the upper two quintiles are categorized as non-poor.

The estimated effects of the HEP on vaccination uptake vary with family wealth. For children living in poor families, Table 10 shows that the probability of receiving POL 1 and 2 increased by around 11 and 9 percentage points, respectively. However, these effects are not significant

at the 10 percent level, unless standard *p*-values are used instead of adjusted ones. For children living in non-poor families, the estimated effects for POL 1 and 2 were close to 0, and even negative for other vaccines, especially for DPT 1.

Table 10: Effects of HEP on vaccination uptake by family wealth – Estimations at the child level

Children living in poor families										
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.027	0.039	0.706	0.480	0.873	0.024	0.039	0.629	0.530	1
DPT 1	0.045	0.040	1.129	0.259	0.569	0.036	0.040	0.918	0.359	1
DPT 2	0.037	0.033	1.134	0.257	0.569	0.036	0.034	1.067	0.286	1
DPT 3	0.014	0.027	0.503	0.615	0.873	0.007	0.028	0.260	0.795	1
POL 0	0.037	0.026	1.419	0.156	0.569	0.025	0.026	0.936	0.349	1
POL 1	0.110	0.043	2.539	0.011	0.112	0.110	0.043	2.561	0.010	0.104
POL 2	0.087	0.041	2.132	0.033	0.152	0.091	0.041	2.217	0.027	0.120
POL 3	0.024	0.034	0.704	0.482	0.873	0.013	0.034	0.398	0.690	1
Measle	-0.014	0.032	-0.432	0.665	0.873	-0.016	0.031	-0.501	0.616	1
Children living in non-poor families										
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	-0.050	0.042	-1.176	0.240	1	-0.043	0.047	-0.913	0.361	1
DPT 1	-0.096	0.048	-2.002	0.045	0.688	-0.077	0.051	-1.509	0.131	1
DPT 2	-0.051	0.053	-0.959	0.338	1	-0.026	0.055	-0.463	0.643	1
DPT 3	-0.036	0.045	-0.793	0.428	1	-0.022	0.045	-0.478	0.633	1
POL 0	-0.015	0.044	-0.340	0.734	1	-0.018	0.045	-0.392	0.695	1
POL 1	0.002	0.048	0.047	0.962	1	0.018	0.049	0.362	0.717	1
POL 2	0.010	0.056	0.174	0.862	1	0.038	0.061	0.618	0.537	1
POL 3	-0.010	0.056	-0.184	0.854	1	0.011	0.054	0.195	0.846	1
Measle	-0.026	0.050	-0.523	0.601	1	-0.014	0.049	-0.288	0.773	1

Notes: Number of observations: 10,125 (poor) and 3,962 (non-poor). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

There are several potential explanations for the program's effect being limited to vaccination uptake for children from poor families. First, poor families might have derived greater utility from the HEP package as the program reduced the financial barriers to accessing basic healthcare. Second, prior to the program, poor rural families likely faced more limited access to information regarding immunization benefits. Indeed, before the program, vaccination coverage was 10 percentage points higher among children from non-poor families, as around

73 percent and 56 percent of children from non-poor families had already received POL 1 and 2 vaccines, respectively. Finally, the HEP relies heavily on intensive community mobilization mechanisms. If non-poor families are less integrated into or less dependent on these community-based networks, they may have been less exposed to the HEP.

Estimations at the family level give estimated ITT effects of similar magnitude (Table 11). The HEP had a significant impact on POL 1 at the 10 percent level and on POL 1 and 2 in estimations with interaction terms, also at the 10 percent level.

Table 11: Effects of HEP on vaccination uptake by family wealth – Estimations at the family level

Children living in poor families										
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	0.011	0.038	0.277	0.782	1	0.005	0.039	0.116	0.907	1
DPT 1	0.044	0.039	1.145	0.252	0.790	0.031	0.038	0.805	0.421	0.965
DPT 2	0.032	0.032	0.984	0.325	0.836	0.027	0.033	0.809	0.418	0.965
DPT 3	0.002	0.026	0.089	0.929	1	-0.003	0.027	-0.107	0.915	1
POL 0	0.034	0.027	1.250	0.211	0.790	0.022	0.027	0.814	0.416	0.965
POL 1	0.111	0.042	2.602	0.009	0.092	0.115	0.043	2.690	0.007	0.069
POL 2	0.085	0.040	2.101	0.036	0.167	0.096	0.041	2.321	0.020	0.089
POL 3	0.021	0.034	0.619	0.536	1	0.020	0.034	0.599	0.549	1
Measle	-0.021	0.032	-0.653	0.514	1	-0.030	0.032	-0.939	0.348	0.965
Children living in non-poor families										
	Without interaction terms					With interaction terms				
	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value	$\widehat{ITT}$	SE	*t*-stat	p-value	q-value
BCG	-0.062	0.042	-1.477	0.140	0.594	-0.052	0.044	-1.179	0.238	0.958
DPT 1	-0.099	0.045	-2.193	0.028	0.342	-0.095	0.048	-1.987	0.047	0.730
DPT 2	-0.065	0.050	-1.289	0.197	0.653	-0.061	0.052	-1.164	0.245	0.958
DPT 3	-0.075	0.044	-1.705	0.088	0.545	-0.067	0.045	-1.507	0.132	0.958
POL 0	0.001	0.043	0.020	0.984	1	0.006	0.044	0.145	0.885	1
POL 1	0.028	0.045	0.608	0.543	0.827	0.036	0.047	0.760	0.447	1
POL 2	0.015	0.053	0.278	0.781	0.954	0.026	0.057	0.452	0.651	1
POL 3	-0.021	0.051	-0.417	0.676	0.935	-0.009	0.052	-0.166	0.868	1
Measle	-0.042	0.05	-0.828	0.408	0.8	-0.031	0.048	-0.63	0.529	1

Notes: Number of observations: 6,445 (poor) and 2,561 (non-poor). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

6. Impact of the HEP on child anthropometric outcomes

6.1 Main results

Table 12 shows a positive and significant impact of the HEP on two of the three anthropometric variables, namely the weight-for-age z- and weight-for-height z-scores. For estimations computed at the child level without interaction terms in the specification, the estimated effect is 0.264 SD for the weight-for-age z-score and 0.259 SD for the weight-for-height z-score. Estimations including interaction terms yield similar results. At the household level, the estimated effects are slightly smaller in magnitude; however, the impacts on the weight-for-age and weight-for-height z-scores remain significant at the 10 percent level.

Overall, these results are consistent with studies analyzing the effects of health and women's empowerment programs on children's health. Nguyen et al. (2025) examined the effects of interventions targeting child malnutrition, sanitation, and remittances in rural Northeast Thailand and Central Vietnam, finding that access to improved rural toilet facilities and public water systems reduced underweight in children. According to their results, public health interventions to upgrade to flush toilets reduced the z-score for the level of underweight by 0.17 and 0.12 in the short and long term, respectively. A similar study by Imai et al. (2014) regarding the effects of access to health programs on children's nutrition in India found that health schemes and women's empowerment interventions helped improve children's nutritional status. Holland and Rammohan (2019) also found that women's autonomy in household productive decisions and confidence in public speaking were associated with significantly higher height-for-age z-scores and a decreased probability of stunting in rural Bangladesh, while children's weight-per-height declined by 0.23 units.

Table 12: Effects of the HEP on anthropometric outcomes

Estimations at the child level								
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.164	0.128	1.281	0.200	0.110	0.133	0.824	0.410
Weight-for-age z-score	0.264	0.097	2.726	0.006	0.258	0.102	2.521	0.012
Weight-for-height z-score	0.259	0.100	2.569	0.010	0.290	0.098	2.960	0.003
Estimations at the family level								
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.177	0.134	1.322	0.186	0.141	0.14	1.002	0.316
Weight-for-age z-score	0.244	0.103	2.366	0.018	0.245	0.108	2.269	0.023
Weight-for-height z-score	0.212	0.109	1.953	0.051	0.237	0.110	2.162	0.031

Notes: Number of observations: 8,780 (child level) and 6,194 (family level). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

The placebo analysis shown in Table 13 confirms these results.

6.2 Robustness checks

Table 13 shows that the proportion of pseudo *t*-statistics drawn from the placebo distribution that are greater than the *t*-statistic for the treatment effect calculated from the real treatment and control groups are low. Therefore, the *t*-statistics for the treatment effect are unusual with respect to the distribution of placebo *t*-statistics, indicating that the estimated effects are due to the Health Extension program instead of coincidence. The placebo analysis thus confirms the positive effect of the HEP on children's health. However, this overall positive effect masks significant disparities.

Table 13: Distribution of pseudo *t*-statistics

	Without interaction terms		With interaction terms	
	Weight-for-age z-score	Weight-for-height z-score	Weight-for-age z-score	Weight-for-height z-score
Estimations at the child level				
Proportion	0.005	0.008	0.012	0.004
Estimations at the family level				
Proportion	0.014	0.035	0.021	0.024

Note: The proportion of placebo effects for which the *t*-stastitic is higher than the *t*-statistic calculated from real treatment and control groups is 0.005 for Weight-for-age z-score, and 0.008 for Weight-for-height-z-score. The placebo distribution is computed for a number of random draws equal to 199,999.

6.3 Heterogenous effects by sex and family wealth

The effects vary by sex. Table 14 shows that in the specification without interaction terms, the program significantly improved all anthropometric variables for boys, including the height-for-age z-score. The inclusion of interaction terms leads to a smaller point estimate and a larger standard error for the height-for-age z-score; consequently, the effect is no longer statistically significant at conventional levels. For girls, the HEP had a positive and significant impact but only for the weight-for-height z-score.

Table 14: Effects of the HEP on anthropometric outcomes by sex – Estimations at the child level

	Boys							
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.325	0.163	1.995	0.046	0.276	0.173	1.598	0.110
Weight-for-age z-score	0.360	0.121	2.967	0.006	0.330	0.126	2.610	0.009
Weight-for-height z-score	0.256	0.128	2.004	0.045	0.243	0.131	1.854	0.064
	Girls							
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	-0.020	0.162	-0.122	0.903	0.018	0.162	0.109	0.913
Weight-for-age z-score	0.165	0.127	1.303	0.193	0.205	0.123	1.658	0.097
Weight-for-height z-score	0.276	0.137	2.007	0.045	0.299	0.131	2.285	0.022

Notes: Number of observations: 4,443 (boys) and 4,337 (girls). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

Table 15 includes the results of the family-level estimations. The conclusions are similar for boys. For girls, the effect of the program on the weight-for-height z-score is only significant in the specification without interaction terms.

Table 15: Effects of the HEP on anthropometric outcomes by sex – Estimations at the family level

	Boys							
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.358	0.165	2.173	0.030	0.333	0.169	1.968	0.049
Weight-for-age z-score	0.394	0.121	3.247	0.001	0.379	0.125	3.023	0.003
Weight-for-height z-score	0.279	0.131	2.132	0.033	0.266	0.131	2.023	0.043
	Girls							
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	-0.026	0.165	-0.160	0.873	-0.019	0.164	-0.119	0.905
Weight-for-age z-score	0.136	0.134	1.010	0.312	0.165	0.128	1.284	0.199
Weight-for-height z-score	0.234	0.148	1.580	0.114	0.264	0.138	1.914	0.056

Notes: Number of observations: 3,776 (boys) and 3,703 (girls). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

This stronger effect for boys contrasts somewhat with prior reports in the literature. Kofinti et al. (2022) studied the effects of maternal health insurance on the health outcomes of children under 5 years in 32 sub-Saharan African countries; they found a greater reduction in the incidence of underweight and stunting among girls. Likewise, the case study by Nguyen et al. (2025) concluded that girls benefited more from the interventions. Furthermore, a study by Augsburg and Rodriguez-Lesmes (2018) on the impact of sanitation coverage on child height-for-age in India found a significant and positive effect on height growth during the first years of life, especially for girls. However, Pongutta (2024) examined the effects of a school nutrition intervention among Thai primary school children, finding that the program had a positive effect on overweight and obesity but an adverse effect on wasting in girls.

Table 16 presents the results of the child-level estimations for children from poor and non-poor households. Contrary to previous findings from the main sample, the HEP also had a positive and significant effect on the height-for-age z-score for children from non-poor families. This effect is particularly pronounced in the specification without interaction terms, reaching 0.523 SD. The program's impact on the weight-for-age z-score is also substantial, ranging from 0.493 SD to 0.629 SD, depending on whether interaction terms are included in the specification. For children from poor households, the estimated parameters are considerably lower, and the effects are not significant at conventional thresholds. These results contrast with Nguyen et al. (2025), who found that the impact of sanitation access and remittances on child malnutrition more

strongly benefited children from poor households based on data from rural Northeast Thailand and Central Vietnam. Likewise, a study by Fang and Zhu (2022) on the long-term impacts of school nutrition in China found that early exposure to the program significantly improved children's cognitive and health outcomes in the long run, with these effects notably being more substantial among children from low socioeconomic groups.

Several factors might explain why HEP-treated children from poor families benefit less from interventions targeting anthropometric outcomes. First, limited access to health facilities could play a significant role, as poorer families often reside in remote areas with insufficient infrastructure, which might make it difficult to reach healthcare services or receive timely interventions. Second, financial constraints could limit their ability to afford supplementary nutrition, transportation to health centers, and basic hygiene products essential to complement health interventions. Third, possible inequities in terms of the program's implementation could potentially favor the relatively better-off, leaving the most vulnerable beneficiaries with more limited access, less qualified staff, or inconsistent program delivery. The WHO emphasizes the importance of public policies that address socioeconomic determinants of health variables (Quesnel-Vallée et al., 2016), a dimension perhaps insufficiently integrated into the HEP.

Table 16: Effects of the HEP on anthropometric outcomes by family wealth – Estimations at the child level

Children living in poor families								
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.046	0.136	0.335	0.738	0.008	0.145	0.054	0.957
Weight-for-age z-score	0.097	0.115	0.838	0.402	0.060	0.117	0.513	0.608
Weight-for-height z-score	0.124	0.118	1.050	0.294	0.095	0.116	0.818	0.414
Children living in non-poor families								
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.528	0.254	2.083	0.037	0.380	0.229	1.665	0.096
Weight-for-age z-score	0.629	0.195	3.221	0.001	0.493	0.191	2.575	0.010
Weight-for-height z-score	0.446	0.197	2.261	0.024	0.394	0.190	2.068	0.039

Notes: Number of observations: 6,314 (poor) and 2,466 (non-poor). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

Table 17 includes the results of the family-level estimations. The conclusions are similar, as no significant program effect is found for children from poor households. For children from non-

poor families, the estimated effects are lower in the specification with interaction terms. This was also observed in the child-level estimations (Table 16).

Table 17: Effects of the HEP on anthropometric outcomes by family wealth – Estimations at the family level

Children living in poor families								
	Without interaction terms				With interaction terms			
	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.055	0.150	0.366	0.714	0.038	0.156	0.246	0.806
Weight-for-age z-score	0.083	0.119	0.695	0.487	0.060	0.119	0.504	0.614
Weight-for-height z-score	0.078	0.126	0.622	0.534	0.056	0.127	0.442	0.659
Children living in non-poor families								
	Without interaction terms				With interaction terms			
*	$\widehat{ITT}$	SE	*t*-stat	p-value	$\widehat{ITT}$	SE	*t*-stat	p-value
Height-for-age z-score	0.621	0.242	2.566	0.010	0.450	0.230	1.957	0.050
Weight-for-age z-score	0.648	0.199	3.412	0.001	0.476	0.177	2.691	0.007
Weight-for-height z-score	0.403	0.189	2.133	0.033	0.325	0.179	1.819	0.069

Notes: Number of observations: 4,453 (poor) and 1,741 (non-poor). Clustered standard errors. As the administrative unit (Kebele) used for program implementation is not identified in the data, standard errors are clustered at the level of the broader geographic area containing the Kebele.

7. Conclusion

This research analyzes the impact of the HEP on children's vaccination uptake and anthropometric health outcomes in rural Ethiopia. Initially implemented in 2003 across the rural regions of Tigray, Amhara, Oromia, and SNNPR, the program was subsequently scaled up nationwide starting in 2010. Our analysis is retrospective and covers the 2000–2005 period, utilizing two waves of the EDHS.

We find that the program had a limited effect on children's vaccination uptake as only the coverage for POL 1 and 2 showed significant improvement. The program's impact on anthropometric scores proved more conclusive. However, these aggregate results mask significant disparities. In terms of vaccination uptake, the program appears to have more benefited girls and children from poor families, and regarding anthropometric variables, the positive effects were primarily observed in boys and children from non-poor families.

To test the robustness of our findings, we employed both a baseline specification and an alternative model including interaction terms between control variables. We also estimated these models using two different samples—one at the child level and another at the household level—to control for potential spillover effects within households. Finally, we conducted

placebo analysis to ensure that the observed effects are indeed attributable to the program instead of coincidence or omitted factors.

One limitation of this study stems from the absence of a direct treatment indicator in the dataset. Consequently, we could only measure an ITT effect. Therefore, our results may underestimate the program's true impact. Another limitation is the inability to measure the program's long-term effects. In 2016, in rural areas, all basic vaccinations reached 35.1 percent of the EDHS sample population, while the stunting rate was 39.9 percent (EDHS, 2016). This suggests that the program resulted in modest improvements in immunization coverage and nutritional status among children in Ethiopia's rural states.

References

Abadie, A. (2005). Semiparametric Difference-in-Differences Estimators. *The Review of Economic Studies*, *72*(1), 1–19. https://doi.org/10.1111/0034-6527.00321

Abadie, A., Diamond, A., and Hainmueller, A. J. (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, *105*(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746

Abadie, A., Diamond, A., and Hainmueller, J. (2015). Comparative Politics and the Synthetic Control Method. *American Journal of Political Science*, *59*(2), 495–510. https://doi.org/10.1111/ajps.12116

Abramovich, F., Benjamini, Y., Donoho, D. L., and Johnstone, I. M. (2006). Adapting to unknown sparsity by controlling the false discovery rate. *Annals of Statistics*, *34*(2), 584–653. https://doi.org/10.1214/009053606000000074

Adams, K. P., Lybbert, T. J., Vosti, S. A., Ayifah, E., Arimond, M., Adu-Afarwuah, S., and Dewey, K. G. (2018). Unintended effects of a targeted maternal and child nutrition intervention on household expenditures, labor income, and the nutritional status of non-targeted siblings in Ghana. *World Development*, *107*, 138–150. https://doi.org/10.1016/J.WORLDDEV.2018.02.025

Admassie, A., Abebaw, D., and Woldemichael, A. D. (2009). Impact evaluation of the Ethiopian Health Services Extension Programme. *Journal of Development Effectiveness*, *1*(4), 430–449. https://doi.org/10.1080/19439340903375724

Aiyar, A., and Cummins, J. R. (2021). An age profile perspective on two puzzles in global child health: The Indian Enigma and economic growth. *Journal of Development Economics*, *148*, 102569. https://doi.org/10.1016/J.JDEVECO.2020.102569

Alemayehu, Y. K., Medhin, G., and Teklu, A. M. (2023). National Assessment of the Health Extension Program in Ethiopia: Study Protocol and Key Outputs. *Ethiopian Journal of Health Sciences*, *33*(2). https://doi.org/10.4314/ejhs.v33i1.2S

Anderson, M. L. (2008). Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American Statistical Association*, *103*(484), 1481–1495. https://doi.org/10.1198/016214508000000841

Assebe, L. F., Belete, W. N., Alemayehu, S., Asfaw, E., Godana, K. T., Alemayehu, Y. K., Teklu, A. M., and Yigezu, A. (2021). Economic evaluation of Health Extension Program packages in Ethiopia. *PLoS ONE*, *16*(2 February). https://doi.org/10.1371/journal.pone.0246207

Augsburg, B., and Rodríguez-Lesmes, P. A. (2018). Sanitation and child health in India. *World Development*, *107*(2), 22–39. https://doi.org/10.1016/j.worlddev.2018.02.005

Behrman, J. R., and Deolalikar, A. B. (1988). Chapter 14 Health and nutrition. *Handbook of Development Economics*, *1*, 631–711. https://doi.org/10.1016/S1573-4471(88)01017-4

Beltran-Silva, F. (2023). Fighting against hunger: A country-wide intervention and its impact on birth outcomes. *World Development*, *165*, 106202. https://doi.org/10.1016/J.WORLDDEV.2023.106202

Borusyak, K., and Hull, P. (2023). Nonrandom Exposure to Exogenous Shocks. *Econometrica*, *91*(6), 2155–2185. https://doi.org/10.3982/ECTA19367;WGROUP:STRING:PUBLICATION

Callaway, B., and Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230. https://doi.org/10.1016/J.JECONOM.2020.12.001

Cummins, J., Guo, J., Agarwal, N., Aiyar, A., Jain, V., and Bergmann, A. (2024). Caste Differences in Child Growth: Disentangling Endowment and Investment Effects. *World Development*, *179*, 106598. https://doi.org/10.1016/J.WORLDDEV.2024.106598

Dang, T. (2025). Language training, refugees' healthcare integration, and the next generation's health. *Journal of Development Economics*, *174*, 103470. https://doi.org/10.1016/J.JDEVECO.2025.103470

de Groot, R., Yablonski, J., and Valli, E. (2022). The impact of cash and health insurance on child nutrition during the first 1000 days: Evidence from Ghana. *Food Policy*, *107*, 102217. https://doi.org/10.1016/J.FOODPOL.2021.102217

De, P. K., and Timilsina, L. (2020). Cash-based maternal health interventions can improve childhood vaccination—Evidence from India. *Health Economics*, *29*(10), 1202–1219. https://doi.org/10.1002/HEC.4129

Durevall, D., and Isaksson, A. S. (2024a). Aid and child health: A disaggregated analysis of the effects of aid on impaired growth. *World Development*, *182*, 106689. https://doi.org/10.1016/J.WORLDDEV.2024.106689

Durevall, D., and Isaksson, A. S. (2024b). Aid and child health: A disaggregated analysis of the effects of aid on impaired growth. *World Development*, *182*, 106689. https://doi.org/10.1016/J.WORLDDEV.2024.106689

Economic Development, Population Dynamics, and Welfare Editors: Mengistu Ketema and Getachew Diriba. (2021). http://www.eea-et.org

Eshetu, F., and Beshir, M. (2017). Dynamics and determinants of rural-urban migration in Southern Ethiopia. *Journal of Development and Agricultural Economics*, *9*(12), 328–340. https://doi.org/10.5897/JDAE2017.0850

Fang, G., and Zhu, Y. (2022). Long-term impacts of school nutrition: Evidence from China's school meal reform. *World Development*, *153*(1), 105854. https://doi.org/10.1016/j.worlddev.2022.105854

Gebrehiwot, T. G., Sebastian, M. S., Edin, K., and Goicolea, I. (2015). The Health Extension Program and Its Association with Change in Utilization of Selected Maternal Health Services in Tigray Region, Ethiopia: A Segmented Linear Regression Analysis. *PLOS ONE*, *10*(7), e0131195. https://doi.org/10.1371/JOURNAL.PONE.0131195

Gopalan, M., and Edara, R. (2023). Health Policies as Education Policies? A Review of Causal Evidence and Mechanisms. *Https://Doi.Org/10.1177/23328584231177616*, *9*. https://doi.org/10.1177/23328584231177616

Grossman, M. (2017). 1. On the Concept of Health Capital and the Demand for Health. *Determinants of Health*, 6–41. https://doi.org/10.7312/GROS17812-004/HTML

Hailemariam, A., Adugna, A., and Hailemariam, A. (2011a). Migration and Urbanization in Ethiopia: Addressing the Spatial Imbalance. *The Demographic Transition and Development in Africa*, 145–165. https://doi.org/10.1007/978-90-481-8918-2_8

Hailemariam, A., Adugna, A., and Hailemariam, A. (2011b). Migration and Urbanization in Ethiopia: Addressing the Spatial Imbalance. *The Demographic Transition and Development in Africa*, 145–165. https://doi.org/10.1007/978-90-481-8918-2_8

Haji, J. (2022). Impact of agricultural commercialization on child nutrition in Ethiopia. *Food Policy*, *113*, 102287. https://doi.org/10.1016/J.FOODPOL.2022.102287

Han, Y., Kim, H. B., and Park, S. (2021a). The Roles of Nutrition Education and Food Vouchers in Improving Child Nutrition: Evidence from a Field Experiment in Ethiopia. *Journal of Health Economics*, *80*, 102545. https://doi.org/10.1016/J.JHEALECO.2021.102545

Han, Y., Kim, H. B., and Park, S. (2021b). The Roles of Nutrition Education and Food Vouchers in Improving Child Nutrition: Evidence from a Field Experiment in Ethiopia. *Journal of Health Economics*, *80*, 102545. https://doi.org/10.1016/J.JHEALECO.2021.102545

Headey, D., Taffesse, A. S., and You, L. (2014). Diversification and Development in Pastoralist Ethiopia. *World Development*, *56*, 200–213. https://doi.org/10.1016/J.WORLDDEV.2013.10.015

Heckman, J. J., Ichimura, H., and Todd, P. E. (1997). Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *The Review of Economic Studies*, *64*(4), 605–654. https://doi.org/10.2307/2971733

Herrera-Almanza, C., and Rosales-Rueda, M. F. (2023a). Community-based health programs and child vaccinations: Evidence from Madagascar. *World Development*, *170*, 106322. https://doi.org/10.1016/J.WORLDDEV.2023.106322

Herrera-Almanza, C., and Rosales-Rueda, M. F. (2023b). Community-based health programs and child vaccinations: Evidence from Madagascar. *World Development*, *170*, 106322. https://doi.org/10.1016/J.WORLDDEV.2023.106322

Himaz, R. (2008). Welfare Grants and Their Impact on Child Health: The Case of Sri Lanka. *World Development*, *36*(10), 1843–1857. https://doi.org/10.1016/J.WORLDDEV.2008.02.003

Hirani, J. C., and Wüst, M. (2024). Reminder design and childhood vaccination coverage. *Journal of Health Economics*, *93*, 102832. https://doi.org/10.1016/J.JHEALECO.2023.102832

Holford, A., and Rabe, B. (2024). Universal free school meals and children's bodyweight. Impacts by age and duration of exposure. *Journal of Health Economics*, *98*(2), 102937. https://doi.org/10.1016/j.jhealeco.2024.102937

Holland, C., and Rammohan, A. (2019a). Rural women's empowerment and children's food and nutrition security in Bangladesh. *World Development*, *124*(1), 104648. https://doi.org/10.1016/j.worlddev.2019.104648

Holland, C., and Rammohan, A. (2019b). Rural women's empowerment and children's food and nutrition security in Bangladesh. *World Development*, *124*(1), 104648. https://doi.org/10.1016/j.worlddev.2019.104648

Hull, M., and Yan, J. (2024). The impact of children's access to public health insurance on their cognitive development and behavior. *Journal of Health Economics*, *98*, 102935. https://doi.org/10.1016/J.JHEALECO.2024.102935

Ibuka, Y., and Bessho, S. I. (2015). Subsidies for influenza vaccination, vaccination rates, and health outcomes among the elderly in Japan. *Japan and the World Economy*, *36*, 56–66. https://doi.org/10.1016/J.JAPWOR.2015.07.001

Imai, K. S., Annim, S. K., Kulkarni, V. S., and Gaiha, R. (2014a). Women's Empowerment and Prevalence of Stunted and Underweight Children in Rural India. *World Development*, *62*, 88–105. https://doi.org/10.1016/j.worlddev.2014.05.001

Imai, K. S., Annim, S. K., Kulkarni, V. S., and Gaiha, R. (2014b). Women's Empowerment and Prevalence of Stunted and Underweight Children in Rural India. *World Development*, *62*(10), 88–105. https://doi.org/10.1016/j.worlddev.2014.05.001

Imbens, G. W. (2015). Matching Methods in Practice: Three Examples. *Journal of Human Resources*, *50*(2), 373–419. https://doi.org/10.3368/JHR.50.2.373

Imbens, G. W., and Rubin, D. B. (2015). Causal inference: For statistics, social, and biomedical sciences an introduction. *Causal Inference: For Statistics, Social, and Biomedical Sciences an Introduction*, 1–625. https://doi.org/10.1017/CBO9781139025751

Kandpal, E. (2011). Beyond Average Treatment Effects: Distribution of Child Nutrition Outcomes and Program Placement in India's ICDS. *World Development*, *39*(8), 1410–1421. https://doi.org/10.1016/j.worlddev.2010.12.013

Khonje, M. G., Nyondo, C., Mangisoni, J. H., Ricker-Gilbert, J., Burke, W. J., Chadza, W., and Muyanga, M. (2022). Does subsidizing legume seeds improve farm productivity and nutrition in Malawi? *Food Policy*, *113*, 102308. https://doi.org/10.1016/J.FOODPOL.2022.102308

Kusuma, D., Thabrany, H., Hidayat, B., McConnell, M., Berman, P., and Cohen, J. (2017). New Evidence on the Impact of Large-scale Conditional Cash Transfers on Child Vaccination Rates: The Case of a Clustered-Randomized Trial in Indonesia. *World Development*, *98*(10), 497–505. https://doi.org/10.1016/j.worlddev.2017.05.007

Larson, C. P., and Desie, T. (1994). HEALTH IN ETHIOPIA: A SUMMARY OF 52 DISTRICT HEALTH PROFILES. *Ethiopian Journal of Health Development*, *8*(2). https://www.ajol.info/index.php/ejhd/article/view/216724

Le, K., and Nguyen, M. (2020). Shedding light on maternal education and child health in developing countries. *World Development*, *133*, 105005. https://doi.org/10.1016/J.WORLDDEV.2020.105005

Liu, K., Prommawin, B., and Schroyen, F. (2024). Health insurance, agricultural production and investments. *Journal of Health Economics*, *97*, 102918. https://doi.org/10.1016/J.JHEALECO.2024.102918

Louvison, M. C. P. (2019). Regionalization of health systems as a response to territorial inequalities: a necessary debate. *Cadernos de Saude Publica*, *35*. https://doi.org/10.1590/0102-311X00116019

Manley, J., Gitter, S., and Slavchevska, V. (2013). How Effective are Cash Transfers at Improving Nutritional Status? *World Development*, *48*, 133–155. https://doi.org/10.1016/J.WORLDDEV.2013.03.010

Melesse, B., and Nachimuthu, Dr. K. (2017). *A review on Causes and Consequences of Rural-Urban Migration in Ethiopia*.

Meshesha, B. R., Sibhatu, M. K., Beshir, H. M., Zewude, W. C., Taye, D. B., Getachew, E. M., Merga, K. H., Kumssa, T. H., Alemayue, E. A., Ashuro, A. A., Shagre, M. B., and Gebreegziabher, S. B. (2022). Access to surgical care in Ethiopia: a cross-sectional retrospective data review. *BMC Health Services Research*, *22*(1), 1–12. https://doi.org/10.1186/S12913-022-08357-9/TABLES/8

Negussie, A., and Girma, G. (2017). Is the role of Health Extension Workers in the delivery of maternal and child health care services a significant attribute? the case of Dale district, southern Ethiopia. *BMC Health Services Research*, *17*(1), 1–8. https://doi.org/10.1186/S12913-017-2590-8/TABLES/7

Nguyen, T. T., Nguyen, T. T., Do, M. H., Rahut, D., and Nguyen, D. L. (2025). Remittances, sanitation and child malnutrition in middle-income countries: A case study from rural Northeast Thailand and Central Vietnam. *World Development*, *190*(6), 106975. https://doi.org/10.1016/j.worlddev.2025.106975

Nyqvist, M. B., Jayachandran, S., and Zipfel, C. (2024). A mother's voice: Impacts of spousal communication training on child health investments. *Journal of Development Economics*, *168*, 103263. https://doi.org/10.1016/J.JDEVECO.2024.103263

O'Neill, S., Grieve, R., Singh, K., Dutt, V., and Powell-Jackson, T. (2024). Persistence and heterogeneity of the effects of educating mothers to improve child immunisation uptake: Experimental evidence from Uttar Pradesh in India. *Journal of Health Economics*, *96*(27), 102899. https://doi.org/10.1016/j.jhealeco.2024.102899

Panda, B. K., Mishra, S., and Awofeso, N. (2020). Socio-demographic correlates of first dose of measles (MCV1) vaccination coverage in India. *BMC Public Health*, *20*(1), 1–13. https://doi.org/10.1186/S12889-020-09321-0/TABLES/4

Patwardhan, V. (2023). The impact of the Mamata conditional cash transfer program on child nutrition in Odisha, India. *Health Economics*, *32*(9), 2127–2146. https://doi.org/10.1002/HEC.4720

Perumal, N., Namaste, S., Qamar, H., Aimone, A., Bassani, D. G., and Roth, D. E. (2020). Anthropometric data quality assessment in multisurvey studies of child growth. *The American Journal of Clinical Nutrition*, *112*(6), 806S-815S. https://doi.org/10.1093/ajcn/nqaa162

Quesnel-Vallée, A., Willson, A., and Reiter-Campeau, S. (2016). Health Inequalities Among Older Adults in Developed Countries: Reconciling Theories and Policy Approaches. *Handbook of Aging and the Social Sciences, Eighth Edition*, 483–502. https://doi.org/10.1016/B978-0-12-417235-7.00023-8

Quintana-Domeque, C., and Ródenas-Serrano, P. (2017). The hidden costs of terrorism: The effects on health at birth. *Journal of Health Economics*, *56*, 47–60. https://doi.org/10.1016/J.JHEALECO.2017.08.006

Raghunathan, K., Kumar, N., Gupta, S., Chauhan, T., Kathuria, A. K., and Menon, P. (2023). Learning together: Experimental evidence on the impact of group-based nutrition interventions in rural Bihar. *World Development*, *168*, 106267. https://doi.org/10.1016/J.WORLDDEV.2023.106267

Rios-Avila, F., Sant'Anna, P., Naqvi, A., Rios-Avila, F., Sant'Anna, P., and Naqvi, A. (2022). *DRDID: Stata module for the estimation of Doubly Robust Difference-in-Difference models*. https://EconPapers.repec.org/RePEc:boc:bocode:s458977

Roth, J., Sant'Anna, P. H. C., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*, *235*(2), 2218–2244. https://doi.org/10.1016/J.JECONOM.2023.03.008

Rudgard, W. E., Dzumbunu, S. P., Yates, R., Toska, E., Stöckl, H., Hertzog, L., Emaway, D., and Cluver, L. (2022). Multiple Impacts of Ethiopia's Health Extension Program on Adolescent Health and Well-Being: A Quasi-Experimental Study 2002–2013. *Journal of Adolescent Health*, *71*(3), 308–316. https://doi.org/10.1016/J.JADOHEALTH.2022.04.010

Salmi, L. R., Barsanti, S., Bourgueil, Y., Daponte, A., Piznal, E., and Ménival, S. (2017). Interventions addressing health inequalities in European regions: the AIR project. *Health Promotion International*, *32*(3), 430–441. https://doi.org/10.1093/HEAPRO/DAV101

Sant'Anna, P. H. C., and Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, *219*(1), 101–122. https://doi.org/10.1016/J.JECONOM.2020.06.003

Schewel, K. D. (2019). *Moved by modernity: How development shapes migration in rural Ethiopia*. https://dare.uva.nl

Spears, D. (2020). Exposure to open defecation can account for the Indian enigma of child height. *Journal of Development Economics*, *146*, 102277. https://doi.org/10.1016/J.JDEVECO.2018.08.003

Tefera, Y. G. (2022). Community-based health extension policy implementation in Ethiopia: a policy experience to scale-up. *Journal of Public Health in Africa*, *13*(3), 2074. https://doi.org/10.4081/JPHIA.2022.2074

Teller, C. H., Hailemariam, A., Gebreselassie, T., and Seifu, Y. (2011). The uniqueness of the Ethiopian demographic transition within sub-Saharan Africa: multiple responses to population

pressure, and preconditions for rural fertility decline and capturing the demographic dividend. *African Population Studies*, *25*(2). https://doi.org/10.11564/25-2-236

Tesfaye, W. (2022). Crop diversification and child malnutrition in rural Ethiopia: Impacts and Pathways. *Food Policy*, *113*, 102336. https://doi.org/10.1016/J.FOODPOL.2022.102336

Teshome, S. B., and Hoebink, P. (2018). Aid, ownership, and coordination in the health sector in Ethiopia. *Development Studies Research*, *5*(1), 132–147. https://doi.org/10.1080/21665095.2018.1543549

Tiruneh, M. G., Fenta, E. T., Endeshaw, D., Delie, A. M., Adal, O., Tareke, A. A., Bogale, E. K., and Anagaw, T. F. (2024). Health extension service utilization in Ethiopia: systematic review and meta-analysis. In *BMC Health Services Research* (Vol. 24, Number 1). BioMed Central Ltd. https://doi.org/10.1186/s12913-024-11038-4

Van Den Heuvel, M., Hopkins, J., Biscaro, A., Srikanthan, C., Feller, A., Bremberg, S., Verkuijl, N., Flapper, B., Ford-Jones, E. L., and Williams, R. (2013). A comparative analysis of early child health and development services and outcomes in countries with different redistributive policies. *BMC Public Health*, *13*(1), 1–13. https://doi.org/10.1186/1471-2458-13-1049/TABLES/5

von Grafenstein, L., Klasen, S., and Hoddinott, J. (2023). The Indian Enigma revisited. *Economics and Human Biology*, *49*, 101237. https://doi.org/10.1016/J.EHB.2023.101237

Wang, H., Cheng, Z., and Smyth, R. (2024). Parental early-life exposure to land reform and household investment in children's education. *World Development*, *173*, 106391. https://doi.org/10.1016/J.WORLDDEV.2023.106391

Wooldridge, J. M. (2021). Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators. *SSRN Electronic Journal*. https://doi.org/10.2139/SSRN.3906345

Appendix

Table A1: Percentage of undernourished children by year and group

	Year	Stunting (%)	Wasting (%)	Underweight (%)
Treatment group	2000	60.06	43.55	13.65
	2005	52.92	34.44	11.84
Control group	2000	53.65	43.62	17.93
	2005	47.27	41.96	21.06

Source: Ethiopian Demographic Health Survey. Note: authors' calculations.

Table A2: Sociodemographic variables – anthropometric sub-sample

	Mean		Mean	Std		*t*-stat	p.value	Norm.
	Treated	Control	diff.	Treated	Control			diff.
Year 2000								
Child's sex	0.510	0.484	0.026	0.500	0.500	-1.657	0.097	0.052
Mother educ	0.123	0.047	0.076	0.328	0.212	-7.920	0.000	0.274
Mother's age 1st birth	0.449	0.498	-0.049	0.497	0.500	3.180	0.001	-0.099
Mother's age marriage	0.472	0.473	-0.001	0.499	0.499	0.060	0.952	-0.002
Father educ	0.296	0.162	0.135	0.457	0.368	-9.835	0.000	0.324
Head sex	0.871	0.895	-0.024	0.335	0.306	2.333	0.020	-0.075
Clean water	0.143	0.141	0.002	0.350	0.348	-0.206	0.836	0.006
Health card	0.395	0.187	0.208	0.489	0.390	-14.205	0.000	0.470
Year 2005								
Child's sex	0.503	0.534	-0.031	0.500	0.499	1.349	0.178	-0.061
Mother educ	0.187	0.074	0.113	0.390	0.262	-6.782	0.000	0.340
Mother's age 1st birth	0.443	0.442	0.001	0.497	0.497	-0.045	0.964	0.002
Mother's age marriage	0.482	0.492	-0.010	0.500	0.500	0.459	0.647	-0.021
Father educ	0.400	0.150	0.250	0.490	0.357	-11.849	0.000	0.584
Head sex	0.891	0.846	0.046	0.311	0.362	-3.109	0.002	0.136
Clean water	0.115	0.103	0.012	0.319	0.304	-0.818	0.414	0.038
Health card	0.536	0.286	0.250	0.499	0.452	-11.232	0.000	0.525

Source: Ethiopian Demographic Health Survey. Note: authors' calculations.

TEPP Working Papers 2026

26-6. Gender and age diversity of the workforce. Does it matter for firms' performance ?
Laetitia Challe, Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi

26-5. Where women can have it all? The public sector and the rise of women in the higher deciles of wages in French Overseas Departments
Sandhya Apaya

26-4. Externatity effects of climate adaptation policies in urban areas : the case of green schools in Paris
Sylvain Chareyron, Laetitia Tuffery

26-3. Externality effects of building collapses due to insufficient renovation
Sylvain Chareyron, Léna Monasse, Florent Sari

26-2. The effect of monetary incentives on participation and behavior : an online experiment
Ngoc-Thao Noet, Serge Blondel

26-1. Participatory democracy in question: the case of "The Sea in Debate"
François-Charles Wolff, Pierre-Alexandre Mahieu, Brice Trouillet, Alexia Pigeault, Nicolas Rollo

TEPP Working Papers 2025

25-7. The impact of subsidizing early young innovative companies on their access to capital market
Anna Malessan

25-6. Competitiveness and employment or wage distribution. What do we learn from the corporate and payroll tax cuts policies in France ?
Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi

25-5. Marginal employment as an incentive to find a regular job? A meta-regression analysis approach
Fabrice Gilles

25-4. Improving employability for the least qualified unemployed. Lessons from a new French training program
Héloïse Burlat, Fabrice Gilles, Yannick L'Horty

25-3. Production regulation principles and tax reforms
Laurence Jacquet, Etienne Lehmann

25-2. Monetary policy transmission and household indebtedness in Australia
Khuderchuluun Batsukh, Nicolas Groshenny, Naveed Javed

25-1. Payroll tax reductions on low wages and minimum wage in France
Julien Albertini, Arthur Poirier, Anthony Terriau

TEPP Working Papers 2024

24-9. Training and job-to-job mobility with transfer fees
Arnaud Chéron, Anthony Terriau

24-8. Corporate taxation and firm heterogeneity
Julien Albertini, Xavier Fairise, Anthony Terriau

24-7. Effects of a business support program on firm performances in France
Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi

24-6. Increased fine for repeat offenders and conglomerate dynamics
Armel Jacques

24-5. The valuation of energy efficiency labels in the French housing market
Sylvain Chareyron

24-4. A comprehensive analysis of production efficiency : a tax reform perspective
Laurence Jacquet, Etienne Lehmann

24-3. How to measure energy poverty in warm and cold climate territories? A multidimensional approach
Manitra Rakotomena, Olivia Ricci

24-2. Innovating for the good or for the bad. An EU-wide analysis of the impact of technological transformation on job polarisation and unemployment
Ylenia Curci, Nathalie Greenan, Silvia Napolitano

24-1. Is training helpful in boosting the self-confidence and professional integration of young people not in employment, education or training? Results from a randomized experiment
Nicolas Moreau, Alexis Parmentier, Mylène Lebon-Eyquem

TEPP Working Papers 2023

23-8. Dornbusch's overshooting and the systematic component of monetary policy in SOE-SVAR
Nicolas Groshenny, Naveed Javed

23-7. Is participatory democracy in line with social protest? Evidence from French yellow vests movement
Benjamin Monnery, François-Charles Wolff

23-6. On-the-job search, life-cycle training and the role of transfer fees
Arnaud Cheron, Anthony Terriau

23-5. Estimating the laffer tax rate on capital income : cross-base responses matter!
Marie-Noëlle Lefebvre, Etienne Lehmann, Michaël Sicsic

23-4. The trickle-down theory: a reality in French sports?
Florian Moussi-Beylie

23.3. Robotization and unbalanced changes in high-skill employment
Lucas Parmentier

23.2. Knowledge transmission in the second part of careers: does formal training matter?
Pierre-Jean Messe, Nathalie Greenan

23-1. Phantom cycles
Arnaud Chéron, Bruno Decreuse

TEPP Working Papers 2022

22-21. Utility services poverty : addressing the problem of household deprivation in Mayotte
Dorothée Charlier, Bérangère Legendre, Olivia Ricci

22-20. The effects of disability benefits on the employment of low-skilled youth : evidence from France
Sylvain Chareyron, Naomie Mahmoudi

22-19. Does gender equality bargaining reduce child penality? Evidence from France
Pierre-Jean Messe, Jérémy Tanguy

22-18. The effect of pro diversity actions on discrimination in the recruitment of large companies : a field experiment
Laetitia Challe, Sylvain Chareyron, Yannick L'Horty, Pascale Petit

22-17. Impacts of quota policy and employer obligation to adapt workstations on discrimination against people with disabilities : lesson from an experiment
Sylvain Chareyron, Yannick L'Horty, Philomene Mbaye, Pascale Petit

22-16. Are real merchandise imports per capita a good predictor for the standard of living for the small island world : testing for the imports-led growth and the growth-led imports hypotheses in panels over the period 1970-2019
Jean-François Hoarau, Nicolas Lucic

22-15. Extracting the discrimination components from the callback rates
Emmanuel Duguet, Loïc Du Parquet, Pascale Petit

22-14. Strategic debt in a mixed duopoly: the limited liability effect
Armel Jacques

22-13. Short-time work policies during the COVID-19 pandemic
Julien Albertini, Xavier Fairise, Arthur Poirier, Anthony Terriau

22-12. Immigration and labour market flows
Andri Chassamboulli, Idriss Fontaine, Ismael Galvez-Iniesta

22-11. Short-term impact of tropical cyclones in Madagascar : evidence from nightlight data
Idriss Fontaine, Sabine Garabedian, Maël Jammes

22-10. The current and future costs of tropical cyclones: A case study of La Réunion
Idriss Fontaine, Sabine Garabedian, Helene Veremes

22-9. Wealth and income responses to dividend taxation : Evidence from France
Marie-Noëlle Lefebvre, Eddy Zanoutene

22-8. Soccer labour market equilibrium and efficient training of talents
Marnix Amand, Arnaud Chéron, Florian Pelgrin, Anthony Terriau

22.7. Using short-term jobs as a way to fin a regular job. What kind of role for local context?
Fabrice Gilles, Sabina Issehnane, Florent Sari

22-6. Gender and age diversity. Does it matter for firms' productivity?
Laetitia Challe, Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi

22-5. How wages respond to the job-finding and job-to-job transition rates? Evidence from New Zealand administrative data
Christopher Ball, Nicolas Groshenny, Özer Karagedikli, Murat Özbilgind, Finn Robinsona

22-4. Endogenous timing of technological choices of flexibility in a mixed duopoly
Armel Jacques

22-3. Reducing ethnic discrimination through formal warning : evidence from two combined field experiments
Sylvain Chareyron, Yannick L'Horty, Souleymane Mbaye, Pascale Petit

22-2. Cream skimming and Discrimination in access to medical care: a field experiment
Sylvain Chareyron, Yannick L'horty, Pascale Petit

22-1. Optimal taxation with multiple incomes and types
Kevin Spiritus, Etienne Lehmann, Sander Renes, Floris T. Zoutman

TEPP Working Papers 2021

21-11. Intermittent collusive agreements : antitrust policy and business cycles
Emilie Dargaud, Armel Jacques

21-10. Endogenous breadth of collusive agreements : an application to flexible technological choices
Emilie Dargaud, Armel Jacques

21-9. How to tax different incomes?
Laurence Jacquet, Etienne Lehmann

21-8. Does optimal capital taxation under stochastic returns to savings
Eddy Zanoutene

21-7. Does the gender mix influence collective bargaining on gender equality? Evidence from France
Anne-Sophie Bruno, Nathalie Greenan, Jérémy Tanguy

21-6. The effects of the non-financial component of business accelerators
Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi

21-5. Organisational changes and long term sickness absence and injury leave
Mohamed Ali Ben Halima, Nathalie Greenan, Joseph Lanfranchi

21-4. The unexplored discriminations towards youth : equal access to goods and services
David Gray, Yannick L'Horty, Souleymane Mbaye, Pascale Petit

21-3. The zero effect of income tax on the timing of birth: some evidence on French data
Nicolas Moreau

21-2. Tropical cyclones and fertility : new evidence from Madagascar
Idriss Fontaine, Sabine Garabedian, David Nortes-Martinez, Hélène Vérèmes

21-1. On the heterogeneous impacts of the COVID-19 lockdown on US unemployment
Malak Kandoussi, François Langot

TEPP Working Papers 2020

20-8. COVID-19 mortality and health expenditures across European countries: The positive correlation puzzle
Serge Blondel, Radu Vranceanu

20-7. Measuring discrimination in the labour market
Emmanuel Duguet

20-6. The effects of age on educational performances at the end of primary school: cross-sectional and regression discontinuity approach applications from Reunion Island
Daniel Rakotomalala

20-5. Slowdown antitrust investigations by decentralization
Emilie Dargaud, Armel Jacques

20-4. Is international tourism responsible for the pandemic of COVID19? A preliminary cross-country analysis with a special focus on small islands
Jean-François Hoarau

20-3. Does labor income react more to income tax or means tested benefit reforms?
Michaël Sicsic

20-2. Optimal sickness benefits in a principal-agent model
Sébastien Ménard

20-1. The specific role of agriculture for economic vulnerability of small island spaces
Stéphane Blancard, Maximin Bonnet, Jean-François Hoarau

TEPP Working Papers 2019

19-8. The impact of benefit sanctions on equilibrium wage dispersion and job vacancies
Sebastien Menard

19-7. Employment fluctuations, job polarization and non-standard work: Evidence from France and the US
Olivier Charlot, Idriss Fontaine, Thepthida Sopraseuth

19-6. Counterproductive hiring discrimination against women: Evidence from French correspondence test
Emmanuel Duguet, Loïc du Parquet, Yannick L'Horty, Pascale Petit

19-5. Inefficient couples: Non-minimization of the tax burden among French cohabiting couples
Olivier Bargain, Damien Echevin, Nicolas Moreau, Adrien Pacifico

19-4. Seeking for tipping point in the housing market: evidence from a field experiment
Sylvain Chareyron, Samuel Gorohouna, Yannick L'Horty, Pascale Petit, Catherine Ris

19-3. Testing for redlining in the labor market
Yannick L'Horty, Mathieu Bunel, Pascale Petit

19-2. Labour market flows: Accounting for the public sector
Idriss Fontaine, Ismael Galvez-Iniesta, Pedro Gomes, Diego Vila-Martin

19-1. The interaction between labour force participation of older men and their wife: lessons from France
Idriss Fontaine

TEPP Working Papers 2018

18-15. Be healthy, be employed: a comparison between the US and France based on a general equilibrium model
Xavier Fairise, François Langot, Ze Zhong Shang

18-14. Immigrants' wage performance in the routine biased technological change era: France 1994-2012
Catherine Laffineur, Eva Moreno-Galbis, Jeremy Tanguy, Ahmed Tritah

18-13. Welfare cost of fluctuations when labor market search interacts with financial frictions
Elini Iliopulos, François Langot, Thepthida Sopraseuth

18-12. Accounting for labor gaps
François Langot, Alessandra Pizzo

18-11. Unemployment fluctuations over the life cycle
Jean-Olivier Hairault, François Langot, Thepthida Sopraseuth

18-10. Layoffs, Recalls and Experience Rating
Julien Albertini, Xavier Fairise

18-9. Environmental policy and health in the presence of labor market imperfections
Xavier Pautrel

18-8. Identity mistakes and the standard of proof
Marie Obidzinski, Yves Oytana

18-7. Presumption of innocence and deterrence
Marie Obidzinski, Yves Oytana

18-6. Ethnic Discrimination in Rental Housing Market: An Experiment in New Caledonia
Mathieu Bunel, Samuel Gorohouna, Yannick L'Horty, Pascale Petit, Catherine Ris

18-5. Evaluating the impact of firm tax credits. Results from the French natural experiment CICE
Fabrice Gilles, Yannick L'Horty, Ferhat Mihoubi, Xi Yang

18-4. Impact of type 2 diabetes on health expenditure: an estimation based on individual administrative data
François-Olivier Baudot , Anne-Sophie Aguadé,Thomas Barnay, Christelle Gastaldi-Ménager, Anne Fargot-Campagna

18-3. How does labour market history influence the access to hiring interviews?
Emmanuel Duguet, Rémi Le Gall, Yannick L'Horty, Pascale Petit

18-2. Occupational mobility and vocational training over the life cycle
Anthony Terriau

18-1. Retired, at last? The short-term impact of retirement on health status in France
Thomas Barnay, Eric Defebvre

TEPP Working Papers 2017

17-11. Hiring discrimination against women: distinguishing taste based discrimination from statistical discrimination
Emmanuel Duguet, Loïc du Parquet, Pascale Petit

17-10. Pension reforms, older workers' employment and the role of job separation and finding rates in France
Sarah Le Duigou, Pierre-Jean Messe

17-9. Healthier when retiring earlier? Evidence from France
Pierre-Jean Messe, François-Charles Wolff

17-8. Revisting Hopenhayn and Nicolini's optimal unemployment insurance with job search monitoring and sanctions
Sebastien Menard, Solenne Tanguy

17-7. Ethnic Gaps in Educational Attainment and Labor-Market Outcomes: Evidence from France
Gabin Langevin, David Masclet, Fabien Moizeau, Emmanuel Peterle

17-6. Identifying preference-based discrimination in rental market: a field experiment in Paris
Mathieu Bunel, Yannick L'Horty, Loïc du Parquet, Pascale Petit

17-5. Chosen or Imposed? The location strategies of households
Emilie Arnoult, Florent Sari

17-4. Optimal income taxation with composition effects
Laurence Jacquet, Etienne Lehmann

17-3. Labor Market Effects of Urban Riots: an experimental assessment
Emmanuel Duguet, David Gray, Yannick L'Horty, Loic du Parquet, Pascale Petit

17-2. Does practicing literacy skills improve academic performance in first-year university students? Results from a randomized experiment
Estelle Bellity, Fabrices Gilles, Yannick L'Horty

17-1. Raising the take-up of social assistance benefits through a simple mailing: evidence from a French field experiment
Sylvain Chareyron, David Gray, Yannick L'Horty

TEPP Working Papers 2016

16-8. Endogenous wage rigidities, human capital accumulation and growth
Ahmed Tritah

16-7. Harder, better, faster...yet stronger? Working conditions and self-declaration of chronic diseases
Eric Defebvre

16-6. The influence of mental health on job retention
Thomas Barnay, Eric Defebvre

16-5. The effects of breast cancer on individual labour market outcomes: an evaluation from an administrative panel
Thomas Barnay, Mohamed Ali Ben Halima, Emmanuel Duguet, Christine Le Clainche, Camille Regaert

16-4. Expectations, Loss Aversion, and Retirement Decisions in the Context of the 2009 Crisis in Europe
Nicolas Sirven, Thomas Barnay

16-3. How do product and labor market regulations affect aggregate employment, inequalities and job polarization? A general equilibrium approach
Julien Albertini, Jean-Olivier Hairault, François Langot, Thepthida Sopraseuth

16-2. Access to employment with age and gender: results of a controlled experiment Laetitia Challe, Florent Fremigacci, François Langot, Yannick L'Horty, Loïc Du Parquet, Pascale Petit

16-1. An evaluation of the 1987 French Disabled Workers Act: Better paying than hiring
Thomas Barnay, Emmanuel Duguet, Christine Le Clainche, Yann Videau

TEPP Working Papers 2015

15-10. Optimal Income Taxation with Unemployment and Wage Responses: A Sufficient Statistics Approach
Kory Kroft, Kavan Kucko, Etienne Lehmann, Johannes Schmieder

15-9. Search frictions and (in) efficient vocational training over the life-cycle
Arnaud Chéron, Anthony Terriau

15-8. Absenteeism and productivity: the experience rating applied to employer contributions to health insurance
Sébastien Ménard, Coralia Quintero Rojas

15-7. Take up of social assistance benefits: the case of homeless
Sylvain Chareyron

15-6. Spatial mismatch through local public employment agencies. Answers from a French quasi-experiment
Mathieu Bunel, Elisabeth Tovar

15-5. Transmission of vocational skills at the end of career: horizon effect and technological or organisational change
Nathalie Greenan, Pierre-Jean Messe

15-4. Protecting biodiversity by developing bio-jobs: A multi-branch analysis with an application on French data
Jean De Beir, Céline Emond, Yannick L'Horty, Laetitia Tuffery

15-3. Profit-Sharing and Wages: An Empirical Analysis Using French Data Between 2000 and 2007
Noélie Delahaie, Richard Duhautois

15-2. A meta-regression analysis on intergenerational transmission of education: publication bias and genuine empirical effect
Nicolas Fleury, Fabrice Gilles

15-1. Why are there so many long-term unemployed in Paris?
Yannick L'Horty, Florent Sari

TEPP Working Papers 2014

14-14. Hiring discrimination based on national origin and the competition between employed and unemployed job seekers
Guillaume Pierné

14-13. Discrimination in Hiring: The curse of motorcycle women
Loïc Du Parquet, Emmanuel Duguet, Yannick L'Horty, Pascale Petit

14-12. Residential discrimination and the ethnic origin: An experimental assessment in the Paris suburbs
Emmanuel Duguet, Yannick L'Horty, Pascale Petit

14-11. Discrimination based on place of residence and access to employment
Mathieu Bunel, Yannick L'Horty, Pascale Petit

14-10. Rural Electrification and Household Labor Supply: Evidence from Nigeria
Claire Salmon, Jeremy Tanguy

14-9. Effects of immigration in frictional labor markets: theory and empirical evidence from EU countries
Eva Moreno-Galbis, Ahmed Tritah

14-8. Health, Work and Working Conditions: A Review of the European Economic Literature
Thomas Barnay

14-7. Labour mobility and the informal sector in Algeria: a cross-sectional comparison (2007-2012)
Philippe Adair, Youghourta Bellache

14-6. Does care to dependent elderly people living at home increase their mental health?
Thomas Barnay, Sandrine Juin

14-5. The Effect of Non-Work Related Health Events on Career Outcomes: An Evaluation in the French Labor Market
Emmanuel Duguet, Christine le Clainche

14-4. Retirement intentions in the presence of technological change: Theory and evidence from France
Pierre-Jean Messe, Eva Moreno-Galbis, Francois-Charles Wolff

14-3. Why is Old Workers' Labor Market more Volatile? Unemployment Fluctuations over the Life-Cycle
Jean-Olivier Hairault, François Langot, Thepthida Sopraseuth

14-2. Participation, Recruitment Selection, and the Minimum Wage
Frédéric Gavrel

14-1. Disparities in taking sick leave between sectors of activity in France: a longitudinal analysis of administrative data
Thomas Barnay, Sandrine Juin, Renaud Legal

TEPP Working Papers 2013

13-9. An evaluation of the impact of industrial restructuring on individual human capital accumulation in France (1956-1993)
Nicolas Fleury, Fabrice Gilles

13-8. On the value of partial commitment for cooperative investment in buyer-supplier relationship
José de Sousa, Xavier Fairise

13-7. Search frictions, real wage rigidities and the optimal design of unemployment insurance
Julien Albertini, Xavier Fairise

13-6. Tax me if you can! Optimal nonlinear income tax between competing governments
Etienne Lehmann, Laurent Simula, Alain Trannoy

13-5. Beyond the labour income tax wedge: The unemployment-reducing effect of tax progressivity
Etienne Lehmann, Claudio Lucifora, Simone Moriconi, Bruno Van Der Linden

13-4. Discrimination based on place of residence and access to employment
Mathieu Bunel, Emilia Ene Jones, Yannick L'Horty, Pascale Petit

13-3. The determinants of job access channels: evidence from the youth labor market in France
Jihan Ghrairi

13-2. Capital mobility, search unemployment and labor market policies: The case of minimum wages
Frédéric Gavrel

13-1. Effort and monetary incentives in Nonprofit et For-Profit Organizations
Joseph Lanfranchi, Mathieu Narcy

The TEPP Institute

The CNRS **Institute for Theory and Evaluation of Public Policies** (the TEPP Institute, FR n°2024 CNRS) gathers together research centres specializing in economics and sociology:

- L'**Equipe de Recherche sur l'Utilisation des Données Individuelles en lien avec la Théorie Economique** (Research Team on Use of Individuals Data in connection with economic theory), **ERUDITE**, University of Paris-Est Créteil, University of Gustave Eiffel;
- Le **Centre d'Etudes des Politiques Economiques** (Research Centre focused on the analysis of economic policy and its foundations and implications), **EPEE**, University of Evry Paris-Saclay ;
- Le **Centre Pierre Naville** (Research on Work and Urban Policies), **CPN**, University of Evry Paris-Saclay
- Le **Groupe d'Analyse des Itinéraires et des Niveaux Salariaux** (Group on Analysis of Wage Levels and Trajectories), **GAINS**, Le Mans University
- Le **Centre de Recherches en Economie et en Management**, (Research centre in Economics and Management), **CREM**, University of Rennes 1, University of Caen Basse-Normandie ;
- Le **Groupe de Recherche ANgevin en Économie et Management** (Angevin Research Group in Economics and Management), **GRANEM**, University of Angers ;
- Le **Centre de Recherche en Economie et Droit** (Research centre in Economics and Law) **CRED**, University of Paris II Panthéon-Assas ;
- Le **Laboratoire d'Economie et de Management Nantes-Atlantique** (Laboratory of Economics and Management of Nantes-Atlantique) **LEMNA**, Nantes University ;
- Le **Laboratoire interdisciplinaire d'étude du politique Hannah Arendt – Paris-Est**, **LIPHA-PE**, University of Paris-Est Créteil and University of Gustave Eiffel ;
- Le **Centre d'Economie et de Management de l'Océan Indien**, **CEMOI**, University of La Réunion ;
- Le **Laboratoire d'économie de Poitiers**, **LéP**, University of Poitiers ;
- L'UMR **Structures et marchés agricoles, ressources et territoires**, **SMART**, INRAE, Agro Rennes-Angers Institute ;
- Le **Centre de recherche en économie et en droit sur le développement insulaire**, **CREDDI**, University of the Antilles.

TEPP brings together 230 teacher-researchers and 100 doctoral students. It is both one of the main academic operators in the evaluation of public policies in France, and the largest multidisciplinary federation of research on work and employment. It responds to the demand for impact assessment of social programs using advanced technologies combining theoretical and econometric modeling, qualitative research techniques and controlled experiences.