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

Richard Daramola[†] Md Shahadath Hossain [‡] Harounan Kazianga[§]
Karim Nchare[¶]

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Abstract

After being in power in Burkina Faso for about a year, a military regime led by Thomas Sankara vaccinated 77% of children under six years of age against measles, meningitis, and yellow fever within a few weeks. The coverage and success of this program set it apart from other contemporary vaccination programs, thus providing a policy experiment to test the effects of large-scale immunization programs in low-income contexts. Using a difference-in-differences approach, we find significant reductions in child mortality and improvements in educational attainment. Additionally, we show positive long-term effects on employment and agricultural productivity in adulthood for those who received vaccinations. These findings underscore the lasting benefits of early childhood health interventions in low-income countries.

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[†]State College of Florida, FL. Email: daramor@scf.edu
[‡]University of Houston, TX. Email: mhossai7@central.uh.edu
[§]Oklahoma State University, OK. Email: harounan.kazianga@okstate.edu.
[¶]Vanderbilt University. Email: karim.nchare@vanderbilt.edu

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). The formative nature of childhood and the accumulation of effects from early life stages over time contribute to the high returns of early childhood interventions(Nandi et al., 2017). A substantial body of research has examined various policies using various empirical methods and consistently found the efficacy of early childhood health interventions to persist into adulthood.

Although much of the existing research on early childhood interventions focuses on high-income countries and the effects on academic outcomes, labor market participation and earnings(e.g., Carneiro et al., 2021; Currie and Vogl, 2013), early life circumstances may have a greater impact on lifetime outcomes in low- and middle-income countries, where the capacity for remediation is often limited. Furthermore, in these contexts, where a large part of the population is 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, it is crucial to carefully examine the long-term effects of early interventions in low-income contexts, where resource allocation trade-offs may be more severe and the potential benefits may be even greater.

We investigate the long-term impacts of public health policies that target children up to 6 years old 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. This program was unique in its implementation, as the government, with the assistance of several donors, was able to vaccinate 60% of eligible children against preventable diseases in just 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, there were significant regional variations in vaccination rates, leading to differences in exposure among eligible children. We exploit these geographical differences to determine whether the vaccination program had any lasting effects on the individuals who received it.

The program, known locally as the Vaccination Commando Program (VCP), was part of a larger and coordinated international effort to expand vaccination coverage in low-income countries. 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 benefit children who receive them by protecting 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. However, despite these demonstrated benefits, one in five children worldwide in 2020 was not vaccinated for life-threatening infectious diseases, according to the World Health Organization (WHO, 2021). In many developing nations, vaccination rates are even lower, ranging from 40% to 70% (WHO, 2020), highlighting the need for continued efforts to expand access to vaccines.[1]

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

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 underinvestment in vaccines in developing nations, suggests that the impact of vaccines is still not well understood[3].

VCP was implemented in 1984 in Burkina Faso, and 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). The same year, Thomas Sankara's military regime assumed power after a coup. Building on the existing but underperforming expanded immunization program (EPI), the regime initiated the VCP, which vaccinated more than a million children against measles, yellow fever, and meningitis in a two-week campaign. As a result of VCP, the vaccination rate in Burkina Faso increased from 17% to 77% in the second part of December 1984. The success of the VCP was hailed by the World Health Organization (WHO) and presented as a case study of one of the most successful vaccination campaigns (Kessler et al., 1987).

Two features of VCP make it almost a perfect policy quasi-experiment. First, the implementation of the program was sudden. Second, the program relied on the military infrastructure and deployed civil servants, leaving the health system unchanged. We measure the impact of VCP by exploiting cohort-region variations in exposure to the program using a difference-in-differences approach (e.g Bleakley, 2007; Duflo, 2001). Variations across cohorts arise from the timing of the program: individuals who were 6 years old or younger would have been eligible to receive all early childhood vaccinations. In contrast, older people would theoretically not be eligible for childhood vaccination. Spatial variations are due to differences in vaccination rates between districts (i.e., provinces).

12-24 months) in 2020 is 70%; whereas, 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 mandate in the United States and Australia. Some protesters compare state government to Nazis. Conversely, fearmongering is observed with polio vaccines in the past in India.
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)
https://www.comminit.com/global/content/fear-polio-drops-overcome

[3]One potential reason is that there is a 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, respectively. To the best of our knowledge, Nandi et al. (2020) and Atwood (2022) are the only ones to evaluate national-level vaccination efforts to study the impact on human capital and labor market outcomes in India and United States. Nandi et al. (2020) use a household fixed-effect estimation to evaluate the effect of the Universal Immunization Program (UIP) in India and find that vaccination leads to higher schooling attainment. Atwood (2022) uses a variation in pre-vaccine measles incidence rates across states in the USA and differential exposure to the vaccine due to birth year to measure the effects of measles vaccination on earnings and employment in adulthood.

We start by focusing on child health outcome– under-five child mortality rate. We find that vaccination leads to a significant decline in child mortality. This result is similar to Clemens et al. (1988) and Koenig et al. (1990) who find that in Bangladesh, measles vaccination reduces child mortality. Nandi et al. (2019) find measles vaccination leads to better health outcomes in Ethiopia, India, and Vietnam[4]. We then proceed to show that the program raises educational attainment – primary school completion, echoing findings in different contexts, including 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 treated cohorts' labor market outcome in adulthood. We show that vaccinated cohorts are significantly more likely to be employed in the formal sector, and earn higher agricultural yields per hectare. Atwood (2022) found a similar result for the measles vaccine in the United States, where the labor market is well established. However, whether exposure to early child immunization improves labor market outcomes in developing countries with more frictions in the labor markets remains an open question that we address in this paper.

This paper fits into a fast-growing body of research that focuses on understanding 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). We make three major contributions to this strand of literature. 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 to the literature by documenting the impacts of a nationwide health program in the context of a developing country, using a quasi-experimental design. The nation-wide 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 very informative, but 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, that we describe as a positive health shock, a departure from studies that focus 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 asymmetrical effects, particularly in low-income countries(Bloom and Canning, 2003). Therefore, investigating the consequences of these initiatives can provide crucial evidence for designing effective

[4]In contrast to our findings, 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. This can result in 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

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 by Bliss and Stern (1978a,b); Strauss (1986) to show that the vaccination program increased the effectiveness (or quality) of farm labor, rather than the quantity of farm labor supplied. Given the predominance of small-scale agriculture in most of the developing world, we argue that this finding can 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. In Section 2, we describe the VCP, our data, and empirical strategy. We present our main results in Section 3. Next, we present various robustness checks in Section 4. Section 6 concludes the paper.

2 The Program

2.1 Vaccination Commando Program in Burkina Faso

More than half of all deaths of children under five years in Burkina Faso were directly attributed to vaccine-preventable diseases (Bellamy, 1998). As a result, Burkina Faso established its Expanded Program on Immunization (EPI) in 1980 to administer vaccines against measles, meningitis, and yellow fever to eligible children. However, the program performed poorly, reaching only 25000 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. The Vaccination Commando Program (VCP) was established in 1984 to address the failure of the local EPI. In a 15-day campaign between November 25^{th} and December 10^{th} of 1984, Burkina Faso vaccinated well over 1 million children against measles, yellow fever, and meningitis. The VC 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 after VCP (see Figure 1).

The VCP aimed to vaccinate children aged 9 months to 6 years against measles and those aged 1 to 14 against meningitis and yellow fever (Kessler et al., 1987). The government took both demand- and supply-side initiatives to achieve its objective. To maintain the demand for vaccination, the government raised vaccination awareness through a nationwide campaign using multiple mediums[7]. On the supply side, the government 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. 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.

[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.

2.2 Data Sources and Descriptive Statistics

We use microdata from four sources for our analysis: the Demographic and Health Survey (DHS), the General Population and Housing Census (full sample of the 1985 census and sample 10% from 1996 and 2006), the Permanent Agricultural Survey (PAS) and administrative data from the Ministry of Health on immunization. We use the 1993 round of the DHS to calculate the child mortality rate by year of birth[8]. The census data serves 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 used 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 Permanent Agricultural Survey (PAS) (see Kazianga and Wahhaj, 2017)) to calculate agricultural productivity.

We study the impact of increased vaccination on both short-run and long-run outcomes. For short-run outcomes, we focus on child mortality and school completion. Child mortality is a dummy variable that takes the value of one if the parent reported the death of a child under age five. Similarly, primary completion is a dummy variable that takes the value of one if the child is reported to have completed primary school. We present the trends in these variables in Figures 3 - 5. We use labor market outcomes in adulthood to measure the long-term effect of the increased vaccination. We focus on two outcomes: formal employment and agricultural productivity. Formal employment is a dummy variable that takes 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. We present the trends in these variables in Figures 6 - 7.

We now provide more details on the variables used in Table 1. The table shows descriptive statistics on our estimation samples, consisting of data from the DHS in panel A, national censuses in panel B, and agricultural survey data in panel C. We present the sample size, mean, and standard deviation (SD) of the full sample in Columns (1)-(3). 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)[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 and1983 were eligible for measles vaccination in 1984, therefore constitute the treated cohort[10].

The 1993 Demographic Health Survey (DHS) data in panel A show a high child mortality rate of 285 per 1,000 live births for the full sample. The mortality rate is virtually identical for both the low- and high-intensity vaccination provinces. Approximately 53% of the sample belongs to the eligible cohort (cohort of birth 1978-1983), 33% first control cohort (cohort of birth 1972-1977), and the remaining 14 percent second control cohort (cohort of birth 1966-71). The total sample measles

[8]We chose the 1993 round because it is the closest to the program, thus the birth reports of birth histories for the relevant cohorts are less noisy relative to the more recent cohorts. Furthermore, more respondents would still be residing in the same province. Finally, we drop the urban sub-sample since the survey sampled only urban households from one provinve.

[9]High vaccination rate provinces 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.

vaccination rate is approximately 64%, while the vaccination 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. Only a tiny fraction of individuals enter formal jobs by age 27, so we restrict the sample to individuals above age 27 for formal sector employment. With this restriction, about 8% of the sample reported having formal employment in the 2006 Burkina Faso General Population and Housing Census[11]. These figures are slightly higher in the high-intensity vaccination provinces than in low-intensity vaccination ones. The measles vaccination rate is 64% for the entire sample, but substantially higher in high-intensity regions (82%) than in the low-intensity areas (46%). About 58% of the sample is identified as Muslim and 53% is 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 Permanent Agricultural Survey (PAS). The survey, fielded at the plot level, contains detailed information on crop output, inputs, including labor, and plot manager characteristics.

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). Therefore, we restrict the analysis to individual plots since we assign treatment through the year of birth of the plot manager. Columns (1)-(3) present the summary statistics for the full sample, whereas Columns (4)-(6) and Columns (7)-(9) present the summary of the provinces with low and high vaccine intensity, respectively. About 40% of our sample belongs to the treated cohort, 32 percent belongs to the first control cohort, and the remaining 28% belongs to the second control cohort. The mean vaccination rate for the full sample is about 61 percent, while the vaccination rates for the low and high-intensity regions are 44% and 83%, respectively.

We also present the summary statistics of agricultural inputs and agricultural yield. Agricultural inputs include labor hours and fertilizer (NPK and Urea). Furthermore, we have summarized 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 is in the real value of the local currency.

2.3 Empirical Strategy

We estimate the impact of the VCP program by exploiting cohort-region variation in exposure to the program using a difference-in-differences approach (e.g Bleakley, 2007; Duflo, 2001). In our specification, cohort variation arises from the timing of the program: individuals who were 6 years

[11] 2006 Burkina Faso General Population and Housing Census is the last available Census in Burkina Faso for which data is available.

old or younger would have been eligible to receive all early childhood vaccinations. In contrast, older individuals would not theoretically be eligible for childhood vaccination. We start with the following difference-in-difference specification:

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

where Y_{ijk} is the outcome of interest of individual i in cohort j in province k, 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 measles vaccination rate in December 1984, and $HVRM$ is a dummy variable indicating whether a province had a high measles vaccination rate or not in December 1984.[12] Exposure_j is a dummy variable indicating whether the individual belongs to a cohort exposed to the vaccination commando program, and η_k and γ_j represent province and cohort fixed effects, respectively. Furthermore, ε_{ijk} represents the idiosyncratic error. We cluster errors at the province level to account for possible serial correlation. The interaction coefficient β_1 captures the causal effect of 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 difference-in-differences approach identifies the differential effect of the VCP for individuals in high-intensity provinces relative to those in low-intensity provinces. To assess the validity of the common trend assumption in the high- versus low-intensity difference-in-differences estimation, we perform a placebo estimation using the cohort born between 1972 and 1977. Children in this cohort were older than 6 years in December 1984 and could not have received the measles vaccine during the VCP program. 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].

When the heterogeneous treatment effect is assumed, Callaway et al. (2021) and references therein have demonstrated that two-way fixed effects estimator β_1^{twfe} can be severely biased and may not have any causal interpretation, contrary to its interpretation as an average causal response in the existing applied economics literature. Under a common trends assumption on untreated potential outcomes, Callaway et al. (2021), show that β_1^{twfe} is a weighted sum of different treatment effects. To discuss this in detail, let us introduce the following parameters:

$$ATT(d|d) = E[Y_j(d) - Y_j(0)|D = d], ACRT(d|d) = \frac{\partial ATT(l|d)}{\partial l}_{l=d}, ATE(d) = E[Y_j(d) - Y_j(0)], \text{ and, } ACR = \frac{\partial ATE(d)}{\partial d}.$$

[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 high measles vaccination rates. We check robustness of our analysis by exploring any potential misclassification of provinces into either treatment or control groups. Based on the dichotomous treatment definition, we find two provinces with below median vaccination rates fall into the treatment group. We estimate equation Eq. 1 by taking the two potentially misclassified provinces into the control group. Alternatively, we also reestimate Eq. 1 by dropping those two provinces. We discuss the results of these exercises in Section 3. 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 $Y_{ij}(d)$ is the potential outcome of unit i in cohort j under dose d, $ATT(d|d)$ is the causal effect of experiencing dose d among units that experienced treatment dose d. $ACRT(d|d)$ is the causal response of a marginal change in the dose among units that experienced treatment dose d. $ATE(d)$ is the mean difference between potential outcomes under dose d relative to untreated potential outcomes across all units, and ACR is the associated average causal response. Under the standard common trends assumption: for all possible values of the dose d

$$E[Y_j(0) - Y_{j-1}(0)|D = d] = E[Y_j(0) - Y_{j-1}(0)|D = 0]. \tag{2}$$

Callaway et al. (2021) show that β_1^{twfe} is a weighted sum of $ATT(d|d)$ and $ACRT(d|d)$ for all d. Under a stronger common trend assumption: for all d

$$E[Y_j(d) - Y_{j-1}(0)] = E[Y_j(d) - Y_{j-1}(0)|D = d] \tag{3}$$

they show that β_1^{twfe} is a weighted sum of $ATE(d)$ and $ACRT$ for all d. Therefore, in the presence of heterogeneous treatment effects, these authors advise against using the TWFE regression. Instead, they propose to estimate a series of simple 2×2 difference-in-differences comparing dose groups to an untreated comparison group. Under common trends assumption (2) those estimators will identify $ATT(d|d)$ for all d and these can be averaged to obtain $ATE(d)$.

To account for potential heterogeneity in treatment effects, we follow Callaway et al. (2021)'s suggestion and run a series of 2×2 difference-in-differences. 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 the low-intensity provinces. These values are then averaged to obtain the average treatment effect in the high-intensity provinces.

Finally, 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.

$$Y_{ijk} = \alpha_0 + \sum_a \beta_a \left(I_k * \text{VCP}_{ja}\right) + X_{ijk} + \eta_k + \gamma_j + \varepsilon_{ijk} \tag{4}$$

where VCP_{ja} is the share of individuals in the age range a and cohort j who were exposed to VCP, and the other variables are defined above. Because children under the age of 6 are typically the most vulnerable to measles, we consider three age groups in our empirical analysis: Low Exposure (LE, aged 5-6), Moderate Exposure (ME, aged 3-4), and High Exposure (HE, aged 1-2). 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.

3 Results

In this section, we present the short-, medium-, and long-term impacts of VCP. As stated above, we focus on child mortality outcomes to measure short-term impact, educational outcomes to measure medium-term impact, and formal employment and agricultural productivity in adulthood to measure long-term impact. In each table, we present the results from two estimation approaches: continuous treatment intensity TWFE and dummy treatment TWFE. The estimated coefficient

from continuous treatment intensity TWFE ($\hat{\beta}_1$) in Eq. 1 captures the interaction of the treatment cohort dummy (Exposure$_j$, cohort of birth 1978-83=1) and treatment intensity (I_k, vaccination rate of measles (VRM) in province k). Similarly, the estimated coefficient of the dummy treatment TWFE ($\hat{\beta}_1$) in Eq. 1 captures the interaction of the treatment cohort dummy (Exposure$_j$, birth cohort 1978-83 = 1) and the treatment dummy (I_k, indicator of the high measles vaccination rate (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.

3.1 Short-term Outcomes: Mortality

We begin by showing the effect of VCP on child mortality and the most immediate outcomes to which we have access. If the vaccination campaign had been successful, overall health would have improved, leading to lower mortality rates. Therefore, although 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 impact of VCP on mortality based on Eq. 1, using the rural subsample of the 1993 round of the Burkina DHS survey. The dependent variable is child mortality in Columns (1)-(4) [14]. Even columns include additional controls, namely ethnicity, gender of the child, and mother's age and literacy.

The results in Columns (1)-(4) of Table 2 suggest that VCP has significantly reduced child mortality. The effect of treatment in Column (1) is -0.08 and statistically significant at the level of 10%. An increase in the vaccination rate by one percentage point led to a decrease in child mortality by 0.08 percentage points. This point estimate is robust to including additional control variables, as shown by the virtually identical coefficient we get in Column (2). We repeat the exercise in Columns (3)-(4), using the dichotomized treatment, as described in Section 2.3. The point estimate is 0.05 (without and with controls) and significant at the 10% level. In the exposed cohort, child mortality decreased by 0.05 percentage points in provinces with a high vaccination rate.[15] The estimates using the binary version of treatment in Columns (3)-(4) are slightly lower than those in Columns (1)-(2). The estimates imply a reduction of child mortality by 16.2%, starting from the average child mortality of 0.29, or approximately 47 children saved out of 1000 live births.

[14] We follow the practice in the literature and define "child mortality" by dying by 5 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.3 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.4 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.

3.2 Mid-term Outcomes: Education

We now investigate to what extent improved health led to better educational outcomes. Specifically, we estimate the effects of VCP on primary school enrollment and completion[16] that we show in Table 3. The estimation uses the 1996 and 2006 rounds of General Population and Housing Censuses of Burkina Faso. The results demonstrate that 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 Columns 1 is 0.063, and statistically significant at the level 5% level. This point estimate is robust to including additional control variables, as shown by the virtually identical coefficient we get in Column (2). The estimate indicates that an increase in the vaccination rate by one percentage point led to a 0.06 percentage point higher primary school enrollment. We repeat the exercise in Columns (3)-(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, we show in Columns 5-8 that VCP increased completion rates, which may be more critical for lifetime economic outcomes. The effect of treatment in column (6) is 0.05, and statistically significant at the 5% level. The specification using binary treatment (columns 7-8) shows that the completion rates increased by 0.2 percentage points (significant at the 5% level). The estimates imply an increase in school completion of 13.1%, starting from the average school enrollment of 0.16.

3.3 Long-term Outcomes: Labor Market Outcomes

After establishing that VCP improved overall health (reduced child mortality) and educational outcomes, we now focus on the effects on labor market outcomes in adulthood. We report the effects of VCP on labor market outcomes in Table 4. We show the estimates on formal employment participation in columns 1-4, and on farm productivity in columns 5-8.

3.3.1 Formal Employment

We start with the effect on formal employment in Columns (1)-(4). Consistent with the gains in education, we find that VCP significantly increased participation in the formal labor market, which is generally correlated with higher living standards in low-income countries. The effect of treatment in Column (1) is 0.03 (statistically significant at the 5% level), and remains stable when additional controls are included (column 2). When we use the binary treatment, the point estimate is 0.01 in column 3 (significant at the 5% level). In column 4, we show that the coefficient is qualitatively robust to controlling for additional covariates, but is less precise, since it is significant only at the 10% level. These point estimates seem small in magnitude, but they imply non-trivial changes in relative terms. The point estimates in Columns (3)-(4) imply an increase of 14.2% in formal employment participation in the eligible cohort from the high-intensity vaccination areas. However,

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

the continuous treatment specification (Columns (1)-(2)) implies an average increase of 18 % in the participation in formal employment, since the VCP increased the vaccination rate from 17 to 77%.

3.3.2 Agricultural Yield

Columns (5)-(8) of Table 4 show the impact of VCP 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) of Table 4, the effect of treatment is 0.09, and statistically significant at the level of 5%. The estimates indicate that a 1% increase in the vaccination intensity increases farm productivity per hectare by 9%. Adding control variables[17] does not alter the point estimate.

Turning to the dichotomized rendition of the treatment, Columns (7)-(8) provide the estimates, first without and then with the inclusion of control variables. The estimated treatment effect is about 6%. Again, the estimate is robust to the inclusion of the control variables listed above. The point estimates are statistically significant at the 5% level. In the exposed cohort, farm productivity per hectare increased by 6% in provinces with a high vaccination rate.

Overall, the impact of VCP on agricultural productivity is notably pronounced. Individuals who resided in provinces with higher vaccination rates are more productive on the farm as adults. 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 conclusively demonstrates a positive effect of VCP on agricultural productivity. To further understand this effect, we investigate the possible mechanisms at play. Although various channels may contribute to this impact, we first explore the hypothesis that increased labor resulting from improved health due to vaccination, plays a pivotal role in 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 in column (1) of Table 5, where the dependent variable is the natural logarithm of labor per hectare. The estimate is virtually zero, indicating that the treatment did not increase labor intensity. However, it is important to recognize that increased labor supply is just one facet of how health can influence farm productivity. Another critical aspect to consider is the efficiency of labor. It is conceivable that while the quantity of labor (i.e., number of man-days) per hectare remains constant, healthier individuals are more productive because their labor is more efficient.

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

$$F(L, A) \tag{5}$$

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

[17]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.

$\theta(H)$ is bounded between 0 and 1. Thus, we can express L as:

$$L = \theta(H)\,\mathcal{L}(H) \tag{6}$$

Notably, Eq. 6 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[18]. Using 5 and 6, the partial derivative of production (F) with respect to H is

$$\frac{\partial F(L,A)}{\partial H} = \left(\mathcal{L}(H)\frac{d}{dH}\theta(H) + \theta(H)\frac{d}{dH}\mathcal{L}(H)\right)\frac{\partial}{\partial L}F(L,A) \tag{7}$$

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:

$$\frac{\partial F(L,A)}{\partial H} = \left(\mathcal{L}(H)\frac{d}{dH}\theta(H)\right)\frac{\partial}{\partial L}F(L,A) \tag{8}$$

Consequently, the impact of vaccination on productivity primarily stems from making farm labor more efficient, without significantly altering the quantity of labor. This result echoes the findings of Strauss (1986) in Sierra Leone four decades ago.

However, we acknowledge the possibility that productivity gains may arise from a reallocation of productive resources within households. To address this, we explore 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. However, all point estimates are of small magnitude and not statistically different from zero. In essence, our results imply that realized productivity gains cannot be attributed to a change in any of the several factors of production 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 had a substantial positive impact on agricultural productivity, with the source of this increase likely stemming from improved health outcomes rather than changes in labor or agricultural inputs.

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

4 Robustness Check

In this section, we present results of several robustness checks. First, we conduct a falsification exercise using a placebo treatment group. Second, we test the validity of our TWFE estimation using an alternative control group following De Chaisemartin and d'Haultfoeuille (2018). Third, we explore heterogeneity in treatment responses based on age at the time of treatment. Fourth, we explore an alternative estimation approach proposed by Callaway et al. (2021) to address the issue of heterogeneous treatment effects. Finally, we check the consistency of our main results to internal migration.

4.1 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 VCP. We falsely consider the cohort of birth 1972-77 is exposed to VCP instead of the truly exposed cohort of birth 1978-83. In this exercise, the treated cohort of birth is 1972-77 and the control cohort of birth is 1966-1971. As the VCP only affected the cohort of birth 1978-83, this placebo exercise should produce no treatment effects on any outcomes for the falsely exposed cohort. Table 6 displays the placebo estimations in panel A for child mortality and educational outcomes, and panel B for labor market outcomes.

The estimated coefficients are statistically insignificant for child mortality in columns (1)-(2) of panel A, indicating that 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.

We consider the long-term outcomes in panel B. The coefficients for participation in formal employment in columns (1)-(2) are statistically insignificant. Similarly, the statistically insignificant coefficients in columns (3)-(4) suggest that the VCP has no effect on agricultural yield for the placebo cohort. Thus, for the long-term results, 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 if living in a province with high vaccination rates had any impact on the outcomes of the older cohort, which consists of individuals ineligible for the vaccination when VCP was rolled out. Our results show no significant differences in either the short-term or the long-term outcomes between the two groups. Therefore, the placebo exercise strongly suggests that the effects we uncovered are unlikely to be just spurious correlations, which is reassuring.

4.2 Alternative Control

We defined the provinces with a high rate of measles vaccination where the residual of a regression of the number of vaccinated children on the number of children eligible for measles vaccination is 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.

Alternatively, they propose to create a control group with only provinces with a stable distribution of an outcome variable between two cohorts in the pre-treatment period.[19] Therefore, we choose the Kolmogorov-Smirnov test of equality of distribution to assign a province to the control group if the province had a statistically identical distribution of an outcome variable between "CB 1978-83" and "CB 1972-1977 in the pretreatment period.[20] We end up with 14 provinces in the control group and 13 provinces in the treatment group.

We show the result of this exercise in Appendix Table B.5. The result shows that VCP led to a 4.7 percentage point reduction in child mortality, which is identical to our primary result. The estimated coefficients for educational attainment and labor market outcomes are also almost identical. As a result, this exercise corroborates the credibility of our main estimation results.

4.3 Age-based Heterogeneous Treatment Exposure

Next, we consider heterogeneity in treatment exposure due to age differences, following the method proposed by Berg et al. (2023). This approach recognizes that the effects of early childhood interventions may vary depending on the age at which individuals were exposed to the program. Accordingly, we introduce an expanded specification outlined in Eq. 4. In this framework, we consider three distinct age groups: Low Exposure (LE, aged 5-6), Moderate Exposure (ME, aged 3-4), and High Exposure (HE, aged 1-2), acknowledging that young children under 6 years old 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 1-6. On the other hand, Panel B distinguishes between whether the exposure to the vaccination campaign occurred during ages 1–2, 3–4 or 5–6. Column (1) of Panel A shows that VCP exposure led to a 3 percentage point lower child mortality. Column (1) of Panel B reveals no significant reduction in mortality for low exposure (aged 5-6) and moderate exposure (aged 3-4) groups. However, the high-exposure group (aged 1-2) displays significant reductions in child mortality.

Columns (2)-(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 (aged 5-6) experiences a statistically significant increase in school enrollment and completion rates. In contrast, the moderate exposure group (aged 3-4) shows no significant change in enrollment but a statistically significant increase in completion rates. Notably, the high exposure group (aged 1-2) demonstrates noteworthy improvements in school enrollment and completion rates, but the effect is not statistically significant.

[19] 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.

[20] 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 label provinces with changed distribution as controls, posing a more serious concern. Thus, De Chaisemartin and d'Haultfoeuille (2018) argued that misclassifying some provinces as treatment doesn't significantly alter the estimated coefficients.

Furthermore, transitioning to labor market outcomes, Column (4) of Panel A shows a positive and significant effect of VCP exposure on the likelihood of formal employment. In Panel B, we notice that high exposure group displays a statistically significant increase in formal employment. In Panel A, Column (5) shows that VCP exposure positively affects agricultural yield. In Panel B, we find that the low-exposure group does not experience a significant change in agricultural yield. However, the moderate and high exposure groups demonstrate a statistically significant boost in agricultural yield.

4.4 Alternative Estimation Approach: Continuously Distributed Treatment

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 difference-in-differences focusing on distinct doses of VCP (i.e., vaccination rates) in comparison to an untreated group. Subsequently, we calculate the average treatment effect by averaging the estimated effects across the range of doses. Callaway et al. (2021) offers a nuanced understanding of the effects of the VCP, particularly in the context of varying levels of exposure and potential heterogeneity in outcomes.

We present the results of the continuously distributed treatment approach in Table 8. In Column (1), we observe that the VCP has a significant negative effect on child mortality rate. Specifically, a one percent increase in measles vaccination rates leads to a 6.8 percentage points reduction in child mortality rate, respectively. Columns (2)-(3) show the effects of VCP on school enrollment and school completion rates. With a one percent increase in VCP, there is a 1.1 and 1.3 percentage point increase in school enrollment and completion rates, respectively. Moving to Columns (4)-(5), we present the effects of the VCP on formal employment and agricultural yield. While we find a small positive but insignificant effect of VCP on formal employment, we find a substantial impact on agricultural yield. One percent increase in vaccination rate leads to a 5 percent increase in agricultural yield. Overall, continuous treatment results are consistent with our primary estimation results.

4.5 Internal Migration

Internal migration is a potential threat to the identification strategy we used for the microdata up to this point. The treatment status – province level vaccination intensity – is determined at an early stage of individuals' life (up to six years of age), but the outcomes are measured at a later life stage, and the data are collected long after the implementation of the program. Identification imposes that the individuals did not move across provinces between the time treatment was administered and the time the results were measured. To assess the robustness of our results against internal migration-induced bias, we use synthetic control methods to estimate the effect of VCP on aggregated outcomes. Since the outcomes are averaged at the country level, internal migration is accounted for.

In practice, we use data on 27 Sub-Saharan African countries over 19 years and synthetic control method to estimate the treatment effect. Since we do not observe what would have happened in

Burkina Faso in the absence of the VCP, we need a suitable method for estimating the counterfactuals – imputing the missing potential control outcomes – to find the average treatment effects. Causal inference literature provides us with three broad approaches – unconfoundedness, synthetic control, and model-based imputation (Athey et al., 2021).

We use the World Bank's world development indicators to gather data on Sub-Saharan African (SSA) countries from 1972 to 1990. We keep all 27 SSA countries for which we have the required demographic and economic characteristics available for 1972-1990.We follow the exposition with the microdata, and use child health and education outcomes to measure the short- and mid-term impacts and labor market outcomes to measure the long-term impact of vaccination. Child health and educational outcome variables are taken from World Bank development indicators. For labor market outcomes, we use data from the Demographic and Health Survey (DHS) for 27 SSA countries (See Appendix B for further detail of this exercise).

We estimate the impact of increased vaccination on child mortality, primary school outcomes, and adulthood labor market participation. We find that children under age one through five witnesses a significant decline in the child mortality rate. The result also shows an increase in both school enrollment and completion. In adulthood, the vaccinated cohorts are likely to be employed and gainfully employed in the formal labor sector.

4.5.1 Effect of Vaccination on Child Mortality

At first, we focus on how vaccination affects child mortality. We focus on under-five child mortality rate. Figure 8 reports our main result for child mortality. The outcome variable here is the child mortality rate under five years in year t. The treatment variable is the exposure to the VC program. Figure 8 Panel-a plots the dynamic treatment effects of exposure to vaccination. It shows the average treatment effect on the treated (ATT), which is the treatment effect in Burkina Faso relative to counterfactual Burkina Faso. The first point to notice is that the ATTs before the treatments are close to zero, and post-treatment ATTs are negative. Thus, the vaccination has a negative effect on child mortality, and the effect becomes stronger over time. The treatment effect is statistically significant at a 10 percent significance level three years after the inception of the VC program.

The relatively small reduction in under-five child mortality in the first few post-treatment periods is most likely because some of the under-five children are already affected by measles and other vaccine-preventable diseases since the national vaccination rate was extremely low before the VC program. Moreover, vaccine eligibility starts at the age of nine months. At age five, those immunized children have also missed the positive health externality arising from the improved immune system generated by the vaccination. Studies suggest the improved immune system produced by the measles vaccination also protects children from other deadly diseases (Gadroen et al., 2018; Mina et al., 2019; Petrova et al., 2019).

The VC program reduces the under-five child mortality rate by about 10 percent six years after the inception of the VC program. This rise in the VC program effect size comes from the positive externality of vaccinating current cohorts (who are already eligible for measles vaccine nine months to 6 years) and successfully vaccinating the newly vaccine-eligible children (who are less than nine months in 1984 or born after 1984) in coming years. Children who are vaccinated earlier

in their childhood benefited more from the earlier improvement in immune system. Besides, the successive decline in the under-five child mortality rate also suggests that the effect of the vaccines on mortality persists several years after being immunized. This finding indicates that vaccination has a relatively long-term impact on children's morbidity and mortality. Koenig et al. (1990) also reach a similar conclusion.

We test the validity of the identifying assumptions (i.e., strict exogeneity and correct functional form) using a placebo test. The primary idea of the test is based on the "panel placebo test," which hides a few periods of observations right before the onset of the treatment for the treated units and use a model trained using the rest of the untreated observations to predict the untreated outcome of those holding out periods. If the identifying assumptions are valid, the average differences between the observed and predicted outcomes in those periods should be close to zero. On the other hand, if these differences are significantly different from zero, the evidence will indicate that the identifying assumptions are not valid. In our case, we assume the treatment started three periods earlier than its actual onset in Burkina Faso and obtain the ATT estimates for those three periods using the usual counterfactual estimator.

In Figure 8 Panel (b), we see the confidence bounds for placebo ATTs are not statistically significant. The confidence bounds are set by the prespecified parameters or equivalence thresholds $\theta_1 = \theta_2 = 0.36\hat{\delta}_\epsilon$ following Hartman and Hidalgo (2018). Here, $\hat{\delta}_\epsilon$ is the standard deviation of the residualized untreated outcome. The null hypothesis based on the placebo $ATTs(ATT^p)$ is $ATT^p < -\theta_2$ or $ATT^p > \theta_1$. We show that fake ATT (i.e., ATT^p) falls within the equivalence range $[-\theta_2, \theta_1]$ with a probability of 0.517. Thus, we can not reject the null that the placebo ATTs are bigger than the true ATTs. The placebo test result suggests that our identifying assumptions hold.

Next, we present the pre-treatment fit between Burkina Faso and counterfactual Burkina Faso in Figure 8 Panel c. A common approach to test the pre-treatment fit is to jointly test a set of null hypotheses – that the average of the residuals in each pre-treatment period is zero, i.e., $ATT_s = 0$ for all pre-treatment period s– using a F-test. However, Liu et al. (2021) provides a better test called the "Equivalence Test" that is robust to the limitation of the F-test. The null of the equivalence test is $ATT_s < -\theta_2$ or $ATT_s > \theta_1$, $\forall_s \leq 0$. Here, s indicates the pre-treatment periods, and $[-\theta_2, \theta_1]$ is the equivalence range. The null hypothesis is rejected (i.e., equivalence holds) only when the tests for all pre-treatment periods generate significant results. In addition, they also calculate the minimum range, the smallest symmetric bound within which we can reject the null of inequivalence using the sample at hand. A rule of thumb is that the test is considered passed when the minimum range is within the equivalence range. In our case, the pre-treatment fit is great as the minimum range is within the equivalence range.

4.5.2 Effect of the Vaccination on Educational Outcome

The improved health outcome of the vaccinated children may also lead to better educational outcomes. In this section, we explore how vaccination affects children's educational outcomes. We focus on two educational outcomes– primary school enrollment and primary school completion.

Figure 9 Panel (a) shows the dynamic treatment effect of vaccination on children's primary school enrollment. The post-treatment ATTs are positive, which indicates the vaccination increases

the likelihood of primary school enrollment. Six years after the inception of the VC program, there is a 4 percent rise in the primary school enrollment rate. Figure 9 Panel (b) shows that the placebo test is satisfied. We can not reject the null that the placebo ATTs are different than the true ATTs. Figure 9 Panel (c) shows the equivalence test is passed as the minimum range is within the equivalence range. This result provides evidence that the control and the treatment countries do not have any differential pre-trends for primary school enrollment.

Next, we show the dynamic treatment effect of vaccination on children's primary school completion rate in Figure 10 Panel (a). We see that vaccination increases the likelihood of primary school completion rate. Six years after the inception of the VC program, there is a 6 percent rise in the primary school completion rate. Figure 10 Panel (b) shows that the placebo test is satisfied. We cannot reject the null that the placebo ATTs are different from the true ATTs. Figure 10 Panel (c) shows the equivalence test is passed as the minimum range is within the equivalence range. This result suggests no differential trend in primary school completion rates in treatment and control countries.

4.5.3 Effect of Vaccination on Labor Market Outcome

In this section, we focus on the relatively long-run outcomes of vaccination. We explore labor market outcomes of the vaccinated children when they become adults (25-30 years). We present the dynamic treatment effect of vaccination on adults' formal sector employment rate in Panel (a) of Figure 11. The post-treatment ATTs are positive and increasing over time, which indicates the vaccination increases the likelihood of adults working in the formal sector. The result shows that the vaccinated children after six years of the inception of the VC program are about 4 percent more likely to work in the formal sector. Since formal sector workers earn on average more than informal sector workers, our result suggests that vaccinated children earn more when they enter the labor market. Atwood (2022) finds a similar result in the United States for measles vaccination. Figure 11 Panel (b) shows that the placebo test is satisfied, which indicates that we cannot reject the null that the placebo ATTs are different than the true ATTs. However, Figure 11 Panel (c) shows that the equivalence test failed as the minimum range is outside the equivalence range. This result suggests that for some years, the pre-treatment fits are not good.

5 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.

$$NPV = -C + \sum_{t=10}^{59} \Delta\bar{A}_t(1+r)^{-t} + \sum_{t=22}^{59} \Delta\bar{F}_t(1+r)^{-t} \tag{9}$$

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. Furthermore, $\Delta\bar{A}_t$ and

$\Delta\bar{F}_t$ capture adult earnings gains in agriculture and formal jobs, respectively. We assume the agricultural yield gain started 9 years after the vaccination campaign when the vaccinated cohort reached age 15. On the other hand, the gains from formal jobs started 21 years after the vaccination campaign when the vaccinated cohort reached age 28. We assume that these earnings gains are constant and persist over the individuals' working lives till retirement at age 65.

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.[21] Additionally, we consider two alternative scenarios for gain from the formal job: a low rate of return and a high of return. On the cost side, we use the cost of a vaccination campaign based on the average cost of running a vaccination campaign, which gives a lower bound of $1 and an upper bound of $15 (Brenzel and Claquin, 1994). Finally, we consider two alternative discount rates, namely 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, where Panel A shows the most conservative estimates, and Panel D shows the most favorable estimates. The most conservative estimates are based on the low rate of returns to education, high cost of vaccination campaigns, and high discount rate (10%). Panel-A Column (2) of Table 9, with our low impact estimates, shows that per capita NPV is USD PPP 44.40 and the cost-benefit ratio of 2.96.[22] Similarly, Column (1), with our high impact estimates, shows that per capita NPV is USD PPP 44.42 and a cost-benefit ratio of 2.96. The corresponding internal rate of return (IRR) estimates in Columns (1) and (2) are 9.05% and 7.70%. With a lower discount rate in Columns (3) and (4), the cost-benefit ratio becomes 4.4 and IRR above 13%.

The cost-benefit analysis highlights two key findings. Firstly, the return to vaccination is substantially higher than the cost of vaccination. Across all cost-benefit estimates, the returns from the Vaccination Campaign Program (VCP) markedly surpass its costs, underscoring the program's role as a pivotal social investment that enhances human capital. Secondly, our analysis reveals that 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 formal sectors employ only a limited portion of the labor force in many developing countries. 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.

6 Conclusion

Measles and other infectious diseases affect millions of people yearly, and Sub-Sahara African countries are no exception. Before 1984, most child mortality in Burkina Faso was due to diseases that are preventable with vaccination. This is still true for many developing countries. Vaccines are the most effective but gravely underutilized tool to prevent child morbidity and mortality. Such

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

[22] 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.

under-investment and under-utilization of vaccines may be due in part to a misunderstanding of the overall impact of vaccines. This is not surprising given the dearth of studies that empirically estimate the impact of vaccines. To the best of our knowledge, there are only two studies that evaluate the impact of vaccination on human capital and labor market outcomes using national-level vaccination programs.

VCP provides important insights into the long-term impacts of early childhood health interventions. Our analysis indicates that the VCP, implemented rapidly in 1984, yielded substantial benefits for the cohorts exposed as young children. Leveraging the program as a natural experiment, we find significant improvements in mortality, education, employment, and agricultural productivity. These results highlight the profound and lasting effects of health investments in early life.

In particular, we document that VCP led to a significant 16% decrease in mortality in children under five years of age for the treated cohort. This striking reduction highlights the success of the campaign to mitigate the negative effects of infectious diseases such as measles. Beyond averting mortality, we also uncover pervasive gains in human capital accumulation. Exposure to VCP is associated with higher primary school enrollment and completion rates, suggesting that its positive influence extends into the educational domain.

Furthermore, we demonstrate that the program's impacts reach into adulthood, as treated individuals display higher rates of formal sector employment. For a predominantly agricultural economy such as Burkina Faso, perhaps the most notable finding is a substantial increase in agricultural productivity of around 6-9%. These productivity gains are primarily due to improved labor efficiency rather than increased use of inputs such as fertilizer. This novel result has important implications for the measurement of returns in contexts dominated by small-holder farming.

Our study provides long-term, unique evidence on the economic returns of early childhood interventions in a low-income Sub-Saharan African context. Much of the seminal research on early childhood interventions is focused on high-income settings with well-developed labor markets and educational systems. However, the magnitude and mechanisms of the gains for disadvantaged populations in developing economies remain less understood, despite their acute political relevance. Our findings help bridge this knowledge gap while validating the efficacy of vaccination initiatives in enhancing welfare.

Our most conservative benefit-to-cost ratio is 2.96, with an implied internal rate of return of 9.05%. The sizable measured returns indicate that investments in child health can yield substantial social dividends, even considering delivery and administration costs. From a policy perspective, the results provide robust empirical support for prioritizing immunization campaigns to improve human capital and productivity.

In summary, our study demonstrates the profound and lasting benefits of a nationwide vaccination campaign in Burkina Faso. We find that the program markedly reduced child mortality while increasing educational attainment, employment, and agricultural productivity. These results 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

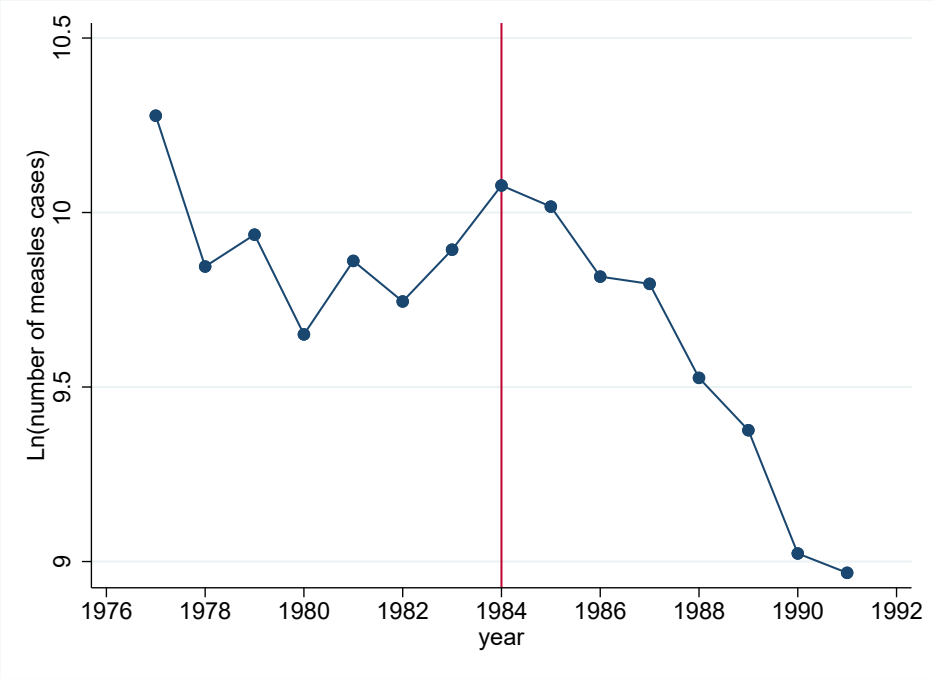


Figure (1) Measles Prevalence Over Time

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.

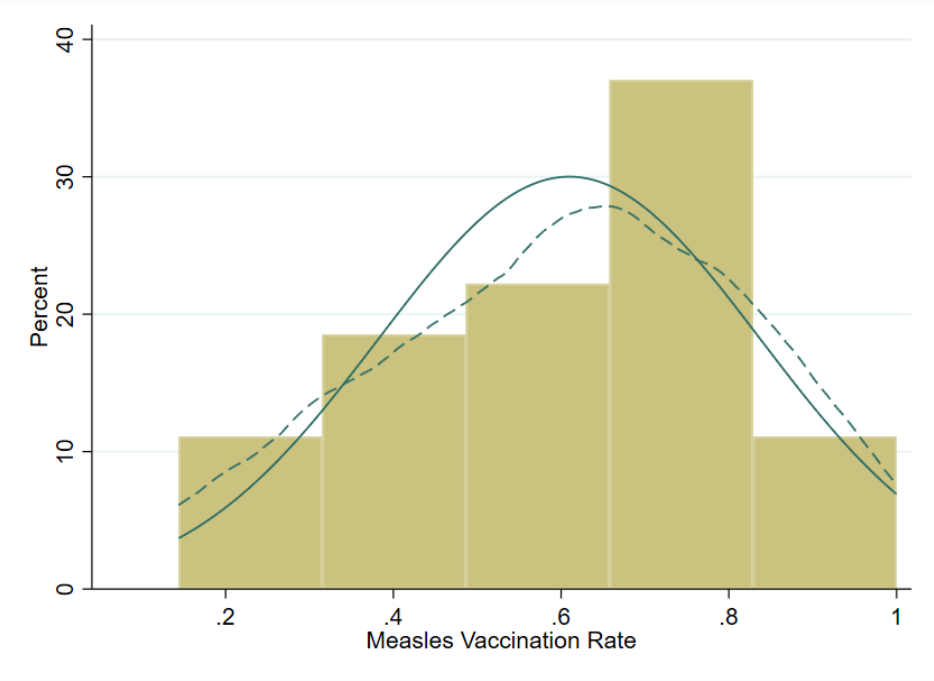


Figure (2) Distribution of Measles Vaccination Rates

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.

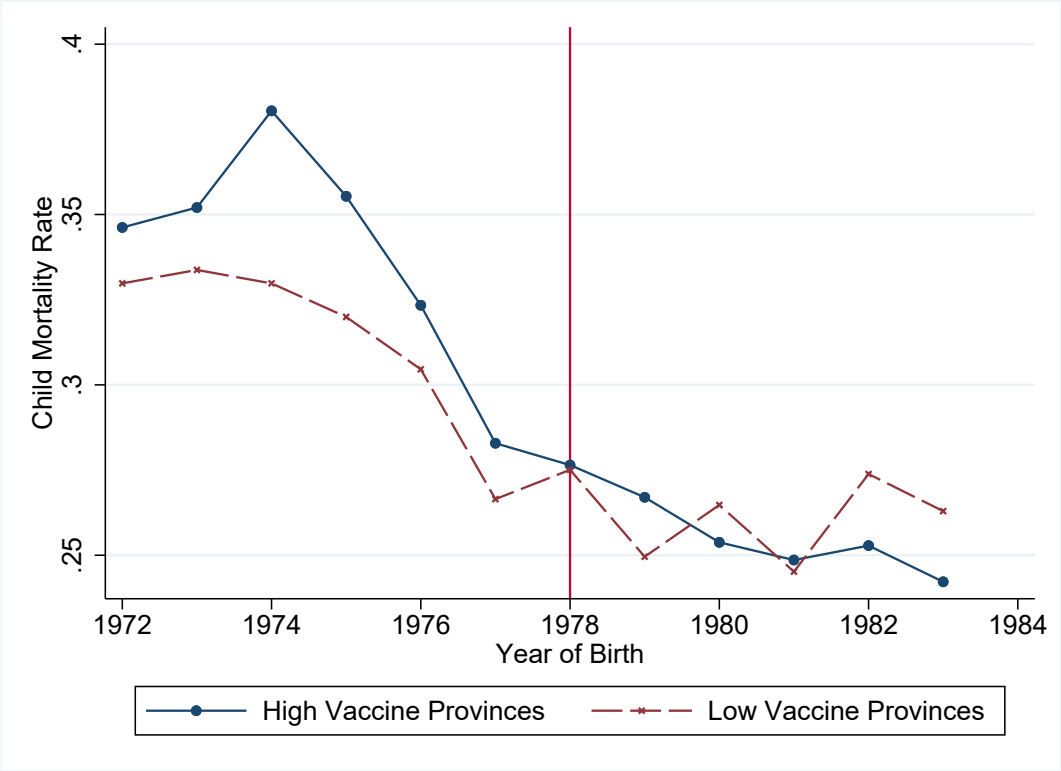


Figure (3) Child Mortality Rate by Year of Birth

Note: This figure presents the child mortality rates by year of birth (per 1,000 live births) 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 1984.

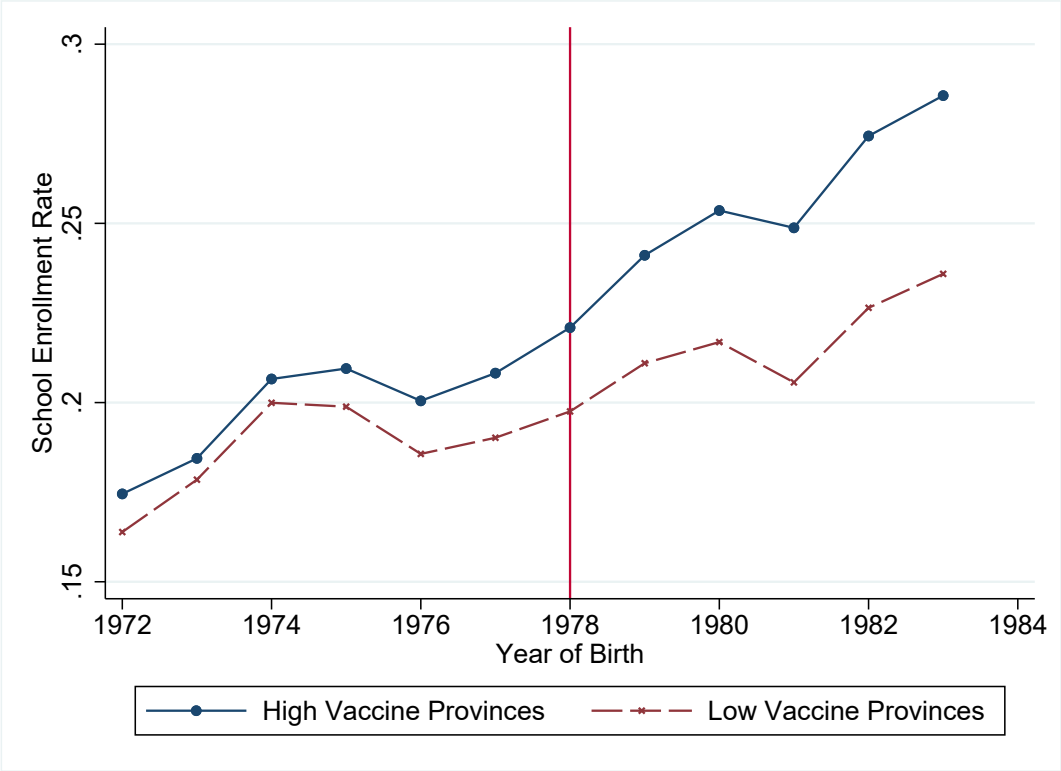


Figure (4) Primary School Enrollment Rate by Year of Birth

Note: This Figure presents the school enrollment rates by year of birth 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 1984.

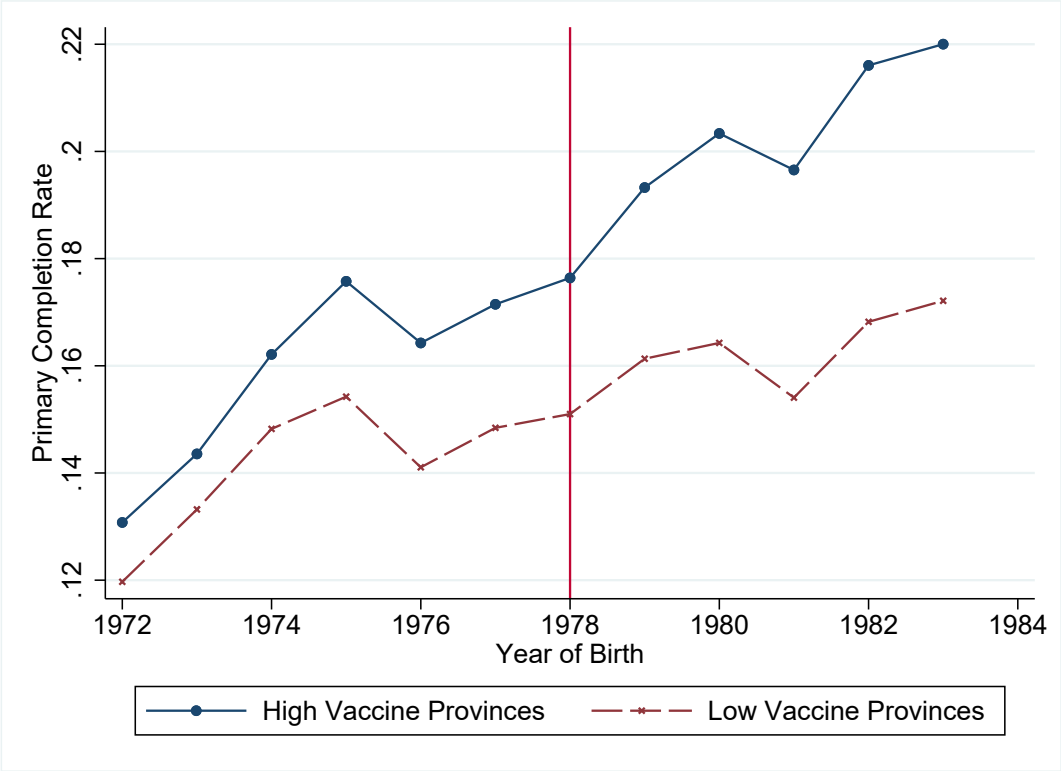


Figure (5) Primary School Completion Rate by Year of Birth

Note: This figure presents the primary school completion rates by year of birth 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 1984.

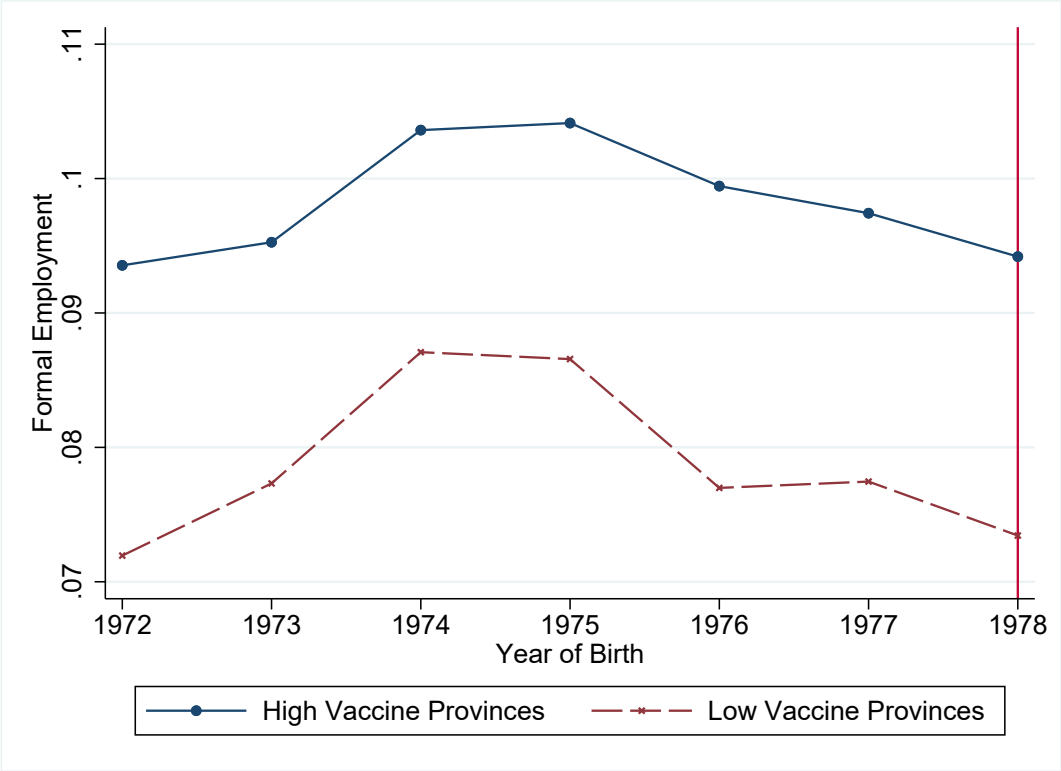


Figure (6) Formal Employment by Year of Birth

Note: This figure presents the formal employment rates by year of birth 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 1984. Individuals aged above 27 years are kept in the sample.

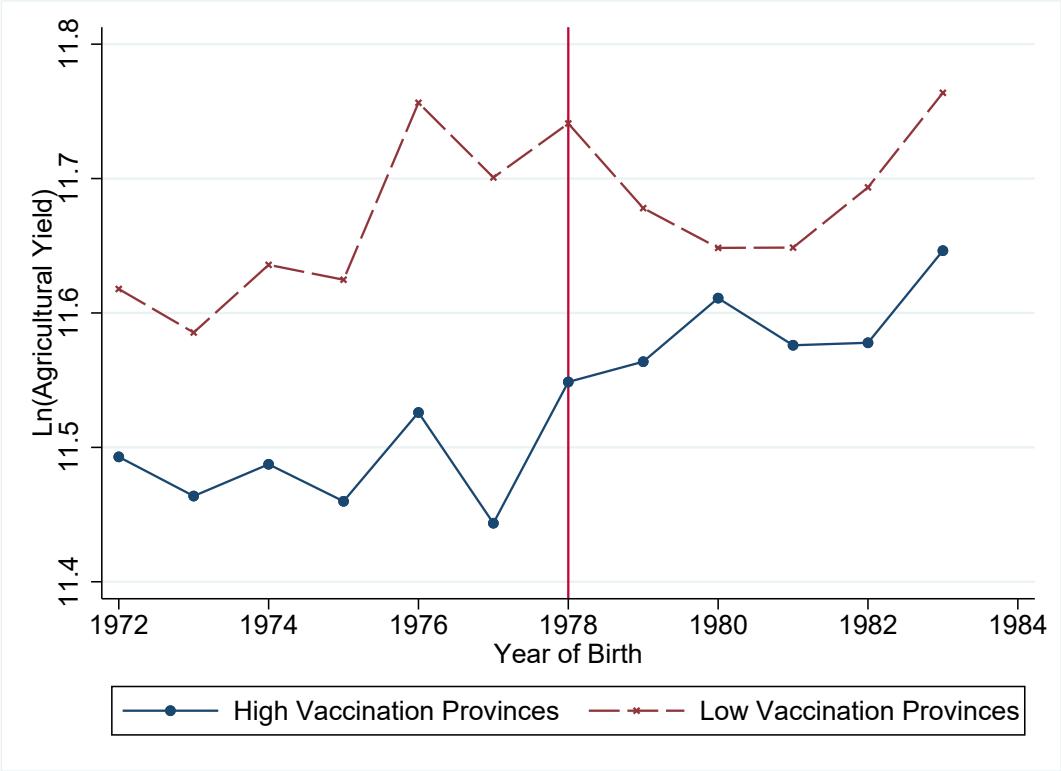
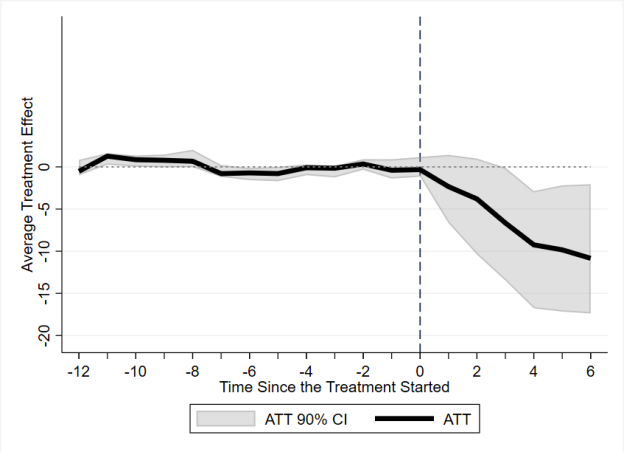
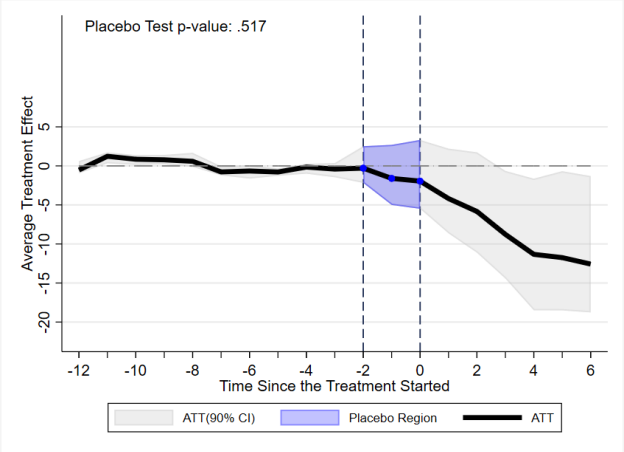


Figure (7) Agricultural Yield by Year of Birth

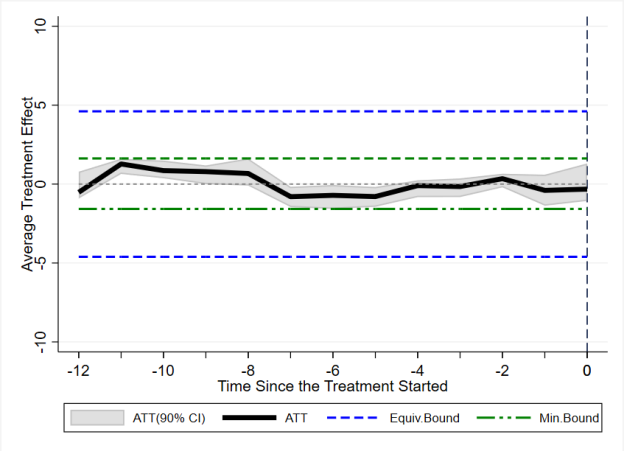
Note: This figure presents the agricultural yield by year of birth for provinces with high and low measles vaccination coverage. Data for this graph comes from the 2010-2012 panel Permanent Agricultural Survey (PAS) of the Ministry of Agriculture of Burkina Faso. Each data point represents a three-year moving average and covers the period from 1969 to 1984. Only private plots' agricultural yield is used in the sample.



(a) Mortality rate under five



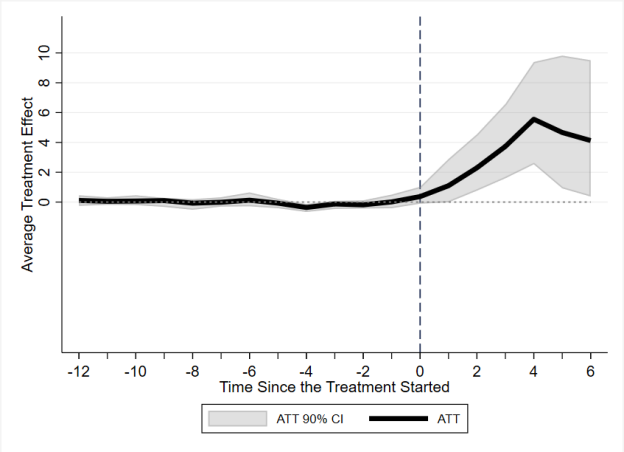
(b) Mortality rate placebo test



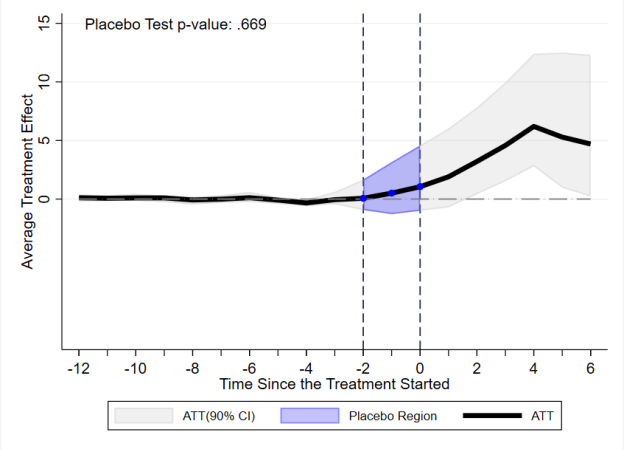
(c) Mortality rate equivalence test

Figure (8) Under-five Child Mortality Results

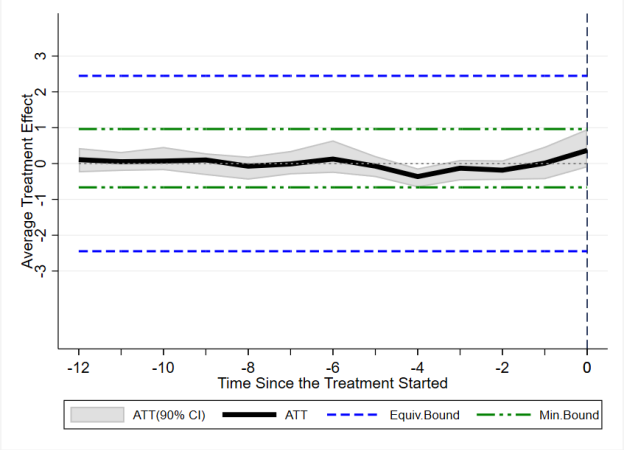
Note: Panel (a) of this figure shows the dynamic treatment effect of VCP on under-five child mortality rate. Panel (b) shows the result of placebo test and Panel (c) shows the result of an equivalent test. Data for this exercise comes from World Bank's world development indicators for 27 Sub-Saharan African (SSA) countries from 1972 to 1990.



(a) Primary school enrollment



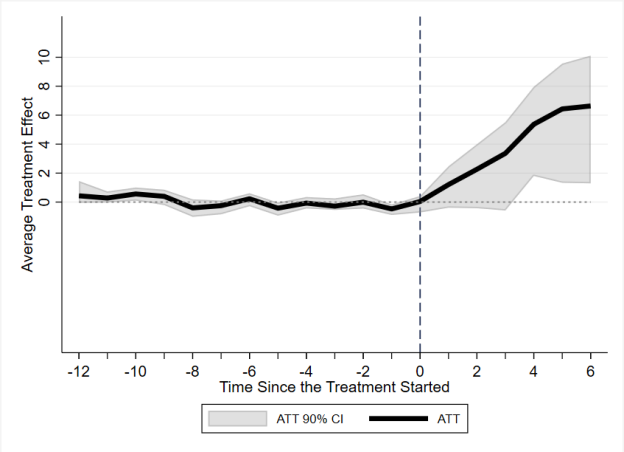
(b) Placebo test for primary school enrollment



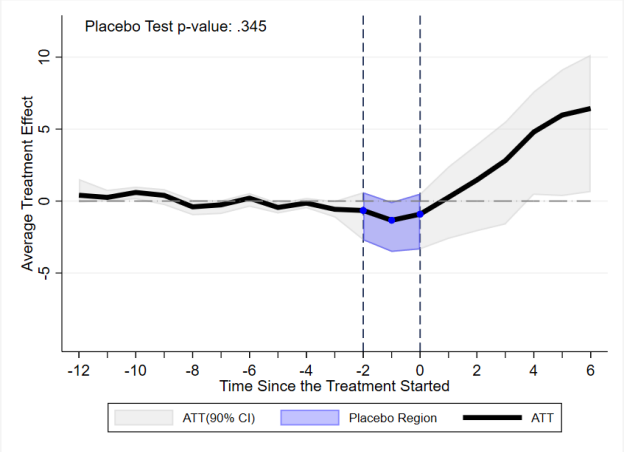
(c) Equivalence test for primary school enrollment.

Figure (9) Primary School Enrollment Results

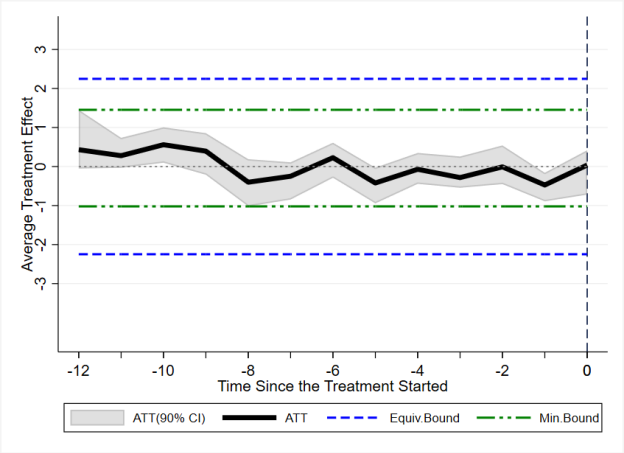
Note: Panel (a) of this figure shows the dynamic treatment effect of VCP on primary school enrollment rate. Panel (b) shows the result of placebo test and Panel (c) shows the result of an equivalent test. Data for this exercise comes from World Bank's world development indicators for 27 Sub-Saharan African (SSA) countries from 1972 to 1990.



(a) Primary school completion rate



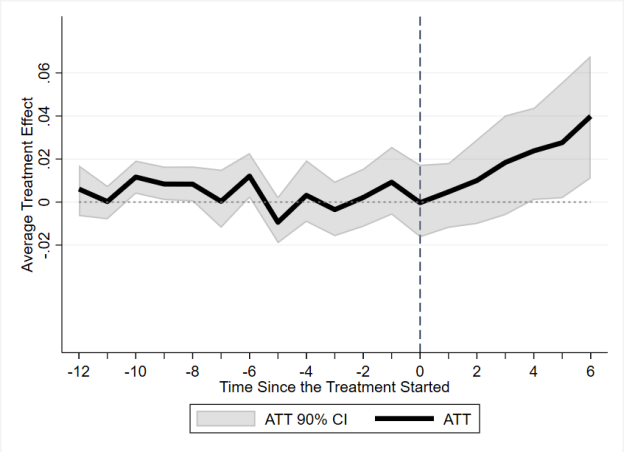
(b) Placebo test for primary school completion rate



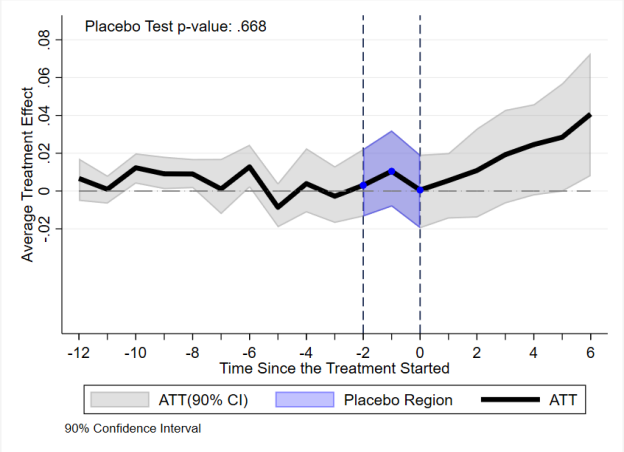
(c) Equivalence test for primary school completion rate.

Figure (10) Primary School Completion Results

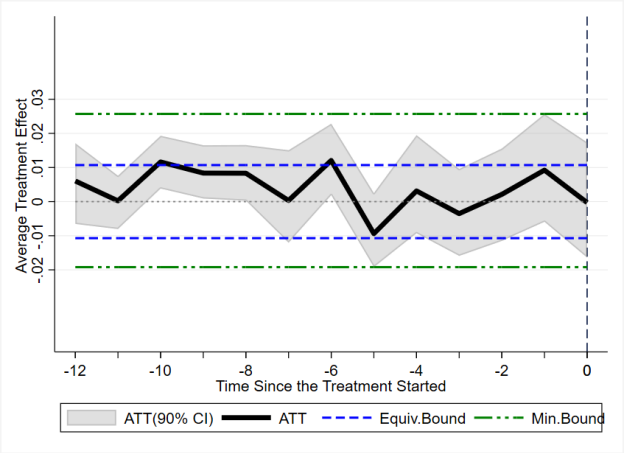
Note: Panel (a) of this figure shows the dynamic treatment effect of VCP on primary school completion rate. Panel (b) shows the result of placebo test and Panel (c) shows the result of an equivalent test. Data for this exercise comes from World Bank's world development indicators for 27 Sub-Saharan African (SSA) countries from 1972 to 1990.



(a) Formal employment.



(b) Placebo test for formal employment.



(c) Equivalence test for formal employment.

Figure (11) Formal Employment Results

Note: Panel (a) of this figure shows the dynamic treatment effect of VCP on formal employment. Panel (b) shows the result of placebo test and Panel (c) shows the result of an equivalent test. Data for this exercise comes Demographic and Health Survey (DHS) of 37 Sub-Saharan African (SSA) countries.

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 1	5,585	0.326	0.469	2,503	0.324	0.468	3,082	0.328	0.47
Cohort 1	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*		
	(0.0.041)	(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	0.05	0.03	0.26	0.16
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	2.96	2.96	4.44	4.43
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	0.07	0.04	0.34	0.21
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)	44.44	44.41	66.69	66.56
Cost Benefit Ratio	2.96	2.96	4.45	4.44
Internal Rate of Return (IRR)	9.05%	7.70%	14.62%	13.20%
Panel C: Low Returns to Education and Low Cost of Vaccination Campaign				
Discounted Wage Earnings Gains Per Capita	0.05	0.03	0.26	0.16
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	58.42	58.40	80.61	80.51
Cost Benefit Ratio	58.42	58.40	80.61	80.51
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	0.07	0.04	0.34	0.21
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	58.44	58.41	80.69	80.56
Cost Benefit Ratio	58.44	58.41	80.69	80.56
Internal Rate of Return (IRR)	36.37%	34.21%	43.47%	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 is 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 considerable majority of patients (87%) are children younger than 5 years old (WHO, 2021). Additionally, it has emerged as a leading cause of blindness in low-income countries. The introduction of 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 and 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

Since we do not observe what would have happened in Burkina Faso in the absence of a Vaccination Commando program, in this situation, we need a suitable method of counterfactual estimation to find the average treatment effects.

The identification strategy we employ requires aggregate (macro) level data over a long period from a set of countries. We use World Bank's world development indicators to gather data on Sub-Saharan African (SSA) counties from 1972 to 1990. We keep all SSA countries for which we have the required demographic and economic characteristics available for 1972-1990. That gives us data on 27 countries including Burkina Faso. The demographic and economic indicators we use

from the world development indicators are population growth rate, percentage of male population, percentage of female population, percentage of age 0-14 population, percentage of rural population, life expectancy at birth, mortality rate for adult females, mortality rate for adult males, percentage of land used in agricultural, crop production index, food production index, livestock production index, and gross domestic product (GDP) per capita (see Table B.2).
In Table B.2, we provide the descriptive statistics of the key variables. We present the statistics for two broad groups: Burkina Faso and other Sub-Saharan countries. Columns (1) and (4) present the mean and standard deviation for all observations (i.e., 1972 to 1990) of Burkina Faso and other SSA countries, respectively. Similarly, Columns (2) and (5) show the statistics before the implementation of the VC program covering the years from 1972 to 1983. Conversely, Columns (3) and (6) present the statistics after the VC program from 1984 to 1990. For demographic characteristics, Burkina Faso looks similar to other SSA countries, but they are quite different in economic characteristics. However, these differences are not a concern for the estimation method we use.

Outcome Variables We focus on both the short-term and long-term effects of vaccination. To measure the short-term outcome, we focus on both health and educational outcomes. We focus on two health outcomes– under-five child mortality rate and the prevalence of thinness among children aged 5-9 years (see Table B.2). Under-five child mortality rates data comes from the World Bank's world development indicators. The prevalence of thinness (i.e., the proportion of extremely unhealthy) among children aged 5-9 years data comes from the World Health Organization (WHO) country nutrition profile. We also used two educational outcomes– primary school enrollment rate and primary school completion rate. We only focus on primary school outcomes because we lack data on secondary and above-secondary school outcomes. Educational outcome data comes from the World Bank's world development indicators.

Our first health indicator under-five child mortality rate provides an overall health status of the children. Children under five are more susceptible to disease and have a significantly higher mortality rate than other age groups. The under-five child mortality rate is measured by the percentage of total live births who die before reaching age five. Our second health outcome, the prevalence of thinness another indicator of the overall health status of children 5-9 years. Children are labeled as thin if their body mass index (BMI) is two standard deviations below the WHO-defined median BMI. Thus, the prevalence of thinness shows what percentage of all children 5-9 years are extremely thin. A high prevalence of thinness indicates that the children are severely unhealthy.

Our first educational outcome is primary school enrollment rate, which measures the percentage of children who are enrolled in school among the relevant age group. Children in Burkina Faso usually start their primary school at age 6 and complete it at age 12. Similarly, the primary school completion rate, our second educational outcome, measures the percentage of the relevant age group who completed primary school. If vaccination leads to better child health, we expect to see better educational outcomes.

We also explore the potential long-run effects of vaccination. We study labor market outcomes

of the vaccinated children when they become adults (25-30 years). We look at two labor market outcomes– employment rate and employment in a formal sector. We use these two measures due to the lack of other more direct measures such as hours worked and earnings. The idea here is if measles vaccination leads to long-term improvement in human capital (i.e., health and educational outcomes) formation of the children, we should observe that vaccinated children are more likely to work and work in a formal sector. The employment rate is measured by the percentage of adults who are employed among all the adults born in a year. Similarly, employment in a formal sector is measured by the percentage of adults who are employed in the formal sector (i.e., professional jobs, services, and clerical work) among all the adults born in a year.

We construct the labor market outcomes from the Demographic and Health Survey (DHS) for Sub-Saharan African (SSA) countries. the Demographic and Health Survey (DHS) collects data on individuals' labor force participation decisions and occupations. We aggregate the individual-level data of employment and formal section employment by birth-year to construct our measures. Since DHS surveys are conducted in different years in our sample countries, we use a DHS survey round for each country between 2010 to 2015. For a country-DHS round, we observe birth-year and employment data for adults (15 years and above) in that country. Then, we find the employment rate by taking the ratio of the total number of employed individuals over the total number of individuals in a birth year.

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. Causal inference literature provides us three broad approaches– unconfoundedness, synthetic control, and model-based imputation (Athey et al., 2021).

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 weighted average outcome for control units with the weights 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., 2021).

Model-based imputation is more efficient and flexible than the other two approaches. It 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). The matrix completion approach nests both unconfoundedness and

synthetic control approaches and outperform those approaches.

We use the matrix completion approach in this study and apply the "counterfactual estimators" proposed by (Liu et al., 2021)[23]. The counterfactual estimators take observations under the treatment condition as missing and use observation under the control condition to build models and impute the counterfactuals of treated units based on the estimated models. Although the 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:

$$Y_{it}(0) = f(X_{it}) + h(U_{it}) + \epsilon_{it} \tag{10}$$

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:

$$Y_{it} = \delta_{it} D_{it} + L_{it} + x_{it}\beta + \eta_i + \gamma_t + \epsilon_{it} \tag{11}$$

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 $(N \times T)$ matrix can be approximated by a lower rank matrix $L_{(N\times T)}$ (unobserved cofounders). The method

[23]Liu et al. (2021) provides both Stata and R packages to implement the estimation. The package is called Fixed Effects Counterfactual Estimators (Fect).

estimate L by solving the minimization problem.

$$\hat{L} = \min_{L} \frac{1}{\mid \mathbb{A} \mid} \sum_{(i,t)\in\mathbb{A}} ((Y_{it} - L_{it})^2 + \lambda_L \|L\|) \tag{12}$$

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

$$\hat{\delta}_{it} = Y_{it}(1) - \hat{Y}_{it}(0) \tag{13}$$

where $\hat{\delta}_{it}$ 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.

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

	Burkina Faso			Other SSA Countries		
	All	Before	After	All	Before	After
	(1)	(2)	(3)	(4)	(5)	(6)
Population, female	50.92	50.79	51.15	50.47	50.47	50.46
	(0.26)	(0.24)	(0.01)	(1.22)	(1.26)	(1.14)
Population, male	49.08	49.22	48.86	49.54	49.53	49.54
	(0.26)	(0.24)	(0.01)	(1.22)	(1.26)	(1.14)
Population growth	45.75	45.03	46.98	45.48	45.25	45.87
	(1.20)	(0.89)	(0.29)	(2.32)	(2.43)	(2.04)
Population ages 0-14	2.27	2.07	2.61	2.91	2.85	3.02
	(0.34)	(0.26)	(0.04)	(0.76)	(0.62)	(0.95)
Life expectancy at birth	45.95	43.93	49.41	50.13	48.96	52.14
	(3.56)	(2.94)	(0.20)	(5.72)	(5.45)	(5.61)
Mortality rate, adult female (per 1,000)	323.86	343.27	290.578	320.50	330.31	303.49
	(39.90)	(38.51)	(3.21)	(53.20)	(49.92)	(54.54)
Mortality rate, adult male (per 1,000)	387.60	410.75	347.919	383.88	391.28	371.05
	(46.48)	(44.06)	(3.71)	(55.057)	(50.37)	(60.38)
Agricultural land	32.46	31.60	33.93	45.44	44.82	46.51
	(1.42)	(0.74)	(1.03)	(17.76)	(17.40)	(18.37)
Crop production index	28.94	24.35	36.79	47.26	44.69	51.71
	(7.25)	(2.87)	(5.34)	(25.68)	(24.93)	(26.42)
Food production index	28.88	24.07	37.12	43.21	40.84	47.32
	(7.28)	(2.53)	(4.70)	(19.59)	(19.13)	(19.75)
Livestock production index	28.89	23.69	37.81	42.20	39.37	47.11
	(8.58)	(2.97)	(7.58)	(17.22)	(16.54)	(17.31)
Rural population	359.19	343.60	385.905	1682.3	1719.6	1617.6
	(29.42)	(24.11)	(14.61)	(2533.2)	(2661.6)	(2299.4)
GDP per capita (constant 2010 US$	90.32	92.21	87.08	73.87	75.97	70.24
	(2.90)	(1.67)	(0.78)	(13.43)	(12.29)	(14.52)
Mortality rate, under-5 (per 1,000 live births)	241.56	261.70	207.029	182.06	193.74	161.81
	(35.82)	(29.44)	(.57)	(59.16)	(58.28)	(55.22)
Prevalence of thinness aged 5-9 years (%)	14.23	14.80	13.49	12.62	13.13	11.97
	(0.79)	(0.47)	(0.35)	(3.08)	(2.93)	(3.14)
Primary School enrollment rate (%)	17.25	13.35	23.95	56.57	54.63	59.93
	(5.78)	(2.38)	(2.63)	(29.08)	(31.58)	(23.85)
Primary school completion rate (%)	11.27	8.68	15.70	49.05	47.41	51.91
	(3.92)	(1.55)	(2.31)	(22.81)	(23.20)	(21.90)
Employed (= if Yes)	0.89	0.92	0.84	0.83	0.87	0.76
	(0.05)	(0.02)	(0.04)	(0.13)	(0.10)	(0.16)
Formal employment (=1 if yes)	0.04	0.06	0.02	0.16	0.18	0.13
	(0.02)	(0.01)	(0.01)	(0.11)	(0.11)	(0.10)
Observations	19	12	7	492	312	180

Notes: The table presents 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 in parentheses. The data for this table comes from World Bank's world development indicators.

Table (B.3) 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 × 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.4) 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 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.5) 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.