The Lasting Effects of Early Childhood Interventions: The National Vaccination Commando Program in Burkina Faso *

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Abstract

This study evaluates the long-term impacts of the National Vaccination Commando Program, an early childhood health intervention in Burkina Faso, during the 1980s. Using a difference-in-differences approach, we find significant reductions in child mortality and improvements in educational attainment, including increased primary school completion rates. We also find significant positive effects on adult employment and agricultural productivity, yielding a substantial rate of return on the initial health intervention. These findings underscore the lasting benefits of early childhood health interventions in low-income countries.

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1 Introduction

Early childhood health interventions have been shown to generate long-lasting positive effects on health, education, and labor market outcomes, ultimately reducing poverty and inequality (Currie and Vogl, 2013; Almond et al., 2018; Case et al., 2005; Flores et al., 2020; Heckman et al., 2013; Gertler et al., 2014). This is attributed to the formative nature of childhood and the cumulative impact of early life interventions, which contribute to their high returns (Nandi et al., 2017). A substantial body of research, using various empirical methods, has consistently demonstrated the persistence of these intervention benefits into adulthood.

Much of the existing research on early childhood interventions focuses on high-income countries, highlighting the effects on academic outcomes, participation in the labor market, and earnings (e.g., Carneiro et al., 2021). However, early life circumstances can have a more significant impact on lifetime outcomes in low- and middle-income countries, where remediation opportunities are often limited (e.g., Currie and Vogl, 2013). Furthermore, in these contexts, where many are self-employed in agriculture or the informal sector, the returns to early childhood interventions may extend beyond academic gains and participation in the formal labor market. Therefore, carefully examining the long-term effects of early interventions in low-income settings is crucial given the starker trade-offs in resource allocation and potentially greater benefits.

In this paper, we investigate the long-term impacts of public health policies targeting children up to six years of age in economies where the formal labor market is limited and low-technology agriculture is the main source of livelihood. Specifically, we examine the impact of a nationwide immunization program in Burkina Faso during the 1980s, using a difference-in-differences (DiD) approach to assess its outcomes. This program, supported by the government and several donors, was unique in its implementation, vaccinating 60% eligible children against preventable diseases in two weeks. As a result, the overall immunization rate rose sharply from around 17% to 77% in the last two weeks of December 1983. However, vaccination rates varied significantly by region, leading to differences in exposure among eligible children. We exploit these geographical differences to assess the lasting effects of the vaccination program on recipients.

The program, known locally as the Vaccination Commando Program (VCP), was a coordinated effort by the government of Burkina Faso, World Health Organization, and several international government donors to expand vaccination coverage. This effort was based on the premise that vaccination is one of the most cost-effective ways to save lives and increase human capital. Not only do vaccines protect the children who receive them from life-threatening infectious diseases, but high vaccination rates also benefit future generations by reducing the spread of infections and lowering the burden of targeted diseases over time. Despite these demonstrated benefits, in 2020, one in five children worldwide was not vaccinated for life-threatening infectious diseases, according to the World Health Organization (WHO, 2021). This rate is even lower in many developing nations—ranging from 40% to 70%—highlighting the need for continued efforts to expand access to vaccines (WHO, 2020).[1]

[1] The average vaccination rate for the diphtheria-tetanus-pertussis (DTP3) vaccine in low-income countries was 70% in 2020. For the same vaccine and year, the immunization rate was 37% in Papua New Guinea, 42% in Central African Republic, 49% in South Sudan, and 52% in Chad (WHO, 2021). Similarly, the global measles vaccination

In developing countries with relatively weak infrastructure and healthcare systems, an outbreak of an infectious disease places a tremendous burden on the economy and undermines years of development efforts. Well-designed and effectively administered vaccination programs could prevent such catastrophic events and increase economic growth by reducing the burden on the health system and improving human capital. Therefore, a functional vaccination program could be an effective early childhood intervention and potentially growth-inducing in the long run. Yet, increasing vaccine hesitancy[2] in developed nations, and continued under-investment in vaccines in developing nations, suggest that the impact of vaccines is still not well understood.[3]

Implemented in 1984 in Burkina Faso, the VCP provides a unique natural experiment to evaluate the impact of a national-level vaccination program. In 1983, the national vaccination rate was only 17% (UNICEF, 2007; Kessler et al., 1987). That same year, Thomas Sankara's military regime assumed power after a coup. Building on the existing but underperforming Expanded Program on Immunization (EPI), the regime initiated the VCP, which vaccinated more than a million children against measles, yellow fever, and meningitis in a two-week campaign. Consequently, the vaccination rate in Burkina Faso increased from 17% to 77% in the second half of December 1984. The success of the program was hailed by the WHO and presented as a case study of one of the most successful vaccination campaigns (Kessler et al., 1987).

Two features of the VCP make it an ideal policy quasi-experiment. First, its implementation was sudden. Second, it relied on the military infrastructure and deployed civil servants, leaving the health system unchanged. We measure the VCP's impact by exploiting cohort-region variations in exposure to the program, using a DiD approach (e.g., Bleakley, 2007; Duflo, 2001). Variations across cohorts arise from the timing of the program: individuals who were six years old or younger would have been eligible to receive all early childhood vaccinations, while older individuals would not have been theoretically eligible. In addition, spatial differences emerge from the varying vaccination rates between districts (that is, provinces), which further contribute to the observed variations.

We start by focusing on the under-five child mortality rate, finding that the vaccination program led to a significant decline in child mortality. This result is similar to that of Clemens et al. (1988) and Koenig et al. (1990), who find that in Bangladesh, measles vaccination reduces child mortality,

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rate (among children aged 12–24 months) in 2020 was 70%, whereas it was 46% in Somalia, 47% in Guinea, 51% in Angola, and 54% in Nigeria (World Bank, 2021).

[2] COVID-19 vaccine hesitancy has led to severe protests against vaccination mandates in the United States and Australia, with some protesters comparing the state government to Nazis. Conversely, fearmongering was observed with polio vaccines in the past in India. See https://www.nytimes.com/2021/11/10/health/vaccine-mandate-state-lawsuit.html, https://www.usnews.com/news/world/articles/2021-11-13/australia-vaccine-mandate-protesters-compare-state-govt-to-nazis-media, and https://www.comminit.com/global/content/fear-polio-drops-overcome.

[3] One potential reason is the limited number of studies evaluating the impact of national-level vaccination programs (e.g., Uddin et al., 2016; Pezzotti et al., 2018; Sindoni et al., 2021; Nandi et al., 2020; Atwood, 2022). Uddin et al. (2016), Pezzotti et al. (2018), and Sindoni et al. (2021) evaluate how national-level vaccination programs affect vaccine coverage and incidence of diseases in Bangladesh and Italy. To the best of our knowledge, Nandi et al. (2020) and Atwood (2022) are the only studies to evaluate national-level vaccination efforts to examine their impact on human capital and labor market outcomes in India and the United States, respectively. Nandi et al. (2020) use a household fixed effect estimation to evaluate the effect of the Universal Immunization Program in India, finding that vaccination leads to higher schooling attainment. Atwood (2022) uses a variation in pre-vaccine measles incidence rates across states in the US and differential exposure to the vaccine due to birth year to measure the effects of measles vaccination on earnings and employment in adulthood.

as well as Nandi et al. (2019), who find that measles vaccination leads to better health outcomes in Ethiopia, India, and Vietnam.[4] We also find an increase in educational attainment, as evidenced by higher primary school completion rates, a trend consistent with outcomes observed in South Africa (Anekwe et al., 2015), Ethiopia and Vietnam (Nandi et al., 2019), and India (Nandi et al., 2020). Finally, we investigate how the program affects the labor market outcomes of vaccinated cohorts in adulthood. We find that they were significantly more likely to be employed in the formal sector and earned higher agricultural yields per hectare. Atwood (2022) finds a similar result for the measles vaccine in the United States, where the labor market is well established. However, whether exposure to early childhood immunization improves labor market outcomes in developing countries with more frictions in labor markets remains an open question that we address in this paper.

This paper makes three major contributions to the literature examining the long-term returns of large health interventions (Atwood, 2022; Nandi et al., 2020) and early childhood interventions in general (Currie and Vogl, 2013; Almond et al., 2018; Case et al., 2005; Flores et al., 2020; Heckman et al., 2013; Gertler et al., 2014). First, among the active literature on "early origins," most causal studies focus on high-income countries with an adequate supply of educational services and well-functioning labor markets. Although an increasing number of empirical findings provide persuasive evidence that the impacts of early life conditions can be lasting, results from low-income settings are scarcer. We contribute by documenting the impacts of a nationwide health program in the context of a developing country, using a quasi-experimental design. The nationwide setting of our study adds a new dimension to several studies on the impacts of vaccination that focus mainly on local programs (Anekwe et al., 2015; Koenig et al., 1990). Studies based on local vaccination programs are informative but are also likely to mischaracterize the true effect of the program due to failure to capture spillover effects.[5]

Second, we concentrate on documenting the long-term effects of a nationwide policy initiative, which we describe as a positive health shock, a departure from studies focusing on the long-term effects of natural or human-made shocks such as droughts, conflicts, or disease outbreaks. While studies using these types of shocks (e.g., Andrabi et al., 2023; Maccini and Yang, 2009)[6] have provided valuable insights, they may not fully capture the potential benefits and transformative effects that positive health shocks can have on societies if negative and positive health shocks have asymmetric effects, particularly in low-income countries (Bloom and Canning, 2003). Therefore, investigating the consequences of these initiatives can provide crucial evidence for designing effective policies and interventions to improve overall population health.

Third, we uncover the potential channel through which early childhood health interventions raise agricultural productivity. Specifically, we build on the early insights of Bliss and Stern (1978a,b) and Strauss (1986) to show that the vaccination program increased the effectiveness (or quality)

[4]Bloom et al. (2011) find that vaccination has no impact on children's height and weight in the Philippines.

[5]Specifically, while the spillover effects on disease burden are unquestionably positive in the short run, the effects on education and labor outcomes can be ambiguous. Improved child health due to vaccination can increase the demand for education, which can then lower enrollment rates if the supply of educational services does not increase to match changes in demand. Similar arguments can be made for the formal labor market. These types of frictions are presumably more severe in resource-constrained countries such as Burkina Faso.

[6]Dell et al. (2014) provide a good review of this literature.

of farm labor rather than the quantity of farm labor supplied. Given the prevalence of small-scale agriculture in most of the developing world, we argue that this finding may have a broad influence on how returns to early childhood health interventions are perceived in the developing world.

The rest of the paper is organized as follows. Section 2 provides information on the program and our data, and Section 3 discusses our empirical strategy. Section 4 presents our main results. Section 5 provides various robustness checks, Section 6 presents a cost-benefit analysis to estimate the net present value of the VCP, and Section 7 concludes.

2 Program Background and Data

2.1 VCP in Burkina Faso

Before the VCP, vaccine-preventable diseases were a leading cause of under-five child mortality in Burkina Faso (Bellamy, 1998). In response, the government established its EPI in 1980 to administer vaccines against measles, meningitis, and yellow fever to eligible children. However, the program performed poorly, reaching only 25,000 of the half million children under two years of age who were eligible in 1981 (Bellamy, 1998), a coverage of 5%. The lack of vaccines and the ineffective transportation of immunization personnel were cited for the low coverage. To address the EPI's failure, in 1984 the government launched the VCP. In a 15-day campaign between November 25 and December 10 of 1984, over one million children were vaccinated against measles, yellow fever, and meningitis. The campaign covered 68%–75% of previously unvaccinated children and saw an increase in national vaccination coverage from 17% to 77%. Consequently, the incidence of measles decreased dramatically (see Figure 1).

The VCP targeted children aged 9 months to 6 years for measles vaccinations and those aged 1 to 14 years against meningitis and yellow fever (Kessler et al., 1987). The government implemented both demand- and supply-side measures to ensure the program's success. To maintain the demand for vaccination, the government raised vaccination awareness through a nationwide campaign using multiple mediums.[7] On the supply side, it ensured that vaccines were acquired on the international market and distributed locally in a timely manner. The WHO, UNICEF, and several bilateral donors helped finance vaccine purchases, while the Ministry of Health provided a refresher course for health workers and temporarily reassigned workers to ensure adequate staffing. Moreover, military and paramilitary resources were deployed to facilitate transportation logistics.

2.2 Data Sources and Descriptive Statistics

We use microdata from four sources for our analysis: the Demographic and Health Survey (DHS), the Burkina Faso General Population and Housing Census (entire sample of the 1985 census and 10% of the sample from the 1996 and 2006 censuses), the Permanent Agricultural Survey (PAS), and administrative data from the Ministry of Health on immunizations. We use the 1993 round of

[7] The government used radio and television messaging, distributed educational brochures (including in several local languages), displayed posters, organized local fairs, and staged theaters. Artists were encouraged to write and perform songs about the program.

the DHS to calculate the child mortality rate by year of birth.[8] The census data serve two purposes. First, we use the full census of 1985 and administrative data on the number of children immunized in each province in December 1984 to calculate the vaccination rates in each province. Second, we use census data from 1996 and 2006 to calculate education and labor market outcomes. Finally, we use plot-level data collected between 2008 and 2014 by the PAS (see Kazianga and Wahhaj, 2017) to calculate agricultural productivity.

We study the impact of increased vaccination on both short-, medium-, and long-run outcomes. For short-, and medium-term outcomes, we focus on child mortality and educational attainment. Child mortality is a dummy variable equal to one if the parent reported the death of a child under age five. Similarly, primary completion is a dummy variable equal to one if the child is reported to have completed primary school. Figures 3—5 present the trends, where we use labor market outcomes in adulthood to measure the long-term effect of the increased vaccination.[9] We focus on two labor market outcomes: formal employment and agricultural productivity. Formal employment is a dummy variable equal to one if an individual engages in formal employment in adulthood. We measure agricultural productivity as the harvest value divided by the size of the farm plot. Figures 6–7 present the trends of these variables.

Table 1 provides descriptive statistics on our estimation samples, consisting of DHS data in Panel A, national census data in Panel B, and agricultural survey data in Panel C. Columns (1)–(3) present the sample size, mean, and standard deviation of the entire sample. We also provide the same statistics separately for the low-intensity vaccination provinces in columns (4)–(6) and the high-intensity vaccination provinces in columns (7)–(9). We focus on individuals born between 1966 and 1983 and construct three cohorts based on year of birth: 1966–1971, 1972–1977, and 1978–1983. Only individuals born between 1978 and 1983 were eligible for measles vaccination in 1984, and therefore they constitute the treated cohort.[10]

The DHS data in Panel A show a high child mortality rate of 285 per 1,000 live births for the entire sample. This rate is virtually identical for both the low- and high-intensity vaccination provinces. Within the sample, approximately 53% belong to the eligible cohort, comprising individuals born between 1978 and 1983. About 33% are part of the first control cohort, with birth years ranging from 1972 to 1977, and the remaining 14% fall into the second control cohort, consisting of those born between 1966 and 1971. The measles vaccination rate for the entire sample is approximately 64%, while the rates for the low- and high-intensity regions are 45% and 79%, respectively.

We summarize the education and employment outcomes in Panel B, using census data. About 20% of all individuals have ever enrolled in school, and only 16% have completed at least primary education. Since only a tiny fraction of individuals enter formal jobs by age 27, we restrict the sample to those above age 27 for formal sector employment. With this restriction, about 8% of the

[8]We selected this particular round as it is the closest to the program's initiation in 1984, and thus the birth reports of birth histories for the relevant cohorts are less noisy relative to the more recent cohorts. In addition, more respondents would still be residing in the same province in that year. We drop the urban sub-sample since the survey sampled only urban households from one province.

[9]Provinces with high vaccination rates are defined as provinces where the residual of a regression of the number of vaccinated children on the number of children is positive, following Duflo (2001).

[10]Children aged nine months to six years were eligible for measles vaccination.

sample reported having formal employment in the 2006 General Population and Housing Census.[11] These figures are slightly higher in the high-intensity vaccination provinces than in low-intensity ones. The measles vaccination rate is 64% for the entire sample but substantially higher in high-intensity regions (82%) than in low-intensity ones (46%). About 58% of the sample is identified as Muslim and 53% female. Only 20% of the sample ever enrolled in a primary school, and 16% completed primary school.

Panel C provides the summary statistics of the agricultural production data that we use to investigate the effect on farm productivity. The data were collected between 2008 and 2014 by the Burkina Faso Ministry of Agriculture, commonly referred to as the PAS. The survey, fielded at the plot level, contains detailed information on crop output, inputs (including labor), and plot manager characteristics. Because the organization of farm households in Burkina Faso differentiates individual plots managed by a household member from collective ones (Kazianga and Wahhaj, 2017, 2013; Udry, 1996), we restrict the analysis to individual plots since we assign treatment through the plot manager's year of birth. Columns (1)–(3) present the summary statistics for the entire sample, whereas columns (4)–(6) and columns (7)–(9) present summary statistics for low- and high-intensity vaccination provinces, respectively. About 40% of our sample belongs to the treated cohort, 32% belong to the first control cohort, and the remaining 28% belong to the second control cohort. The mean vaccination rate for the entire sample is about 61%, while the vaccination rates for the low- and high-intensity regions are 44% and 83%, respectively.

We also present the summary statistics of agricultural yield and agricultural inputs, which include labor hours and fertilizer (Nitrogen, Phosphorus, and Potassium (NPK) and Urea). Furthermore, we summarize the data on plot characteristics, including toposequence, plot distance from a village, plot ownership status, and plot size in hectares. The slope of the land (i.e., toposequence) is categorized into three groups: toposequence 1 (flat ground), toposequence 2 (low ground), and toposequence 3 (sloping ground). Plot distance from a village is categorized as distant plot (furthest), intermediate plot (midway), and proximity plot (closest). Finally, the harvest value per hectare (in natural log) is in the real value of the local currency.

3 Empirical Strategy

We estimate the impact of the VCP by exploiting cohort-region variation in exposure to the program, using a DiD approach (e.g., Bleakley, 2007; Duflo, 2001). In our specification, cohort variation arises from the timing of the program: individuals who were six years old or younger would have been eligible to receive measles vaccination, while older individuals would not have been theoretically eligible. We start with the following DiD specification:

$$Y_{ijk} = \alpha_0 + \beta_1 \left(I_k * \text{Exposure}_j \right) + X_{ijk}\Pi + \eta_k + \gamma_j + \varepsilon_{ijk}, \tag{1}$$

where Y_{ijk} is the outcome of interest of individual i in cohort j in province k and I_k is the treatment intensity in province k. We consider two versions of $I \in \{VRM, HVRM\}$ in our identification strategy. VRM is the provincial vaccination rate of measles (VRM) in December 1984, and $HVRM$

[11] This census is the last available census in Burkina Faso for which data are available.

is a dummy variable indicating whether a province had a high vaccination rate of measles (HVRM) in December 1984.[12] Exposure$_j$ is a dummy variable indicating whether the individual belongs to a cohort exposed to the VCP, and η_k and γ_j represent province and cohort fixed effects, respectively. ε_{ijk} represents the idiosyncratic error. To account for possible serial correlation, we cluster errors at the province level. The interaction coefficient β_1 captures the causal effect of the VCP on the outcome of interest when the treatment intensity increases by one per 100 children. We show estimates with and without control variables X_{ijk}, which, depending on the outcome variable considered, is a vector of variables including gender, ethnicity, religion, and agricultural plot characteristics.

It is important to highlight that our DiD approach identifies the differential effect of the VCP for individuals in high-intensity provinces relative to those in low-intensity ones. To assess the validity of the common trends assumption in the high- versus low-intensity DiD estimation, we perform a placebo estimation using the cohort born between 1972 and 1977. Children in this cohort were older than six years in December 1984 and could not have received the measles vaccine during the VCP. We also conduct a series of robustness checks on the Duflo (2001) approach by adopting a binary treatment that compares provinces with vaccination rates below the national median and those with higher vaccination rates.[13]

The treatment and control groups created using Duflo (2001) assume a homogeneous treatment effect across provinces. To assess the robustness of our results to possible heterogeneous treatment effects, we perform additional analyses. First, we assign provinces to estimated treatment and control groups following an approach developed by De Chaisemartin and d'Haultfoeuille (2018). These authors argue that using treatment and control groups of provinces as defined in Duflo (2001) can lead to biased estimates. The De Chaisemartin and d'Haultfoeuille (2018) approach classifies as controls only provinces with a stable pre-treatment distribution of the outcome variable between the two cohorts considered. Equality of distribution is performed using a Kolmogorov-Smirnov test. As De Chaisemartin and d'Haultfoeuille (2018) point out, as long as the number of observations within each province is significantly larger than the number of provinces, the newly created groups will not affect the asymptotic variance of the treatment effect estimates. We consider this comment and apply their approach to the 1972-1977 and 1978-1983 birth cohorts.

To account for heterogeneity in treatment responses based on the age range at which an individual was exposed to vaccination, we follow Berg et al. (2023) and use the following specification:

$$Y_{ijk} = \alpha_0 + \sum_a \beta_a \left(I_k * \mathrm{VCP}_{ja}\right) + X_{ijk}\Pi + \eta_k + \gamma_j + \varepsilon_{ijk}, \tag{2}$$

[12] Provinces with a positive residual in the regression of vaccinated children on the number of children eligible for measles vaccination, as per Duflo (2001), are designated as having a HVRM. We check the robustness of our analysis by exploring any potential misclassification of provinces into either the treatment or control groups. Based on the dichotomous treatment definition, we find that two provinces with vaccination rates below the median fall into the treatment group. We estimate equation Eq. 1 by taking the two potentially misclassified provinces into the control group. Alternatively, we also re-estimate Eq. 1 by dropping those two provinces. We discuss the results of these exercises in Section 4. In short, we conclude that the dichotomous treatment definition does not misclassify any provinces.

[13] In our specific case, we assume that provinces with lower vaccination rates can serve as a good counterfactual for those with higher vaccination rates if the evolution of the outcomes of interest at lower vaccination rates would have been the same.

where VCP_{ja} is the share of individuals in the age range a and cohort j who were exposed to the VCP, and the other variables are defined above. Because children under six years are typically the most vulnerable to measles, we consider three age groups in our empirical analysis: low exposure (LE, ages five to six), moderate exposure (ME, ages three to four), and high exposure (HE, ages one to two). For all $a \in \{LE, ME, HE\}$, β_a captures the causal effect of VCP exposure at the age range a on the outcome variable Y.

Callaway et al. (2021) highlight the limitations of the two-way fixed effects (TWFE) estimator, β_1^{twfe} when the treatment variable is continuous. Contrary to its common interpretation as an average causal response in the existing applied economics literature, they demonstrate that this estimator can be significantly biased and may lack a clear causal interpretation under heterogeneity. Specifically, under the common trends assumption for untreated potential outcomes, they show that β_1^{twfe} is a weighted sum of different treatment effects. Given these findings, Callaway et al. (2021) advise against using the TWFE regression in the presence of heterogeneous treatment effects. Instead, they propose estimating a series of simple 2×2 DiD comparing dose groups to an untreated comparison group. Under common trends assumption, those estimators will identify $ATT(d|d)$ for all d, and these can be averaged to obtain $ATE(d)$. We follow their recommendation and run a series of 2×2 DiD. Since we do not have an untreated group in our case (there is no province with a 0% vaccination rate), we instead compare each high-intensity province with low-intensity provinces. These values are then averaged to obtain the average treatment effect in the high-intensity provinces. Finally, since our empirical strategy uses multiple cohorts over time, we check the robustness of our results with respect to internal migration using counterfactual methods (see Appendix B for more details).

4 Results

In this section, we present the short-, medium-, and long-term impacts of the VCP. As stated above, we focus on child mortality outcomes to measure the short-term impact, educational outcomes to measure the medium-term impact, and formal employment and agricultural productivity in adulthood to measure the long-term impact. In each table, we present the results from two estimation approaches: the continuous treatment intensity TWFE and the dummy treatment TWFE. For the continuous treatment intensity TWFE, the estimated coefficient ($\hat{\beta}_1$) in Eq. 1 captures the interaction between the treatment cohort dummy (Exposure$_j$, 1978–1983 birth cohort = 1) and the treatment intensity (I_k, VRM in province k). Similarly, for the dummy treatment TWFE, the estimated coefficient ($\hat{\beta}_1$) in Eq. 1 captures the interaction between the treatment cohort dummy (Exposure$_j$, 1978–1983 birth cohort = 1) and the treatment dummy (I_k, indicator of the HVRM in province k). Odd columns present the estimation results without any covariates, whereas even columns present the estimation results with covariates. All specifications control for province and year of birth fixed effects, and the standard errors are clustered at the province level (the unit of treatment). All tables follow the same structure unless indicated otherwise.

4.1 Short-Term Outcomes: Child Mortality

We begin by showing the VCP's impact on child mortality, the most immediate outcomes we have access to. If the vaccination campaign had been successful, overall health would have improved, leading to lower mortality rates. Therefore, while mortality rates are key indicators of well-being in their own right, they also measure changes in the health of the population of interest.

Table 2 presents the VCP's impact on mortality based on Eq. 1, using the rural sub-sample of the 1993 round of the DHS. The dependent variable is child mortality in columns (1)–(4).[14] Even columns include additional controls, namely the child's ethnicity and gender and the mother's age and literacy. The results in columns (1)–(4) suggest that the VCP significantly reduced child mortality. Specifically, the effect of the treatment in column (1) is –0.08, which is statistically significant at the 10% level. This suggests that an increase in the vaccination rate by 1 percentage point decreased child mortality by 0.08 percentage points. Furthermore, this point estimate is robust to including additional control variables, as shown by the virtually unchanged coefficient in column (2).

We repeat the exercise in columns (3) and (4), using the dichotomized treatment, as described in Section 3. We find a point estimate of 0.05 (without and with controls), significant at the 10% level. This indicates that in the cohort exposed to the program, child mortality in provinces with a high vaccination rate decreased by 0.05 percentage points.[15] These estimates, derived using the binary version of treatment in columns (3) and (4), are slightly lower than those in columns (1) and (2). The reduction translates to a 16.2% decrease in child mortality from the average baseline of 0.29, equivalent to saving approximately 47 children per 1,000 live births.

4.2 Medium-Term Outcomes: Education

We now investigate to what extent improved health led to better educational outcomes. Specifically, we estimate the VCP's effect on primary school enrollment and completion,[16] using the 1996 and 2006 rounds of the General Population and Housing Census. The results in Table 3 show that the VCP induced more individuals to enroll in school (columns (1)–(4)) and to complete at least primary education (columns (5)–(8)). The point estimate in column (1) is 0.06, which is statistically significant at the 5% level. This estimate remains robust when including additional control variables, as shown by the virtually identical coefficient in column (2). The analysis suggests that an increase in the vaccination rate by 1 percentage point leads to an increase in primary school

[14] We follow the practice in the literature and define "child mortality" as dying by five years of age.

[15] To check the robustness of the dichotomous treatment definition, we investigate potential misclassifications of provinces. We identify two provinces with below-median vaccination rates categorized as high vaccination provinces. We re-estimate Eq. 1 by incorporating these provinces into the control group, anticipating a larger treatment effect if misclassified. The results in Appendix Table B.4 show a smaller treatment effect on child mortality and statistically indifferent effects on other outcomes. Additionally, we re-estimate Eq. 1 by excluding the two provinces, expecting larger treatment effects if misclassified. However, Appendix Table B.5 similarly indicates a smaller treatment effect on child mortality and indifferent effects on other outcomes. These consistent findings suggest that the initial dichotomous treatment definition is robust, and adjustments do not significantly alter observed treatment effects.

[16] Children in Burkina Faso usually start their primary school at age 6 and complete it at age 12.

enrollment by 0.06 percentage points.[17] We repeat the exercise in columns (3) and (4), using the dichotomized treatment, and find that primary school enrollment increased by 0.02 percentage points (significant at the 10% level) in provinces with high vaccination rates. Again, we find that the estimates are robust to controlling for the covariates. Although relatively small in absolute terms, the estimates imply an increase in school enrollment of 10.5%, starting from the average school enrollment of 21%.

Beyond enrollment per se, columns (5)–(8) show that the VCP increased completion rates, which may be more critical for lifetime economic outcomes. The effect of the treatment in column (6) is 0.05 and statistically significant at the 5% level. The specification using the binary treatment (columns (7) and (8)) shows that completion rates increased by 0.02 percentage points (significant at the 5% level). This increase translates to a 13.1% improvement in school completion rates, calculated from a baseline average school completion of 0.16.

4.3 Long-Term Outcomes: Labor Market Outcomes

In this section, we report the effects of the VCP on labor market outcomes, shown in Table 4. Columns (1)–(4) present the results for formal employment, and columns (5)–(8) report the results for agricultural productivity.

4.3.1 Formal Employment

Consistent with the gains in education, columns (1)–(4) show that the VCP significantly increased participation in the formal labor market, which is generally correlated with higher living standards in low-income countries. The effect of the treatment in column (1) is 0.03 (statistically significant at the 5% level) and remains stable when including additional controls (column (2)). Using the binary treatment, we find a point estimate of 0.01 in column (3), significant at the 5% level. In column (4), the analysis shows that the coefficient remains qualitatively robust when additional covariates are included, though its statistical precision decreases, being significant only at the 10% level.

While these point estimates seem small in magnitude, they imply non-trivial changes in relative terms. Specifically, the estimates from columns (3) and (4) imply a 14.2% increase in formal employment participation among the eligible cohort from high-intensity vaccination areas. In contrast, the continuous treatment specification, as shown in columns (1) and (2), implies an average increase of 18% in formal employment participation, attributed to the VCP.

[17] Our estimates of medium-, and long-term impact on education and labor market outcomes could potentially be biased downward if a strong survival effect exists, wherein relatively healthier children survive while marginally weaker children do not (Karlsson, 2022). By reducing child mortality, VCP might enable relatively weaker children to survive. These marginally weaker children are likely to have relatively lower educational attainment and labor market outcomes, potentially attenuating the differences between treated and non-treated individuals with the same initial health endowment.

4.3.2 Agricultural Productivity

Columns (5)–(8) of Table 4 show the VCP's impact on agricultural productivity. The dependent variable, agricultural productivity, is defined as the value of harvest per hectare (in natural logarithm scale). Our specification follows the common practice in the literature (e.g., Goldstein and Udry, 2008; Udry, 1996) and incorporates the variable of VCP treatment to assess its impact. In column (5), the estimated effect of the treatment is 0.09, which is statistically significant at the 5% level. This suggests that each 1% increase in vaccination intensity is associated with a 9% increase in farm productivity per hectare. Adding control variables does not change the point estimate.[18]

Turning to the dichotomized rendition of the treatment, as reported in columns (7) and (8), we first present estimates without the inclusion of control variables, followed by estimates that incorporate them. The estimated treatment effect is about 6%, and this finding remains robust upon including the control variables previously mentioned. The point estimates are statistically significant at the 5% level, indicating that in the cohort exposed to the treatment, farm productivity per hectare in provinces with a high vaccination rate increased by 6%.

Overall, the VCP's impact on agricultural productivity is notably pronounced. Individuals who resided in provinces with higher vaccination rates were more productive on the farm as adults, and the effect remains significant after accounting for various control variables that are potentially correlated with plot-level productivity. These findings reinforce the potential broader benefits of early childhood health interventions in agriculture.

Sources of Agricultural Productivity. Our analysis shows the VCP's sizable positive effect on agricultural productivity. To delve deeper into the underlying causes of this effect, we examine potential mechanisms, first exploring the hypothesis that health improvements from vaccination increased labor supply, thus enhancing productivity per hectare. This hypothesis aligns with extensive research in low-income settings that highlights the connection between health status and farm productivity.

We test this hypothesis using the data presented in column (1) of Table 5, where the dependent variable is the natural logarithm of labor per hectare. The resulting estimate is virtually zero, indicating that the treatment did not increase labor intensity. However, increased labor supply is just one way health improvements from the VCP could influence farm productivity. Another critical aspect to consider is labor efficiency. While the quantity of labor (i.e., number of man-days) per hectare remains constant, the productivity gains might stem from the program having made individuals more efficient in their work due to improved health.

To formalize this proposition, let us consider the following farm production function:

$$F(L, A), \tag{3}$$

where L is effective labor units, i.e., time spent working in the field ($\mathcal{L}$) adjusted for physical fitness (θ), and A is land. We assume that both $\mathcal{L}$ and θ are concave functions in health (H), and $\theta(H)$

[18]The controls include plot owner characteristics (i.e., gender, age), plot characteristics (i.e., toposequence, plot size, land tenure regime, and distance to the village), and types of crops cultivated on the plot.

is bounded between 0 and 1. Thus, we can express L as

$$L = \theta\left(H\right)\mathcal{L}\left(H\right). \tag{4}$$

Notably, Eq. 4 is similar to the efficient labor supply function pioneered by Bliss and Stern (1978a,b) and Strauss (1986) when the quantity of labor also depends on health.[19] Using Eqs. 3 and 4, the partial derivative of production (F) with respect to H is

$$\frac{\partial F\left(L,A\right)}{\partial H} = \left(\mathcal{L}(H)\frac{d}{dH}\theta(H) + \theta(H)\frac{d}{dH}\mathcal{L}(H)\right)\frac{\partial}{\partial L}F(L,A). \tag{5}$$

In our data, we observe $\mathcal{L}$ but not θ. The DID estimate in column (1) of Table 5 identifies $\frac{d}{dH}\mathcal{L}(H)$, which is negligible. Therefore, the effect of health on production reduces to

$$\frac{\partial F\left(L,A\right)}{\partial H} = \left(\mathcal{L}(H)\frac{d}{dH}\theta(H)\right)\frac{\partial}{\partial L}F(L,A). \tag{6}$$

Consequently, the impact of vaccination on productivity primarily stems from improvements in health that enhanced the efficiency of farm labor rather than from any significant change in the the quantity of labor used. This result echoes the findings of Strauss (1986) in Sierra Leone four decades ago.

However, productivity gains could also arise from a reallocation of productive resources within households. To explore this possibility, we consider two potential explanations. First, we investigate whether the observed higher productivity per hectare results from a combination of treated individuals farming smaller plots, possibly indicating an inverse farm size-productivity relationship. Our analysis in column (2) of Table 5 reveals an estimated effect of 0.019, which is not statistically significant. This suggests that gains in productivity are unlikely to be driven by a reduction in farm size.

Second, we consider the hypothesis that treated individuals might employ more modern inputs or possess more secure land tenure rights, contributing to increased productivity. In columns (3)–(10) of Table 5, we examine the treatment effects on modern fertilizers (NPK and urea), plot characteristics, location, and tenure regime. All point estimates are of small magnitude and not statistically different from zero. In essence, our results imply that the realized productivity gains cannot be attributed to a change in any of the several factors of production that we investigate.

The absence of any statistically detectable association between agricultural inputs and the observed increase in agricultural productivity supports the argument that improved health outcomes resulting from the VCP played a central role. Improved health likely contributed to greater physical fitness, translating into enhanced efficiency in farm work. In summary, our analysis indicates that the VCP positively and substantially impacted agricultural productivity, with the source of this increase likely stemming from improved health outcomes rather than from changes in labor or agricultural inputs.

[19] In general, health determines how many hours one can work and the worth of one hour of work.

5 Robustness Checks

In this section, we present the results of several robustness checks. We first conduct a falsification exercise using a placebo treatment group. This is followed by an examination of the validity of our TWFE estimation using an alternative control group following De Chaisemartin and d'Haultfoeuille (2018). Subsequently, we explore heterogeneity in treatment responses based on age at the time of treatment, and then adopt an alternative estimation approach proposed by Callaway et al. (2021) to address the heterogeneous treatment effects. Finally, the consistency of our main results is checked against the potential influence of internal migration.

5.1 Placebo Analysis

We start with a falsification exercise to examine the validity of our estimation approach. Specifically, we re-estimate Eq. 1 using older cohorts that were not exposed to the VCP. We falsely assume that the 1972–1977 birth cohort is exposed to the VCP instead of the truly exposed 1978–1983 birth cohort. Therefore, for the purposes of this placebo test, we designate the 1972–1977 birth cohort as the treated group and the 1966–1971 birth cohort as the control group. Given that only the 1978–1983 birth cohort was truly affected by the VCP, we anticipate that this placebo exercise will not produce any treatment effects on the outcomes for the falsely exposed cohort.

Table 6 presents the results, with Panel A displaying the placebo estimations for child mortality and educational outcomes. The estimated coefficients are statistically insignificant in columns (1) and (2), indicating that the VCP has no effect on mortality outcomes for the placebo cohort. Similarly, there are no statistically significant effects on educational outcomes in columns (3)–(6). The central finding of this panel is that there is no detectable effect on the short- and medium-term outcomes for the placebo cohort. Panel B displays the placebo estimations for labor market outcomes. The coefficients for formal employment participation in columns (1) and (2) and agricultural yield in columns (3) and (4) show no significant effects, suggesting that the VCP did not impact these labor market outcomes for the placebo cohort. Thus, for the long-term outcomes, there are no detectable differences between high- and low-intensity vaccination areas for individuals belonging to the placebo cohort.

In summary, the falsification exercise tests whether living in a province with high vaccination rates had any impact on the outcomes of the older cohort, which consisted of individuals ineligible for the measles vaccination when the VCP was rolled out. The absence of significant differences in both the short- and long-term outcomes between the two groups reinforces our main findings. This suggests that the effects identified in our analysis are not merely spurious correlations, lending further credibility to our results.

5.2 Alternative Control

We defined provinces with high measles vaccination rates as those where the residuals from a regression—predicting the number of vaccinated children based on the number of children eligible for measles vaccination—were positive, following Duflo (2001). However, De Chaisemartin and d'Haultfoeuille (2018) argue that creating treatment and control provinces in such a way may produce unreliable estimates. They instead propose creating a control group with only provinces with a stable distribution of an outcome variable between two cohorts in the pre-treatment period.[20] Therefore, we choose the Kolmogorov-Smirnov test of equality of distribution to assign a province to the control group if it had a statistically identical distribution of an outcome variable between the 1978–1983 birth cohort and the 1972–1977 birth cohort in the pre-treatment period.[21] We end up with 14 provinces in the control group and 13 in the treatment group.

Appendix Table B.6 shows the result of this exercise. We find that the VCP leads to a 0.05 percentage point reduction in child mortality, which is identical to our primary result. Moreover, estimated coefficients for educational attainment and labor market outcomes are almost identical to those previously reported. As a result, this exercise corroborates the credibility of our main estimation results.

5.3 Age-Based Heterogeneous Treatment Exposure

Next, we consider heterogeneity in treatment exposure due to age differences, following the method proposed of Berg et al. (2023). This approach recognizes that the effects of early childhood health interventions may vary depending on the age at which individuals were exposed to the program. Accordingly, we introduce an expanded specification outlined in Eq. 2. In this framework, we consider three distinct age groups: low exposure (ages five to six), moderate exposure (ages three to four), and high exposure (ages one to two), acknowledging that children under six are particularly vulnerable to measles. The estimated coefficient $\hat{\beta}_a$ captures the causal effect of VCP exposure at each specific age range a on the outcomes of interest.

Table 7, Panel A shows the overall effects of VCP exposure, where the interaction term "Exposure $\times$ VRM" represents the average impact across ages one to six. Panel B distinguishes between whether the exposure occurred during ages one to two, three to four, or five to six. Column (1) of Panel A shows that VCP exposure leads to a 0.03 percentage point lower child mortality. Column (1) of Panel B reveals no significant reduction in mortality for children in the low- and moderate-exposure groups. However, the high-exposure group displays significant reductions in child mortality.

Columns (2) and (3) in Panel A show that VCP exposure yields a marginal improvement in school enrollment rates and a modest but statistically significant advancement in school completion rates. Moving to Panel B, we observe more nuanced findings. The low-exposure group experiences a statistically significant increase in school enrollment and completion rates. In contrast, the moderate exposure group shows no significant change in enrollment but a statistically significant increase in completion rates. Notably, the high-exposure group demonstrates noteworthy improvements in school enrollment and completion rates, but the effect is not statistically significant.

[20] This approach works if the size of each group is large compared to the total number of groups. For child mortality outcomes, we have 27 provinces with an average of 177 observations in each province. The average number of observations per province is more than 14,400 for educational attainment outcomes.

[21] Any classification method involves two types of errors. Type 1 errors classify provinces with constant outcome distribution as treatments, which is harmless. Type 2 errors classify provinces with changed distribution as controls, posing a more serious concern. Thus, De Chaisemartin and d'Haultfoeuille (2018) argue that misclassifying some provinces as treatment does not significantly alter the estimated coefficients.

Transitioning to labor market outcomes, Panel A's findings are presented first. Column (4) shows a positive and significant effect of VCP exposure on the likelihood of formal employment, while column (5) shows that VCP exposure also positively affects agricultural yield. Shifting to Panel B, the high-exposure group displays a statistically significant increase in formal employment. For agricultural yield, the low-exposure group does not experience a significant change, whereas both the moderate and high-exposure groups demonstrate a statistically significant boost.

5.4 Alternative Estimation Approach: Continuously Distributed Treatment

In this section, we explore an alternative estimation approach proposed by Callaway et al. (2021) to address the issue of heterogeneous treatment effects. Moving beyond the conventional TWFE estimator, this approach considers a continuous treatment framework. We follow their approach to estimate a series of 2x2 DiD, focusing on distinct doses of the VCP (i.e., vaccination rates) compared to an untreated group. We then calculate the average treatment effect by averaging the estimated effects across the range of doses. Callaway et al. (2021) offer a nuanced understanding of the effects of the VCP, particularly in the context of varying levels of exposure and potential heterogeneity in outcomes.

Table 8 presents the results of the continuously distributed treatment approach. Column (1) shows that the VCP significantly and negatively affected the child mortality rate. Specifically, a 1% increase in measles vaccination rates leads to a 0.07 percentage point reduction in the child mortality rate. Columns (2) and (3) present the effects of the VCP on school enrollment and school completion rates. A 1% increase in VCP coverage is associated with a 0.01 percentage point increase in school enrollment rates and a 0.01 percentage point increase in completion rates. Moving to columns (4) and (5), we present the effects of the VCP on formal employment and agricultural yield. While we find a small, positive but insignificant effect of the VCP on formal employment, there is substantial impact on agricultural yield. A 1% increase in the VCP leads to a 5% increase in agricultural yield. Overall, the continuous treatment results are consistent with our primary estimation results.

5.5 Internal Migration

Internal migration is a potential threat to our identification strategy, as the treatment status—province-level vaccination intensity—is determined at an early stage of an individual's life (up to six years of age), yet the outcomes are measured at a later life stage, well after the program's implementation. Our analysis assumes that individuals did not move across provinces from the time of treatment to the outcome measurement. To address potential biases from internal migration, we use the matrix completion method by Liu et al. (2024), focusing on aggregated outcomes at the national level, which inherently accounts for internal migration effects.

Liu et al. (2024) provides a simple framework of counterfactual estimation for causal inference with time-series cross-sectional data. We utilize their matrix completion estimator to estimate the average treatment effect on the treated by directly imputing counterfactual outcomes for treated observations.[22] This approach helps us to estimate counterfactual scenarios—what might have

[22]See Appendix B for further detail of this exercise.

occurred in Burkina Faso in the absence of the VCP—by imputing missing control outcomes, a crucial step for determining average treatment effects.

Data for this analysis are taken from the World Bank's world development indicators, covering demographic and economic characteristics of 27 countries from 1972 to 1995. We estimate the impact of increased vaccination on child mortality and primary school outcomes.[23] The findings in Figure 8 reveal a significant decline in the under-five child mortality rate for the vaccinated cohort. Both school enrollment and completion also shows significant increase for the vaccinated cohort.

6 Cost-Benefit Analysis

In this section, we conduct a cost-benefit analysis to estimate the net present value (NPV) of the VCP. The NPV of providing childhood vaccination accounts for the cost of the vaccination campaign and economic gains measured through formal job earnings and agricultural yield. Costs and benefits are discounted at the rate of r per year.

$$NPV = -C + \sum_{t=10}^{59} \Delta \bar{A}_t (1+r)^{-t} + \sum_{t=22}^{59} \Delta \bar{F}_t (1+r)^{-t}, \tag{7}$$

where C is the total cost of the vaccination campaign, which is the product of the number of vaccinated children and the cost of the vaccination campaign per child. $\Delta \bar{A}_t$ and $\Delta \bar{F}_t$ capture adult earnings gains in agriculture and formal employment, respectively. We assume that the agricultural yield gain started nine years after the vaccination campaign when the vaccinated cohort reached age 15.[24] On the other hand, the gains from formal employment started 21 years after the vaccination campaign, when the vaccinated cohort reached age 28.[25] We assume that these earnings gains are constant and persist over the individuals' working lives until retirement at age 65.[26]

We assess returns to vaccination campaigns under two alternative cases—high- and low-impact estimates—based on our estimated impacts from Tables 3, 4, and 8.[27] Additionally, we consider two alternative scenarios for gains from formal employment: one with a low rate of return and another with a high rate of return. For costs, we base our estimates on the average cost of a vaccination campaign, with a lower bound of \$1 and an upper bound of \$15 (Brenzel and Claquin, 1994). Finally, we consider two alternative discount rates, 5% and 10%. The combination of these four alternative options results in 16 distinct NPV estimates.

The cost-benefit estimates are presented in Table 9, with Panel A showing the most conservative estimates and Panel D showing the most favorable ones. The most conservative estimates are based

[23]Measures of the long-term outcome such as formal employment and agricultural productivity are not available at the aggregate level in Sub-Saharan African countries. The lack of aggregate-level data limits our ability to study those outcomes in this analysis.

[24]They will continue earning agricultural return till age 65, which gives us a range of t between 10 and 59.

[25]They will continue earning returns from formal jobs till age 65, which gives us a range of t between 22 and 59.

[26]VCP led to an agricultural earnings gain as high as 5.6% per year (see Table 4). Individuals with primary school completion earn as high as 43.9% higher per year than individuals with no primary education (see Appendix Table B.7). Since VCP increased the likelihood of being in a formal job by as high as 2.2 percentage points (see Table 4), the gain in return to primary school completion is about 1% (0.022 x 0.439).

[27]High-impact estimates are from Tables 3 and 4, and low-impact estimates are from Table 8.

on the low rate of returns to education, high cost of vaccination campaigns, and high discount rate (10%). Panel A, column (2), with our low-impact estimates, shows that the per capita NPV is USD PPP 44.40 and a cost-benefit ratio of 2.96.[28] Similarly, column (1), with our high-impact estimates, shows that the per capita NPV is USD PPP 44.42 with a cost-benefit ratio of 2.96. The corresponding internal rate of return (IRR) estimates presented in columns (1) and (2) are 9.05% and 7.70%, respectively. When a lower discount rate is applied in columns (3) and (4), the cost-benefit ratio improves to 4.4, with the IRR exceeding 13%.

The cost-benefit analysis highlights two key findings. First, the returns to vaccination are substantially higher than the cost of vaccination. Across all cost-benefit estimates, the returns from the VCP markedly surpass its costs, underscoring the program's role as a pivotal social investment that enhances human capital. Second, the predominant share of gains from vaccination emanates from agricultural yield improvements, with formal employment contributing a comparatively small fraction. This observation aligns with the reality that in many developing countries, formal sectors employ only a limited portion of the labor force. Consequently, it underscores the importance of considering gains from agricultural yield in assessing the true benefits of vaccination interventions. Studies neglecting these agricultural gains may therefore inadvertently underestimate the holistic impact and social return of vaccination initiatives.

7 Conclusion

Measles and other infectious diseases annually affect millions of people, and SSA countries are no exception. Before 1984, most child mortality in Burkina Faso resulted from vaccine-preventable diseases, a situation still prevalent in many developing countries. Vaccines represent the most effective yet significantly underused tool to prevent child morbidity and mortality. This under-investment and under-use may partly stem from lack of comprehensive understanding of vaccines' overall impact, exacerbated by the scarcity of empirical studies on their effects. To the best of our knowledge, only two studies have evaluated the impact of national vaccination programs on human capital and labor market outcomes.

The VCP in Burkina Faso provides valuable insights into the long-term benefits of early childhood health interventions. Implemented swiftly in 1984, our analysis shows that the program yielded substantial benefits for cohorts exposed during early childhood. Leveraging the program as a natural experiment, we find significant improvements in mortality, education, employment, and agricultural productivity, highlighting the profound and lasting effects of early health investments. Notably, the VCP led to a significant 16% decrease in under-five child mortality, illustrating the campaign's effectiveness in mitigating the negative effects of infectious diseases like measles. Moreover, the program fostered pervasive gains in human capital accumulation, evidenced by increased primary school enrollment and completion rates, thereby extending its positive impact into the educational domain.

Furthermore, we find that the program's impacts persisted into adulthood, with treated individuals displaying higher rates of formal employment. In an agricultural-dominant economy like

[28]The present value of wage earnings gains per capita is USD PPP 0.03, the present value of agricultural yield gains per capita is USD PPP 59.37, and the cost of vaccination per capita is USD PPP 15.

Burkina Faso's, perhaps the most notable finding is the 6%–9% increase in agricultural productivity. These productivity gains are primarily due to improved labor efficiency rather than to increased input usage, such as fertilizers. This novel result carries important implications for evaluating returns in contexts dominated by small-holder farming.

Our study also quantifies the returns from the VCP, highlighting its efficiency as a health investment. With a conservative benefit-to-cost ratio of 2.96 and an implied IRR of 7.70%, these findings underscore the substantial social dividends from child health investments, even when accounting for delivery and administration costs. From a policy perspective, the results provide robust empirical support for prioritizing immunization campaigns to improve human capital and productivity.

Our study bridges a critical knowledge gap by providing long-term, unique evidence on the economic returns of early childhood interventions in a low-income SSA context. Although much of the seminal research on early childhood interventions focuses on high-income settings with well-developed labor markets and educational systems, the magnitude and mechanisms of the gains for disadvantaged populations in developing economies remain less understood despite their acute political relevance. Our findings confirm the effectiveness of vaccination programs in improving economic well-being, and thus support prioritizing such initiatives to boost human capital and productivity.

In summary, our study demonstrates the profound and lasting benefits of a nationwide vaccination campaign in Burkina Faso, revealing significant reductions in child mortality along with gains in educational attainment, employment, and agricultural productivity. These findings reassert the critical value of early health investments, particularly in economically disadvantaged regions. Our conclusions underline both the human welfare justifications and economic returns supporting public health initiatives and the formation of human capital in the developing world.

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Figures

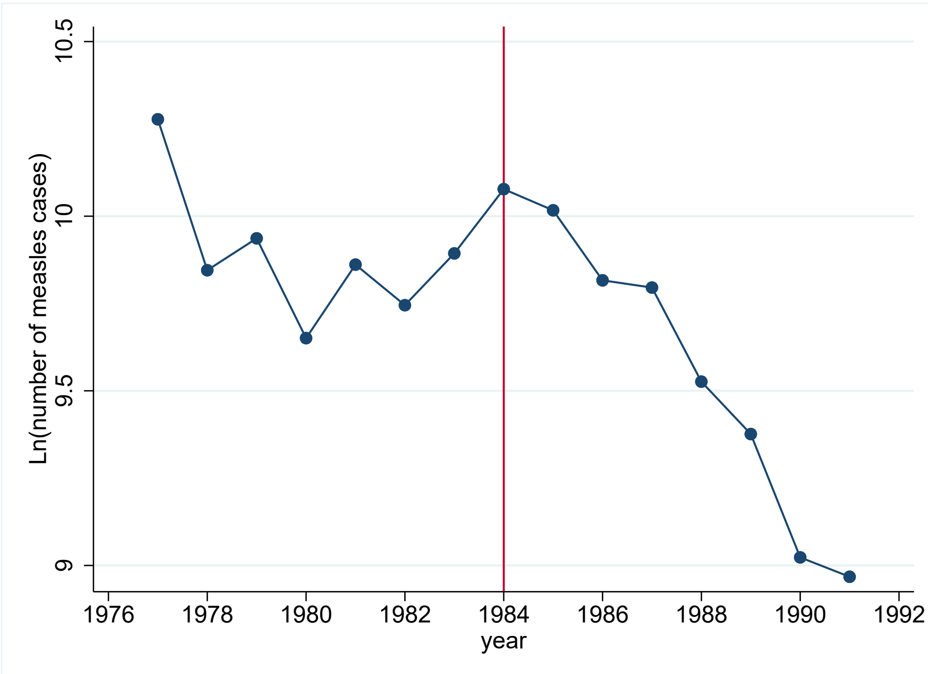


Figure (1) Measles Prevalence Over Time

Notes: This figure presents the prevalence of measles cases per 100,000 population from 1975 to 1992. The log of the number of measles cases is in the vertical-axis scale. Each data point represents a three-year moving average.

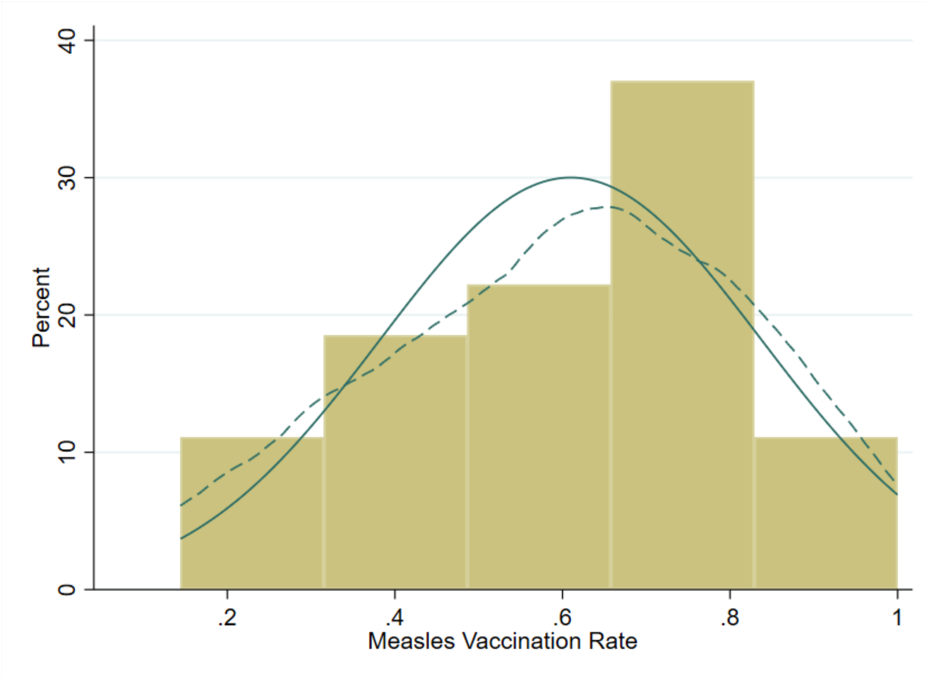


Figure (2) Distribution of Measles Vaccination Rates

Notes: This figure illustrates the distribution of measles vaccination rates in 30 provinces of Burkina Faso in 1985. The number of eligible children in each province comes from the 1985 population census and the number of vaccinated children in each province comes from the Ministry of Health's archive. The measles vaccination rate (in a province) equals the number of children vaccinated (in a province) divided by the number of eligible children (in a province). The horizontal axis represents the vaccination rate categories, while the vertical axis shows the percentage of the province. The Solid line represents a theoretical normal distribution while the dashed line shows the kernel distribution of the measles vaccination rate. Measles vaccination rate is normally distributed as the kernel distribution is not statistically different from the theoretical normal distribution. Shapiro-Wilk W test for normal data shows a p-value of 0.94.

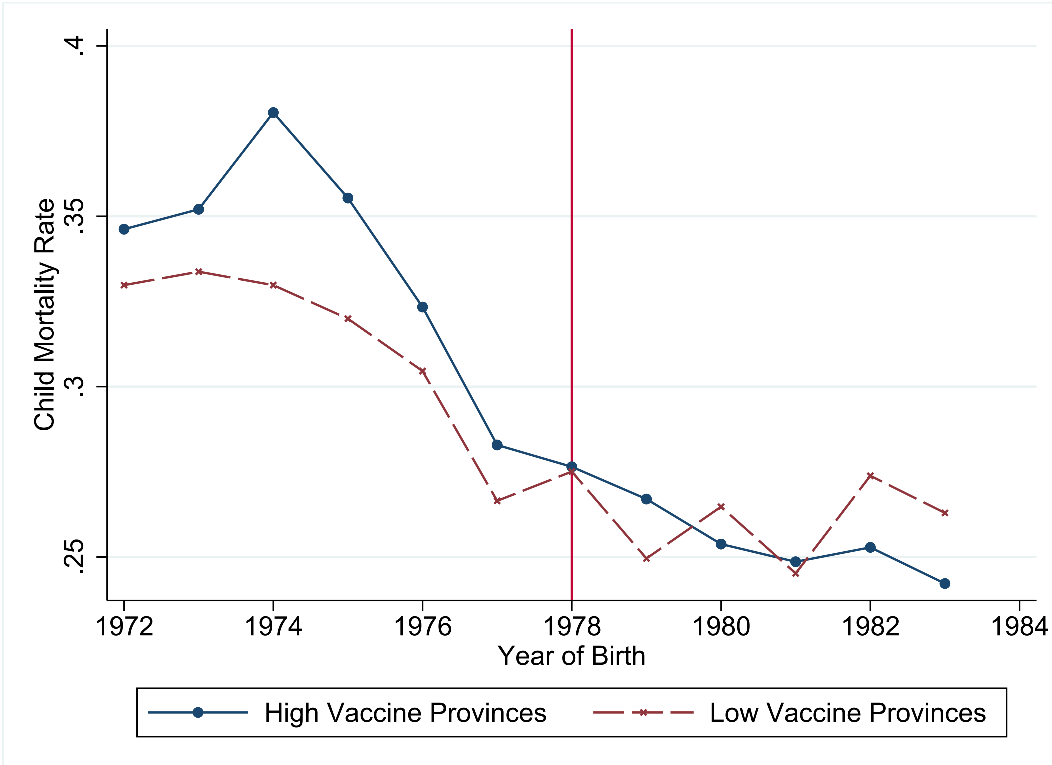


Figure (3) Child Mortality Rate by Year of Birth

Note: This figure presents the child mortality rates by year of birth for provinces with high and low measles vaccination coverage. Data for this graph comes from the 1993 Demographic and Health Survey (DHS). Each data point represents a three-year moving average and covers the period from 1969 to 1983.

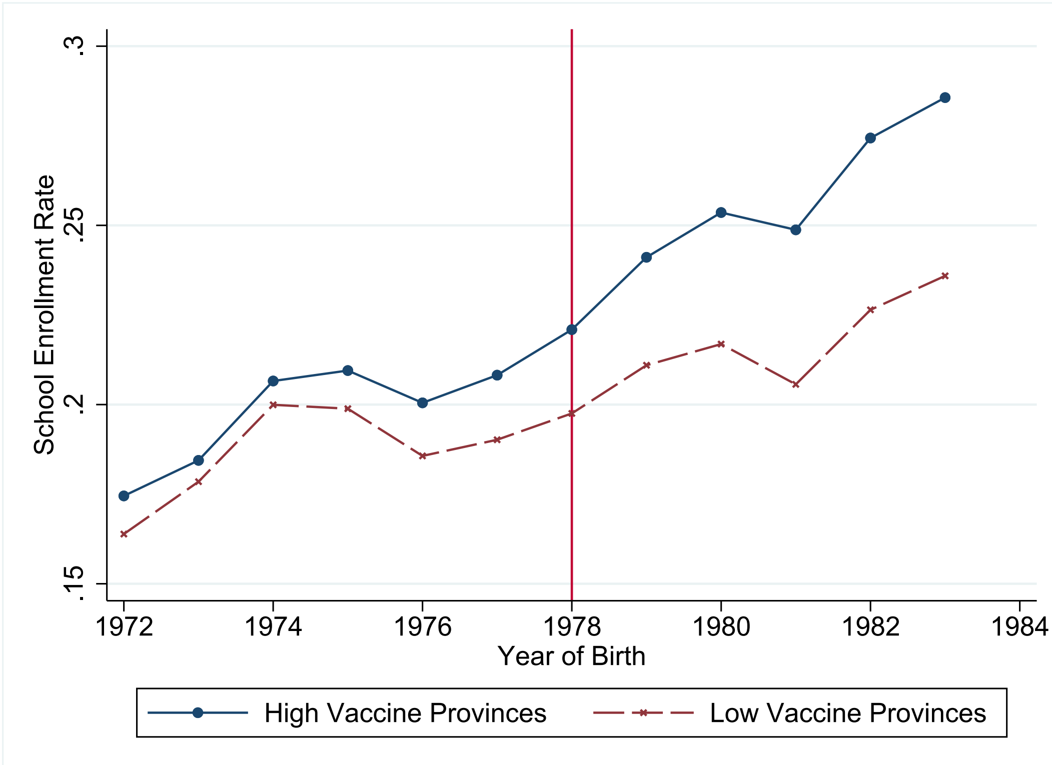


Figure (4) Primary School Enrollment Rate by Year of Birth

Note: This Figure presents the school enrollment rates by birth year for provinces with high and low measles vaccination coverage. Data for this graph comes from the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Each data point represents a three-year moving average and covers the period from 1969 to 1983.

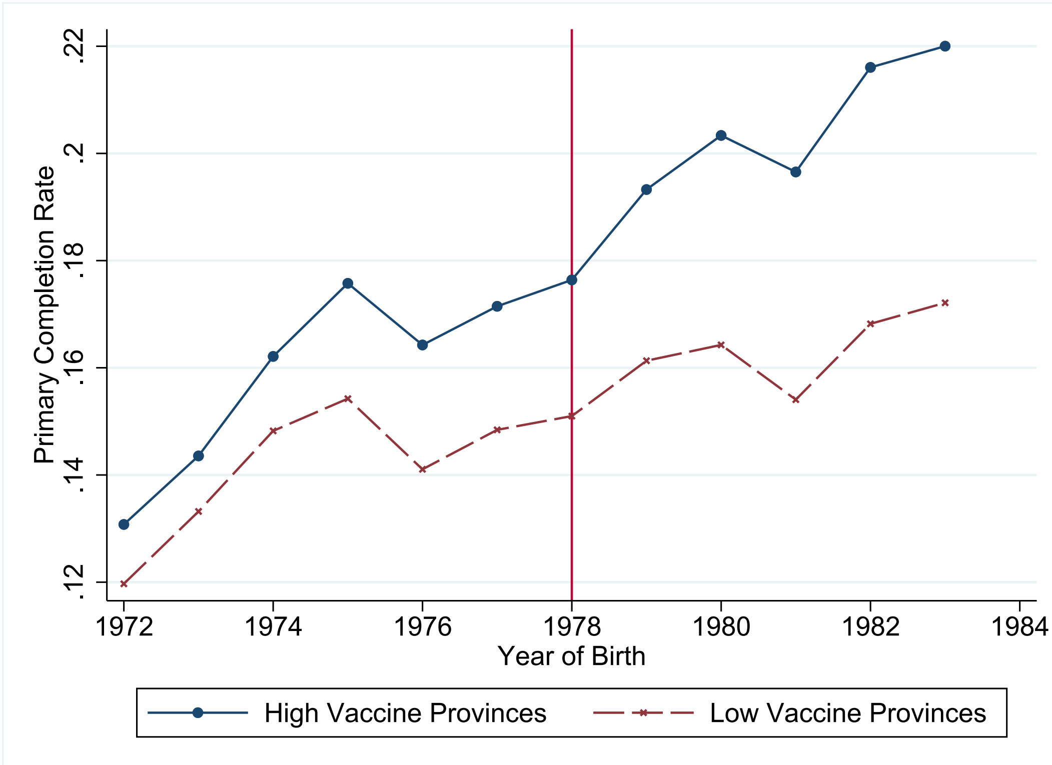


Figure (5) Primary School Completion Rate by Year of Birth

Note: This figure presents the primary school completion rates by birth year for provinces with high and low measles vaccination coverage. Data for this graph comes from the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Each data point represents a three-year moving average and covers the period from 1969 to 1983.

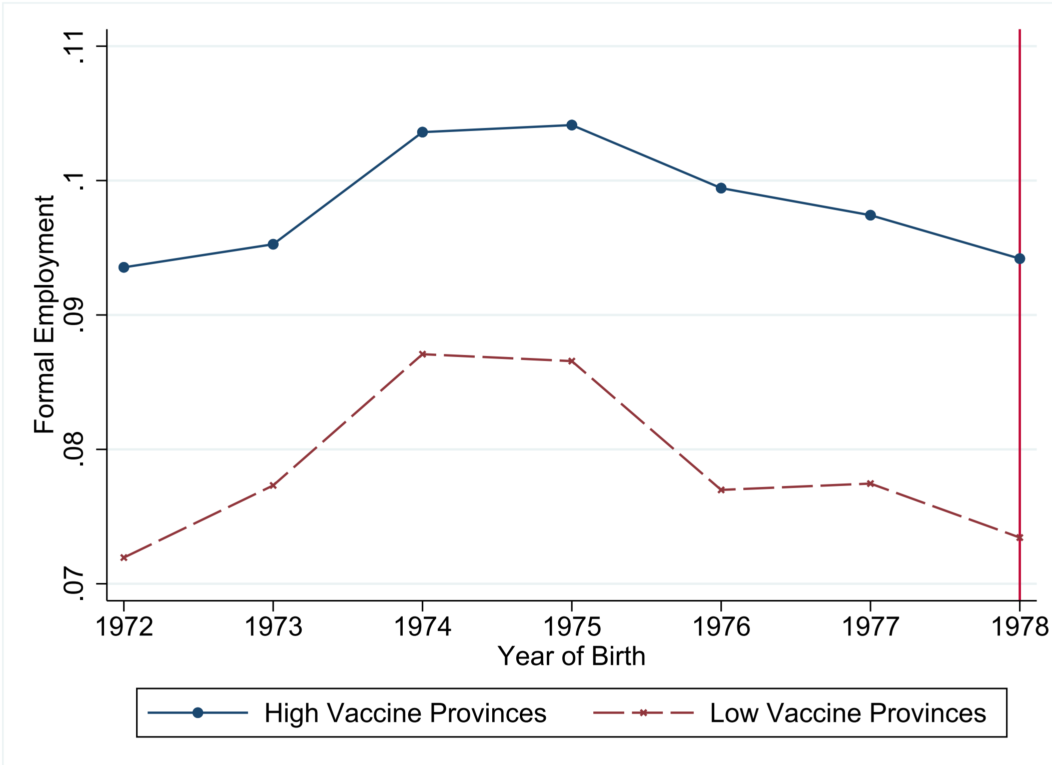


Figure (6) Formal Employment by Year of Birth

Note: This figure presents the formal employment rates by birth year for provinces with high and low measles vaccination coverage. Data for this graph comes from the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Each data point represents a three-year moving average and covers the period from 1969 to 1983. Individuals aged above 27 years are kept in the sample.

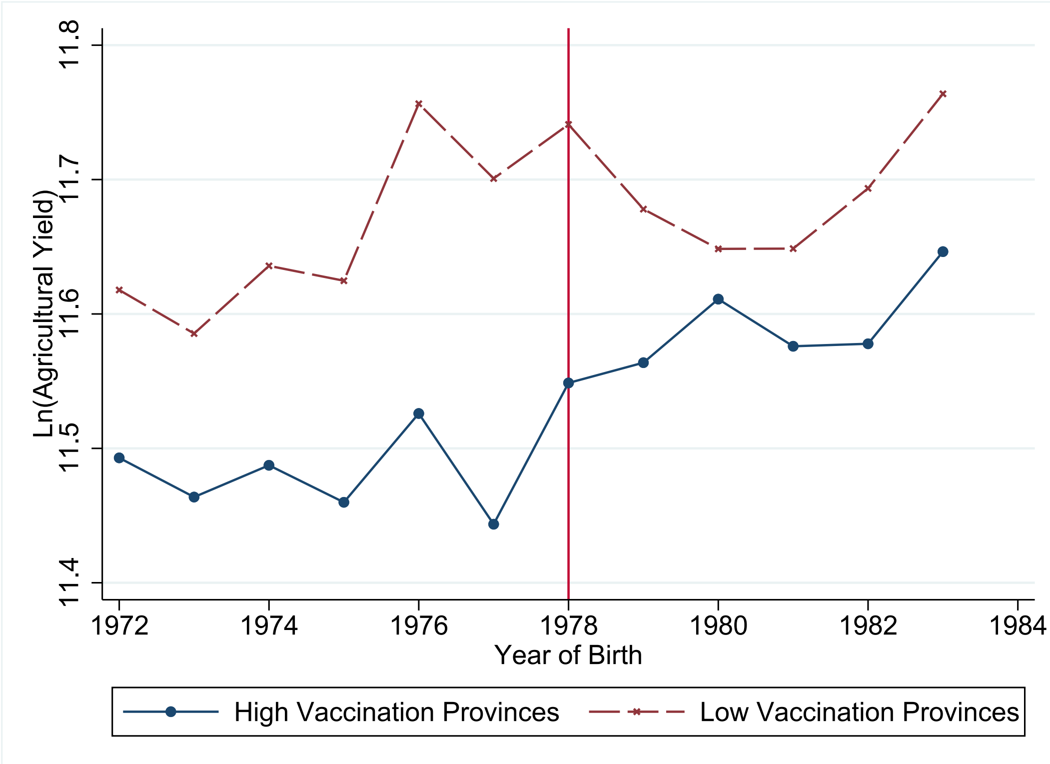
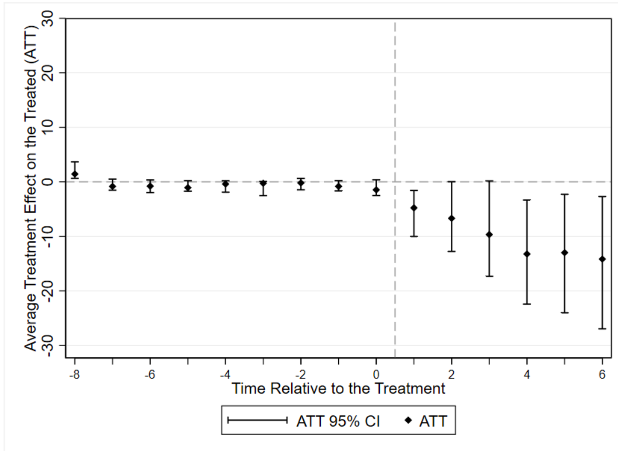
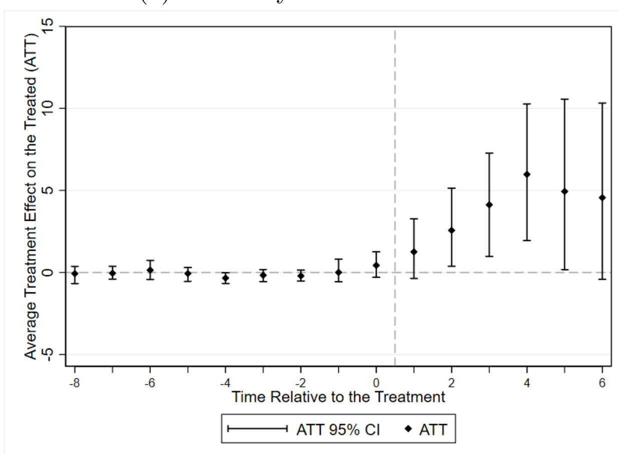


Figure (7) Agricultural Yield by Year of Birth

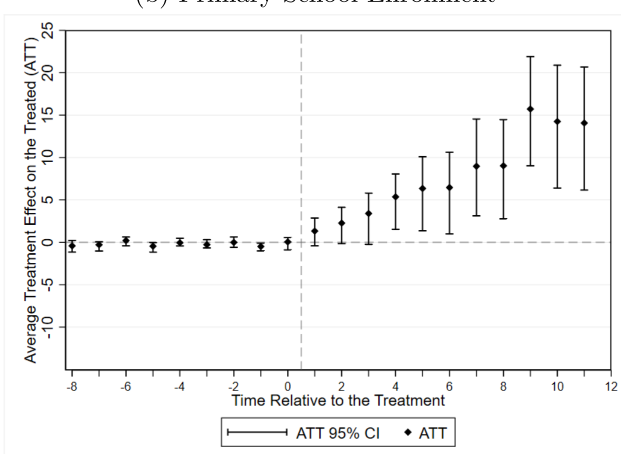
Note: This figure presents the agricultural yield by year of birth for provinces with high and low measles vaccination coverage. Data for this graph comes from the 2010-2012 panel Permanent Agricultural Survey (PAS) of the Ministry of Agriculture of Burkina Faso. Each data point represents a three-year moving average and covers the period from 1969 to 1983. Only private plots' agricultural yield is used in the sample.



(a) Mortality Rate Under Five



(b) Primary School Enrollment



(c) Primary School Completion

Figure (8) Robustness to Internal Migration Using Counterfactual Approach

Note: Panel (a) of this figure shows the dynamic treatment effect of VCP on under-five child mortality rate. Panel (b) shows the dynamic treatment effect on school enrollment (c) shows the dynamic treatment effect on primary school completion. Data for this exercise comes from World Bank's world development indicators for 27 Sub-Saharan African (SSA) countries from 1972 to 1990. Panel (c) extends the data to 1995 to capture the effect on treated cohort.

Tables

Table (1) Descriptive Statistics

	Full Sample			Low Vaccination Rate			High Vaccination Rate		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Demographic and Health Survey									
Outcome									
Child mortality	5,585	0.285	0.452	2,503	0.284	0.451	3,082	0.286	0.452
Treatment and cohorts									
Measles vaccination rate	5,585	0.636	0.219	2,503	0.446	0.153	3,082	0.791	0.122
Cohort 1978-83 =1	5,585	0.53	0.499	2,503	0.536	0.499	3,082	0.526	0.499
Cohort 1972-77	5,585	0.326	0.469	2,503	0.324	0.468	3,082	0.328	0.47
Cohort 1966-71	5,585	0.144	0.351	2,503	0.141	0.348	3,082	0.146	0.353
Controls									
Mossi =1	5,585	0.561	0.496	2,503	0.385	0.487	3,082	0.704	0.457
Female =1	5,585	0.485	0.5	2,503	0.473	0.499	3,082	0.495	0.5
Panel B: National Census Data									
Outcome									
Ever enrolled =1	540,429	0.201	0.401	264,328	0.187	0.39	276,101	0.215	0.411
Completed primary =1	540,429	0.155	0.362	264,328	0.141	0.348	276,101	0.169	0.375
Formal employment =1	131,652	0.08	0.271	66,703	0.071	0.257	64,949	0.088	0.284
Treatment and cohorts									
Measles vaccination rate	573,191	0.643	0.231	280,741	0.461	0.158	292,450	0.817	0.136
Cohort 1978-83 =1	573,191	0.416	0.493	280,741	0.417	0.493	292,450	0.416	0.493
Cohort 1972-77 =1	573,191	0.302	0.459	280,741	0.301	0.459	292,450	0.304	0.46
Cohort 1966-71 =1	573,191	0.281	0.45	280,741	0.282	0.45	292,450	0.281	0.449
Controls									
Muslim =1	573,191	0.58	0.494	280,741	0.509	0.5	292,450	0.649	0.477
Female =1	573,191	0.53	0.499	280,741	0.532	0.499	292,450	0.527	0.499
Panel C: Agricultural surveys data									
Outcome									
Logged harvest value per ha	28,170	11.97	0.921	15,456	11.965	0.861	12,714	11.976	0.989
Logged labor (man-day) per ha	28,147	5.384	1.201	15,439	5.287	1.214	12,708	5.501	1.174
Fertilizer: NPK = 1	27,403	0.105	0.307	15,064	0.105	0.307	12,339	0.105	0.307
Fertilizer: Urea = 1	27,403	0.059	0.235	15,064	0.083	0.276	12,339	0.029	0.168
Treatment and cohorts									
Measles vaccination rate	28,170	0.614	0.255	15,456	0.441	0.161	12,714	0.825	0.177
Plot owner cohort 1978-83 = 1	28,170	0.404	0.491	15,456	0.412	0.492	12,714	0.393	0.488
Plot owner cohort 1972-77 = 1	28,170	0.32	0.466	15,456	0.314	0.464	12,714	0.326	0.469
Plot owner cohort 1966-71 = 1	28,170	0.276	0.447	15,456	0.273	0.446	12,714	0.28	0.449
Controls									
Female =1	28,170	0.785	0.411	15,456	0.744	0.437	12,714	0.836	0.371
Topography: flat ground =1	28,170	0.825	0.38	15,456	0.818	0.386	12,714	0.835	0.371
Topography: low ground =1	28,170	0.114	0.318	15,456	0.129	0.335	12,714	0.096	0.295
Topography: sloping ground =1	28,170	0.059	0.236	15,456	0.052	0.221	12,714	0.069	0.253
Plot location: closest to village =1	28,164	0.339	0.473	15,451	0.337	0.473	12,713	0.342	0.474
Plot location: midway =1	28,164	0.596	0.491	15,451	0.591	0.492	12,713	0.601	0.49
Plot location: farthest =1	28,164	0.065	0.246	15,451	0.072	0.258	12,713	0.057	0.232
Plot owned (=1)	28,170	0.267	0.442	15,456	0.269	0.443	12,714	0.264	0.441
Land rented (=1)	28,170	0.16	0.367	15,456	0.152	0.359	12,714	0.171	0.376
Land size (ha)	28,170	0.294	0.42	15,456	0.343	0.469	12,714	0.233	0.34

Notes: This table shows the summary statistics such as sample size, mean and standard deviation. The data comes from the 1993 Demographic and Health Survey (DHS), the 1996 and 2006 General Population and Housing Censuses, and the 2010-2012 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. Columns (1)-(3) show statistics for the full sample, whereas Columns (4)-(6) and Columns (7)-(9) show statistics for low and high vaccination rate provinces, respectively. Formal employment is a dummy indicator that equals one if an individual earns wages or salaries and takes zero if an individual is self-employed or an unpaid worker. The harvest value per hectare is in the real value of the local currency.

Table (2) Vaccination Effects on Child Mortality

	Child Mortality (=1 if Yes)			
	(1)	(2)	(3)	(4)
CB 1978-83=1 × VRM	-0.076*	-0.075*		
	(0.041)	(0.041)		
CB 1978-83=1 × HVRM =1			-0.047*	-0.047*
			(0.023)	(0.023)
Constant	0.345***	0.371***	0.345***	0.370***
	(0.029)	(0.034)	(0.029)	(0.033)
Observations	4,783	4,783	4,783	4,783
Fixed Effects	Province	Province	Province	Province
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	DHS	DHS	DHS	DHS

Notes: Robust standard errors clustered at the province level. Dependent variable is the child (age less than 5) mortality rate in Columns (1)-(4). The treatment variable is the measles vaccination rate. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level, and HVRM stands for high vaccination rate measles. HVRM equals one if the measles vaccination rate is high and zero otherwise. Controls include ethnicity and gender. Estimations using the 1993 Demographic and Health Survey (DHS) of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (3) Vaccination Effects on Primary School Enrollment and Completion

	School Enrollment (=1 if Yes)				School Completion (=1 if Yes)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB 1978-83=1 × VRM	0.063**	0.063*			0.052**	0.054**		
	(0.029)	(0.032)			(0.024)	(0.026)		
CB 1978-83=1 × HVRM =1			0.022*	0.022*			0.022**	0.021**
			(0.011)	(0.012)			(0.009)	(0.009)
Constant	0.201***	0.309***	0.201***	0.309***	0.176***	0.223***	0.176***	0.261***
	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.009)	(0.005)	(0.009)
Observations	389,389	389,389	389,389	389,389	389,389	389,389	389,389	389,389
Fixed Effects	Province	Province	Province	Province	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes	None	Yes	None	Yes
Data Source	Census	Census	Census	Census	Census	Census	Census	Census

Notes: Robust standard errors clustered at the province level. The dependent variable is primary school enrollment in Columns (1)-(4) and school completion in Columns (5)-(8). The treatment variable is the measles vaccination rate. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level, and HVRM stands for high vaccination rate measles. HVRM equals one if the measles vaccination rate is above average and zero otherwise. Controls include religion and gender. Estimations using the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (4) Vaccination Effects on Formal Employment and Agricultural Yield

	Formal Employment (=1 if Yes)				Agricultural Yield			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB 1978-83=1 × VRM	0.027**	0.025**			0.089**	0.086**		
	(0.011)	(0.012)			(0.037)	(0.037)		
CB 1978-83=1 × HVRM =1			0.011**	0.009*			0.059**	0.057**
			(0.005)	(0.004)			(0.021)	(0.021)
Constant	0.079***	0.154***	0.097***	0.154***	11.938***	11.973***	11.956***	11.987***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.012)	(0.079)	(0.005)	(0.076)
Observations	73,298	73,298	73,298	73,298	20,336	20,336	20,336	20,336
Fixed Effects	Province	Province	Province	Province	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes	None	Yes	None	Yes
Data Source	Census	Census	Census	Census	PAS	PAS	PAS	PAS

Notes: Robust standard errors clustered at the province level. The treatment variable is the measles vaccination rate. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level, and HVRM stands for high vaccination rate measles. HVRM equals one if the measles vaccination rate is above average and zero otherwise. The dependent variable is formal employment in Columns (1)-(4), which equals one if an individual is earning salary or wages and zero otherwise. Controls include religion and gender in Columns (1)-(4) — estimations using the 2006 Burkina Faso General Population and Housing Censuses. Individuals aged above 27 years are kept in this analysis. The dependent variable is the natural log of harvest value per hectare in Columns (5)-(8). Controls include Plot owner characteristics: gender and relationship to household head; plot characteristics: toposequence, distance to the village, ownership status, and years last kept fallow. We also included province, survey year, crop, and plot decile fixed effects in Columns (5)-(8). Estimations using the 2008-2014 panel Permanent Agricultural Survey (PAS) of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (5) Vaccination Effects on Agricultural Input Use

	Labor	Land Size	NPK	Urea	Topo1	Topo2	Distant Plot	Interm. Plot	Land Owned	Land Loaned
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A										
CB 1978-83=1 × VRM	0.029	0.019	0.019	0.003	-0.006	-0.014	0.035	-0.032	0.001	0.013
	(0.046)	(0.031)	(0.017)	(0.015)	(0.013)	(0.016)	(0.045)	(0.039)	(0.032)	(0.021)
Constant	5.491***	0.471***	0.163***	0.098***	0.831***	0.113***	0.351***	0.581***	0.382***	0.113***
	(0.041)	(0.031)	(0.014)	(0.008)	(0.010)	(0.007)	(0.030)	(0.028)	(0.030)	(0.017)
Panel B										
CB 1978-83=1 × HVRM	-0.009	0.014	-0.001	-0.006	-0.012	-0.005	0.020	-0.012	-0.006	0.002
	(0.032)	(0.018)	(0.011)	(0.008)	(0.008)	(0.009)	(0.022)	(0.020)	(0.021)	(0.015)
Constant	5.504***	0.474***	0.170***	0.100***	0.832***	0.110***	0.358***	0.573**	0.383***	0.117
	(0.034)	(0.024)	(0.013)	(0.009)	(0.011)	(0.007)	(0.027)	(0.025)	(0.029)	(0.016)
Observations	20,336	20,336	20,336	20,336	20,336	20,336	20,336	20,336	20,336	20,336
Fixed Effects	Province	Province	Province	Province	Province	Province	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB	YOB	YOB	YOB	YOB	YOB
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Data Source	PAS	PAS	PAS	PAS	PAS	PAS	PAS	PAS	PAS	PAS

Notes: Robust standard errors clustered at the province level. The dependent variables are the agricultural inputs. The outcome variable in Column (1) is the natural log of labor hours worked in a year. The outcome variable in Column (2) is land size. Outcome variables in Columns (3) and (4) are indicators for NPK and Urea fertilizer use. NPK equals one if NPK fertilizer was used and zero otherwise. Similarly, Urea equals one if urea fertilizer was used and zero otherwise. The slope of the land is categorized into three groups: toposequence 1 (lowest or gentlest slope), toposequence 2 (between the gentlest and steepest slopes), and toposequence 3 (highest or steepest slope). Topo 1 and Topo 2 are dummy indicator variables representing toposequence 1 and toposequence 2 are reported in Columns (5) and (6), respectively. Plot distance from a village is categorized as distant plot (furthest), intermediate plot (moderate), and proximity plot (closest). Distant plot and intermediate plot are dummy indicator variables representing furthest and moderate distance plots are reported in Columns (7) and (8), respectively. Outcome variables in Columns (9) and (10) are land ownership status which is categorized as Land owned, land loaned, and stats missing. Land owned is a dummy indicator representing whether the land is owned or not. Similarly, land loaned is a dummy indicator representing whether the land is loaned or not. The treatment variable is the measles vaccination rate. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level, and HVRM stands for high vaccination rate measles. HVRM equals one if the measles vaccination rate is above average and zero otherwise. Controls include Plot owner characteristics: gender and relationship to the household head. We also included province, survey year, crop, and plot decile fixed effects in Columns (1)-(10). Estimations using the 2008-2014 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (6) Placebo Effects on Child Mortality, Educational, and Labor Market Outcomes

Panel A: Child Mortality and Educational Outcomes

	Child Mortality (=1 if Yes)		School Enrollment (=1 if Yes)		School Completion (=1 if Yes)	
	(1)	(2)	(3)	(4)	(5)	(6)
CB 1972-77=1 × VMR	0.142		0.048		0.042	
	(0.110)		(0.032)		(0.028)	
CB 1972-77=1 × HVRM =1		0.044		0.003		0.002
		(0.045)		(0.014)		(0.004)
Constant	0.404***	0.402***	0.216***	0.216***	0.179***	0.179***
	(0.062)	(0.064)	(0.008)	(0.007)	(0.007)	(0.007)
Observations	2,623	2,623	311,436	311,436	311,436	311,436
Fixed Effects	Province	Province	Province	Province	Province	Province
Fixed Effects	-	-	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB	YOB
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Data Source	Census	Census	Census	Census	Census	Census

Panel B: Labor Market Outcomes

	Formal Empl. (=1 if Yes)		Agri. Yield	
	(1)	(2)	(3)	(4)
CB 1972-77=1 × VMR	0.014		0.005	
	(0.009)		(0.067)	
CB 1972-77=1 × HVRM =1		0.001		-0.019
		(0.004)		(0.037)
Constant	0.119***	0.119***	11.959***	11.965***
	(0.007)	(0.007)	(0.065)	(0.064)
Observations	119,749	119,749	16,753	16,753
Fixed Effects	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB
Other Controls	Yes	Yes	Yes	Yes
Data Source	Census	Census	PAS	PAS

Notes: Robust standard errors clustered at the province level. The dependent variable is the under-five child mortality in Columns (1)-(2) of Panel A. The dependent variable is school enrollment in Columns (3)-(4) of Panel A, which takes one if an individual ever enrolled in school and zero otherwise. The dependent variable in Columns (5)-(6) of Panel A is school completion, which takes one if an individual has completed primary school. The dependent variable in Columns (1)-(2) of Panel B is formal employment which takes one if an individual earns a salary or wages. The dependent variable in Columns (3)-(4) of Panel B is the natural log of harvest value per hectare. The treatment variable is the measles vaccination rate in both Panel A and B. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level, and HVRM stands for high vaccination rate measles. HVRM equals one if the measles vaccination rate is above average and zero otherwise. Columns (1)-(2) of Panel A include controls such as ethnicity and gender and use data from the 1993 Demographic and Health Survey (DHS) of Burkina Faso. Columns (3)-(6) Panel A and Columns (1)-(2) of Panel B include controls such as religion and gender and use data from 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Columns (3)-(4) of Panel B include controls: plot owner characteristics such as gender and relationship to the household head; plot characteristics such as toposequence, distance to the village, and land ownership status. We also included province, survey year, crop, and plot decile fixed effects. Estimations using the 2008-2014 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (7) Age-based Heterogeneous Effects of Vaccination

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
Panel A					
Exposure × VRM	-0.030***	0.025	0.011*	0.025**	0.010
	(0.011)	(0.015)	(0.006)	(0.011)	(0.010)
Constant	0.328***	0.106***	0.258***	0.148***	12.00***
	(0.017)	(0.008)	(0.009)	(0.008)	(0.072)
Panel B					
Low Exposure (age 5-6) × VRM	0.045	0.054*	0.043***	0.025**	0.027
	(0.063)	(0.028)	(0.015)	(0.011)	(0.067)
Moderate Exposure (age 3-4) × VRM	-0.068	0.089	0.148***		0.123*
	(0.082)	(0.053)	(0.026)		(0.065)
High Exposure (age 1-2) × VRM	-0.169***	0.139	0.061		0.111**
	(0.059)	(0.087)	(0.037)		(0.045)
Constant	0.336***	0.104***	0.257***	0.148***	12.004***
	(0.017)	(0.008)	(0.037)	(0.008)	(0.073)
Observations	4,783	389,389	389,389	73,298	20,336
Fixed Effects	Province	Province	Province	Province	Province
Fixed Effects	-	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB
Other controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. Dependent variable is child mortality (age less than 5) in Column (1). Dependent variables are dummy indicators of school enrollment and school completion in Columns (2) and (3), respectively. The dependent variable in Column (4) is formal employment which takes one if an individual earns a salary or wages. The dependent variable in Column (5) is the natural log of harvest value per hectare. The treatment variable is the measles vaccination rate. VRM stands for measles vaccination rate at the province level. Low exposure is an indicator variable that takes one if an individual was age 5-6 at the time of treatment. Similarly, moderate and high exposures are indicator variables that take one if an individual was age 3-4 and 1-2 at the time of treatment, respectively. Column (1) includes controls for ethnicity and gender and uses data from the 1993 Demographic and Health Survey (DHS) of Burkina Faso. Columns (2)-(4) include controls for religion and gender. Columns (2)-(3) use data from the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Column (4) uses 2006 census data and kept individuals above 27 years in this analysis. Column (5) includes controls: plot owner characteristics such as gender and relationship to the household head; plot characteristics such as toposequence, distance to the village, and land ownership status. We also included province, survey year, crop, and plot decile fixed effects in Column (5). Estimation uses the 2008-2014 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (8) Vaccination Effects with Continuous Treatment in High Vaccination Intensity Provinces

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
CB 1978-83=1 × VRM	-0.068***	0.011*	0.013***	0.002	0.048***
	(0.029)	(0.006)	(0.005)	(0.004)	(0.014)
Observations	4,783	389,389	389,389	73,298	20,336
Fixed Effects	Province	Province	Province	Province	Province
Fixed Effects	-	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB
Other controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. Dependent variable is child mortality (age less than 5) in Column (1). Dependent variables are dummy indicators of school enrollment and school completion in Columns (2) and (3), respectively. The dependent variable in Column (4) is formal employment which takes one if an individual earns a salary or wages. The dependent variable in Column (5) is the natural log of harvest value per hectare. The treatment variable is the measles vaccination rate. CB stands for cohort of birth, and VRM stands for measles vaccination rate at the province level. Column (1) includes controls for ethnicity and gender and uses data from the 1993 Demographic and Health Survey (DHS) of Burkina Faso. Columns (2)-(4) include controls on religion and gender. Columns (2)-(3) use data from the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Column (4) uses 2006 census data and kept individuals above 27 years in this analysis. Column (5) includes controls: plot owner characteristics such as gender and relationship to the household head; plot characteristics such as toposequence, distance to the village, and land ownership status. We also included province, survey year, crop, and plot decile fixed effects. Estimation uses the 2008-2014 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (9) Cost-Benefit Analysis Results

	High Discount Rate (10%)		Low Discount Rate (5%)	
	High Impact	Low Impact	High Impact	Low Impact
	(1)	(2)	(3)	(4)
Panel A: Low Returns to Education and High Cost of Vaccination Campaign				
Discounted Wage Earnings Gains Per Capita	0.12	0.07	0.56	0.35
Discounted Agricultural Earnings Gains Per Capita	59.37	59.37	81.35	81.35
Cost of Vaccination Campaign Per Capita	15.00	15.00	15.00	15.00
Net Present Value Per Capita	44.42	44.40	66.61	66.51
Cost Benefit Ratio	2.97	2.96	4.46	4.45
Internal Rate of Return (IRR)	9.05%	7.70%	14.62%	13.20%
Panel B: High Returns to Education and High Cost of Vaccination Campaign				
Discounted Wage Earnings Gains Per Capita	0.38	0.23	1.81	1.12
Discounted Agricultural Earnings Gains Per Capita	59.37	59.37	81.35	81.35
Cost of Vaccination Campaign Per Capita	15.00	15.00	15.00	15.00
Net Present Value (NPV)	44.74	44.60	68.16	67.47
Cost Benefit Ratio	2.98	2.97	4.54	4.50
Internal Rate of Return (IRR)	9.06%	7.71%	14.64%	13.21%
Panel C: Low Returns to Education and Low Cost of Vaccination Campaign				
Discounted Wage Earnings Gains Per Capita	0.12	0.07	0.56	0.35
Discounted Agricultural Earnings Gains Per Capita	59.37	59.37	81.35	81.35
Cost of Vaccination Campaign Per Capita	1	1	1	1
Net Present Value	58.48	58.44	80.91	80.70
Cost Benefit Ratio	58.48	58.44	80.91	80.70
Internal Rate of Return (IRR)	36.37%	34.21%	43.47%	41.20%
Panel D: High Returns to Education and Low Cost of Vaccination Campaign				
Discounted Wage Earnings Gains Per Capita	0.38	0.23	1.81	1.12
Discounted Agricultural Earnings Gains Per Capita	59.37	59.37	81.35	81.35
Cost of Vaccination Campaign Per Capita	1.00	1.00	1.00	1.00
Net Present Value	58.74	58.60	82.16	81.47
Cost Benefit Ratio	58.74	58.60	82.16	81.47
Internal Rate of Return (IRR)	36.38%	34.22%	43.48%	41.20%

Notes: High impact estimates are from Tables 3 and 4, and low impact estimates are from Table 8. We assume that the low rate of return from a formal job is 6.3% and the high return from a formal job is 8.2%. The local currency to USD PPP conversion rate in 2014 was 231.33.

Appendix

A Measles

Measles is a highly contagious and severe disease caused by a virus that spreads through water droplets in the air and direct contact (WHO, 2021). Its symptoms include fever, cough, inflamed eyes, cold-like manifestations, and a distinctive skin rash. The disease is highly infectious, with an infected person, in turn, infecting nine to ten individuals (Grais et al., 2006). This disease can lead to serious complications such as pneumonia, encephalitis, and severe diarrhea, which can be fatal, particularly among young children and individuals with weakened immune systems (WHO, 2021; CDC, n.d.). Measles causes short-term weakening of the immune system and can also erase immune memory acquired from previous infections, thus increasing susceptibility to subsequent infections (Gadroen et al., 2018; Mina et al., 2019).

Before the introduction of the measles vaccine in 1963, this disease posed a serious threat, causing an annual death toll of more than 2 million, with a considerable impact on child mortality (WHO, 1998). It is particularly alarming that the vast majority of patients (87%) are children under five years of age (WHO, 2021). Furthermore, it has emerged as one of the leading causes of blindness in low-income countries. Introducing the measles vaccine brought about two crucial effects: a reduction in the incidence of measles and a simultaneous decrease in morbidity and mortality originating from other pathogens. The vaccine not only directly protects against measles, but also strengthens immunological memory, forming a shield against co-infections and consequently improving general child health (Atwood, 2022; Nandi and Shet, 2020).

In the 1970s and 1980s, widespread measles vaccination was implemented in sub-Saharan African countries through the World Health Organization (WHO) Expanded Program on Immunization (EPI). Despite these coordinated efforts to inoculate children against the disease, measles remains a serious concern in the developing world, particularly in sub-Saharan Africa (Goodson et al., 2011; Keja et al., 1988; CDC, 2009). Outbreaks - with fatality rates as high as 5% to 10% - have persisted in Sub-Saharan Africa, including significant flare-ups in the Democratic Republic of Congo, Malawi, Burkina Faso, Zambia, and Nigeria (Cutts et al., 2013; WHO, 2011).

B Robustness Check: Internal Migration

B.1 Data

Our identification strategy requires aggregate (macro) level data from a set of countries over a long period. We extract macroeconomic data from Sub-Saharan Africa (SSA) between 1976 and 1994 from the World Bank's World Development Indicators (WDI). We keep all SSA countries for which we have the required demographic and economic characteristics from 1976-1994, leaving us with 27 countries, including Burkina Faso.

We consider the short- and medium-term effects of vaccination. The short-term outcome we used is under-five (child) mortality rate. Children under five years of age are more susceptible to disease and have a significantly higher mortality rate than other age groups. The medium-term outcomes we used are two educational outcomes– primary school enrollment rate and primary school completion rate. We focus only on primary school outcomes because of limited information on secondary and above-secondary school outcomes. Primary School enrollment rate, the percentage of children enrolled in school among the relevant age group, measures school participation, but does not necessarily translate to successful completion and proficiency gains. Thus, we complement enrollment rate with primary school completion rate, the percentage of the relevant age group completing primary school, which is arguably a stronger predictor of proficiency.

For the analysis of child mortality, we use demographic and economic indicators such as gross domestic product (GDP) per capita, percentage of rural population, percentage of land used in agriculture, crop production index, food production index, and livestock production index. We limit our sample between 1976 and 1990 to capture the under-five child mortality of the treated cohort. Table B.2 shows the descriptive statistics of the key variables. We present the statistics for Burkina Faso in columns 1-3, and the rest of SSA in columns 4-6. For Burkina Faso, we show the mean and standard deviation before and after 1984 in columns 1 and 2, and the difference between the two periods in columns. We report similar statistics for the rest of SSA in columns 4-6. Burkina Faso looks quite different from other SSA countries in both demographic and economic characteristics. However, these differences are not a concern for our estimation method.

For educational outcome analysis, we use demographic and economic indicators such as gross domestic product (GDP) per capita, percentage of rural population, percentage of land used in agriculture, crop production index, food production index, livestock production index, percentage of age 0-14 population, life expectancy at birth, mortality rate for adult females, and mortality rate for adult males. We limit our sample between 1976 and 1994 to capture the treatment effect on school completion. Table B.3 shows the descriptive statistics of the key variables.

B.2 Methods

We want to estimate the causal effects of vaccination using the VC program as a natural experiment. The VC program was implemented in 1984 in Burkina Faso. We need a suitable method for estimating the counterfactuals—imputing the missing potential control outcomes–to find the average treatment effects. The literature on causal inference provides us with three broad approaches - unconfoundedness, synthetic control, and model-based imputation (Athey et al., 2021)[29].

The unconfoundedness approach imputes missing potential control outcomes for treated units using observed control outcomes for control units with similar values for observed outcomes in previous periods (Rosenbaum and Rubin, 1983; Imbens and Rubin, 2015). The synthetic control method imputes missing control outcomes for treated units using the weighted average outcome for control units. The weights are chosen so that the weighted lagged control outcomes match the lagged outcomes for the treated units (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Athey et al., 2021). Finally, the model-based imputation takes observations under the treatment condition as missing and uses model based estimation to impute counterfactuals of treated observations (Liu et al., 2024).

The model-based imputation is more efficient and flexible than the other two approaches. It

[29]The method is well exposed in Athey et al. (2021). For the reader, we describe the main steps we followed here.

allows several alternative counterfactual estimation techniques, such as fixed effects, iterative fixed effects, and matrix completion. The matrix completion approach uses the observed elements of the matrix of control outcomes corresponding to untreated units to impute the missing elements of the control matrix (Athey et al., 2021). This approach nests both the unconfoundedness and synthetic control approaches and outperforms those approaches.

We use the matrix completion approach in this study and apply the "counterfactual estimators" proposed by (Liu et al., 2024).[30]. The counterfactual estimators take observations under the treatment condition as missing and use observations under the control condition to build models and impute the counterfactuals of treated units based on the estimated models. Although counterfactual estimators can deal with both balanced and unbalanced panel data, we describe the estimation framework using a balanced panel notation for notational convenience. Let D_{it} be the treatment status and $Y_{it}(1)$ and $Y_{it}(0)$ be the potential outcomes of unit i in period t when $D_{it} = 1$ and $D_{it} = 0$. Also, let X_{it} be a vector of exogenous covariates, U_{it} be unobserved attributes, and ϵ_{it} be the idiosyncratic error term. The class of outcome models for the untreated potential outcome can be written as follows:

$$Y_{it}(0) = f(X_{it}) + h(U_{it}) + \epsilon_{it} \tag{8}$$

where $f(.)$ and $h(.)$ are known parametric functions.

Let us define observations under the treatment condition as M and observations under the control condition as O, where M stands for missing, and O stands for observed. The counterfactual estimators follow a four-step procedure. First, fit a model of Y_{it} to obtain $\hat{f}$ and $\hat{h}$ using the subset of untreated observations. Second, predict the counterfactual outcomes $Y_{it}(0)$ for each treated observation using the $\hat{f}$ and $\hat{h}$, i.e., $\hat{Y_{it}}(0) = \hat{f}(X_{it}) + \hat{h}(U_{it})$ for all $(i,t) \in M$. Third, for each treated observation $(i,t) \in M$, estimate the treatment effects δ_{it} using $\hat{\delta}_{it} = Y_{it} - \hat{Y_{it}}(0)$. It is important to note that δ_{it} is not identified for each treated observations because of idiosyncratic errors. Finally, to find the average treatment effects, take average of $\hat{\delta_{it}}$, $\hat{ATT} = \frac{1}{|\mathbb{M}|}\sum_{(i,t)\in\mathbb{M}} \hat{\delta}_{it}$. Similarly, the ATT at a period s since the treatment started $\hat{ATT}_s = \frac{1}{|\mathbb{S}|}\sum_{(i,t)\in\mathbb{S}} \hat{\delta}_{it}$ in which $\mathbb{S} = \{(i,t) \mid D_{i,t-s} = 0, D_{i,t-s+1} = D_{i,t-s+2} = \ldots = D_{i,t} = 1\}$. To apply the general framework of counterfactual estimators into the matrix completion, we can express potential outcomes data matrix Y_{it} as the following equation:

$$Y_{it} = \delta_{it} D_{it} + L_{it} + x_{it}\beta + \eta_i + \gamma_t + \epsilon_{it} \tag{9}$$

where $Y_{it} \in (N \times T)$ matrix of untreated outcomes, $x_{it} \in (N \times T \times k)$ array of covariates, η_i represent the unit fixed-effects γ_t represent the time fixed-effects, and ϵ_{it} represent a $(N \times T)$ matrix of idiosyncratic errors. MC treats the treatment observations ($Y_{it}(1)$) as missing data and estimates the treated counterfactual by employing the information of the untreated observations. It uses the donor pool (i.e., other SSA countries) for model training and pre-treated data for model selection (i.e., model building and testing). Then, it uses the trained model to predict the counterfactual outcomes $\hat{Y_{it}}(0)$ for each observation under the treatment condition ($D_{it} = 1$) and obtains an estimate of the individual treatment effect. The method assumes that the $(N \times T)$

[30] Both Stata and R packages–Fixed Effects Counterfactual Estimators (Fect)–developed by Liu et al. (2024), are available for implementing the estimation.

matrix can be approximated by a lower rank matrix $L_{(N\times T)}$ (unobserved cofounders). The method estimate L by solving the minimization problem.

$$\hat{L} = \min_{L} \frac{1}{\mid \mathbb{A} \mid} \sum_{(i,t)\in\mathbb{A}} ((Y_{it} - L_{it})^2 + \lambda_L \|L\|) \tag{10}$$

where $\mathbb{A} = \{(i,t)|D_{it} = 0\}$ is the set of untreated observations and $\|L\|$ is the chosen matrix norm of L, and λ_L is a tuning parameter. λ_L controls the strength of the penalty term. Athey et al. (2021) proposed an iterative algorithm to estimate $\hat{L}$. MC tries to find a lower-rank representation of the matrix L to impute the missing data. Athey et al. (2021) suggests using nuclear norm to construct L, which is by putting regularization on the eigenvalues of the L matrix. One of the advantages of regularization is to prevent the overfitting of the model. The regularization term (λ_L) imposes a cost on the optimization function to make the optimal solution unique. The objective of the method is to construct L_{it} matrix such that the difference between Y_{it} and L_{it} is minimized and also put a penalty on the complexity of the L matrix. As L converges then $\hat{Y}_{it}(0) = \hat{L}^*_{it}$ and thus

$$\hat{\delta}_{it} = Y_{it}(1) - \hat{Y}_{it}(0) \tag{11}$$

where $\hat{\hat{\delta}}_{it}$ is the average treatment of the treated. The estimate is the average difference between the observed outcome and its counterfactual estimate for the treated unit.[31]

[31] See Liu et al. (2024) for further detail on matrix completion approach.

Table (B.1) Placebo Effects with Continuous Treatment in High Vaccination Intensity Provinces

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
CB 1972-77=1 × VRM	0.053***	0.003	0.003	0.001	0.003
	(0.012)	(0.002)	(0.002)	(0.001)	(0.022)
Observations	2,623	311,436	311,436	119,749	16,753
Fixed Effects	Province	Province	Province	Province	Province
Fixed Effects		Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB	YOB
Other controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. The dependent variable is child mortality (age less than 5) in Column (1). Dependent variables are dummy indicators of school enrollment and school completion in Columns (2) and (3), respectively. Dependent variable in Column (4) is formal employment which takes 1 if an individual is earning salary or wages. Dependent variable in Column (5) is the natural log of harvest value per hectare. The treatment variable is measles vaccination rate. CB stands for cohort of birth, VRM stands for measles vaccination rate at the province level. Column (1) include controls ethnicity and gender and use data from the 1993 Demographic and Health Survey (DHS) of Burkina Faso. Columns (2)-(4) include controls religion and gender. Columns (2)-(3) use data from 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Column (4) uses 2006 census data and kept individuals aged above 27 years in this analysis. Column (5) includes controls: plot owner characteristics such as gender and relationship to the household head; plot characteristics such as toposequence, distance to the village, and land ownership status. We also included province, survey year, crop, and plot decile fixed effects. Estimations using the 2008-2014 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (B.2) Descriptive Statistics – Under-5 Mortality Outcome Analysis

	Burkina Faso			Other SSA Countries		
	Before	After	Difference (2)-(1)	Before	After	Difference (5)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita (constant 2010 US$)	357.65	385.90	28.25	1457.83	1287.18	-170.65
	(13.54)	(14.61)	(7.27)	(2638.99)	(2,111.19)	(244.33)
Rural population	91.40	87.07	-4.32	77.15	73.56	-3.59
	(1.45)	(0.77)	(0.61)	(11.69)	(13.59)	(1.28)
Agricultural land	32.02	33.93	1.91	42.30	43.91	1.62
	(0.47)	(1.03)	(0.40)	(17.59)	(18.65)	(1.83)
Crop production index	25.57	36.79	11.22	40.76	47.24	6.47
	(1.90)	(5.34)	(2.01)	(22.29)	(24.75)	(2.38)
Food production index	25.15	37.12	11.97	41.77	47.25	5.48
	(2.09)	(4.70)	(1.83)	(23.10)	(23.16)	(2.34)
Livestock production index	24.51	37.81	13.31	44.25	49.04	4.79
	(2.87)	(7.58)	(2.88)	(28.12)	(24.53)	(2.69)
Mortality rate, under-5 (per 1,000 live births)	244.50	207.03	-37.47	200.34	177.05	-23.29
	(17.39)	(7.57)	(7.12)	(57.82)	(58.46)	(5.89)
Observations	8	7	15	208	182	390

Notes: This table presents the mean and standard deviation of demographic and economic indicators for Burkina Faso and other Sub-Saharan African countries before and after the VCP program in 1984. Standard deviations are presented in parentheses in columns (1)–(2) and (4)–(5), whereas standard errors are presented in parentheses in columns (3) and (6). The data comes from the World Bank's world development indicators.

Table (B.3) Descriptive Statistics – Educational Outcome Analysis

	Burkina Faso			Other SSA Countries		
	Before	After	Difference (2)-(1)	Before	After	Difference (5)-(4)
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita (constant 2010 US$)	357.65	391.16	33.51	1,457.83	1,270.35	-187.47
	(13.54)	(13.79)	(6.36)	(2,638.99)	(2,103.54)	(213.58)
Rural population	91.40	86.52	-4.88	77.15	72.72	-4.43
	(1.45)	(1.00)	(0.56)	(11.69)	(13.97)	(1.19)
Agricultural land	32.02	34.22	2.20	42.30	43.74	1.44
	(0.45)	(0.88)	(0.36)	(17.59)	(19.22)	(1.69)
Crop production index	25.57	40.73	15.16	40.76	49.04	8.27
	(1.90)	(6.97)	(2.55)	(22.29)	(24.08)	(2.13)
Food production index	25.15	41.66	16.52	41.77	49.03	7.26
	(2.09)	(7.34)	(2.69)	(23.10)	(21.75)	(2.03)
Livestock production index	24.51	43.52	19.01	44.25	51.07	6.82
	(2.87)	(9.90)	(3.63)	(28.12)	(22.69)	(2.29)
Population ages 0-14	45.51	47.10	1.59	45.69	46.08	0.039
	(0.64)	(0.29)	(0.22)	(2.28)	(1.80)	(0.18)
Life expectancy at birth	45.50	49.40	3.90	48.76	50.79	2.01
	(2.22)	(0.16)	(0.66)	(5.32)	(5.97)	(0.52)
Mortality rate, adult female (per 1,000)	324.04	294.30	-28.77	324.89	319.95	-4.95
	(29.75)	(5.74)	(9.10)	(44.04)	(70.36)	(4.95)
Mortality rate, adult male (per 1,000)	387.73	353.17	-34.55	386.00	386.35	0.35
	(34.30)	(8.07)	(10.63)	(41.14)	(84.03)	(6.31)
Primary school enrollment rate (%)	14.47	25.56	11.08	50.22	55.63	5.41
	(2.12)	(3.09)	(1.27)	(30.53)	(22.89)	(2.40)
Primary school completion rate (%)	9.49	19.08	9.59	45.91	46.97	1.06
	(1.21)	(5.35)	(1.94)	(26.30)	(23.85)	(2.27)
Observations	8	11	19	208	286	494

Notes: This table presents the mean and standard deviation of demographic and economic indicators for Burkina Faso and other Sub-Saharan African countries before and after the VCP program in 1984. Standard deviations are presented in parentheses in columns (1)–(2) and (4)–(5), whereas standard errors are presented in parentheses in columns (3) and (6). The data comes from the World Bank's world development indicators.

Table (B.4) Robustness: Vaccination Effects with Alternative Province Classification

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
CB 1978-83=1 $\times$ HVRM =1	-0.027	0.023*	0.023**	0.010*	0.060**
	(0.025)	(0.013)	(0.010)	(0.005)	(0.022)
Constant	0.371***	0.309***	0.261***	0.154***	11.988***
	(0.033)	(0.008)	(0.007)	(0.009)	(0.009)
Observations	4,783	389,389	389,389	73,298	20,336
Fixed Effects	Province	Province	Province	Province	Province
Other Controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. The dependent variable is a child (age less than 5) mortality rate in Column (1), primary school enrollment in Column (2), school completion in Column (3), formal employment in Column (4), and the natural log of harvest value per hectare in Columns (5). The treatment variable is high vaccination rate of measles (HVRM), where HVRM equals one if the measles vaccination rate is high and zero otherwise. CB stands for cohort of birth. All columns include their respective controls. This table presents the results of our main estimation equation by reclassifying two provinces that are classified as HVRM but have below-median vaccination rates. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (B.5) Robustness: Vaccination Effects Excluding Potential Misclassified Provinces

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
CB 1978-83=1 × HVRM =1	-0.039*	0.024*	0.023**	0.010*	0.063***
	(0.021)	(0.013)	(0.010)	(0.005)	(0.022)
Constant	0.378***	0.316***	0.267***	0.157***	12.005***
	(0.035)	(0.007)	(0.009)	(0.009)	(0.078)
Observations	4,538	367,738	367,738	69,345	19,386
Fixed Effects	Province	Province	Province	Province	Province
Other Controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. The dependent variable is the child (age less than 5) mortality rate in Column (1), primary school enrollment in Column (2), school completion in Column (3), formal employment in Column (4), and the natural log of harvest value per hectare in Column (5). The treatment variable is the high vaccination rate of measles (HVRM), where HVRM equals one if the measles vaccination rate is high and zero otherwise. CB stands for cohort of birth. All columns include their respective controls. This table presents the results of our main estimation equation by dropping the two provinces classified as HVRM but with below-median vaccination rates. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (B.6) Robustness: Vaccination Effects with Alternative Control Definition

	Child Mortality	School Enrollment	School Completion	Formal Empl.	Agri. Yield
	(1)	(2)	(3)	(4)	(5)
CB 1978-83=1 × HVRM =1	-0.047*	0.037***	0.024***	0.008	0.054**
	(0.023)	(0.009)	(0.008)	(0.005)	(0.021)
Constant	0.370***	0.309***	0.261***	0.154***	11.987***
	(0.033)	(0.008)	(0.009)	(0.009)	(0.075)
Observations	4,783	389,389	389,389	69,345	19,386
Fixed Effects	Province	Province	Province	Province	Province
Other Controls	Yes	Yes	Yes	Yes	Yes
Data Source	DHS	Census	Census	Census	PAS

Notes: Robust standard errors clustered at the province level. The dependent variable is the child (age less than 5) mortality rate in Column (1), primary school enrollment in Column (2), school completion in Column (3), formal employment in Column (4), and the natural log of harvest value per hectare in Column (5). The treatment variable is the high vaccination rate of measles (HVRM), where HVRM equals one if the measles vaccination rate is high and zero otherwise. CB stands for cohort of birth. All columns include their respective controls. This table presents the results of our main estimation equation by using an alternative approach to classify the control province. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.

Table (B.7) Returns to Primary School Completion

	log(Earnings)			
	(1)	(2)	(3)	(4)
Primary School Completion =1	0.439***	0.236***	0.193***	0.136***
	(0.033)	(0.031)	(0.035)	(0.036)
Female =1		-1.235***	-1.253***	-1.235***
		(0.025)	(0.025)	(0.025)
Experience			0.034***	0.033***
			(0.004)	(0.004)
Experience Squared			-0.001***	-0.001***
			(0.0001)	(0.0001)
Formal Sector Employment =1				0.329***
				(0.045)
Constant	-0.063***	0.486***	0.225***	0.215***
	(0.015)	(0.018)	(0.062)	(0.062)
Observations	15,240	15,240	15,240	15,240
Fixed Effects	Location	Location	Location	Location
Other controls	None	Yes	Yes	Yes
Data Source	LSMS 2014	LSMS 2014	LSMS 2014	LSMS 2014

Notes: Robust standard errors are in Parentheses. The dependent variable is the total income of an individual (in log scale). We use the "Mincer Earning Function" with and without controls to estimate the returns to primary school completion. ***Significant at the 1 percent level, **Significant at the 5 percent level, and *Significant at the 10 percent level.