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

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Abstract

After being in power in Burkina Faso for about a year, a military regime-led by Thomas Sankara-, within weeks vaccinated 77% of children under age six against measles, meningitis, and yellow fever. The coverage and the success of this program set it apart from other contemporary vaccination programs, hence providing a policy experiment to test the effects of large immunization programs in low-income contexts. Using a difference-in-differences method, we estimate the impact of increased vaccination on child mortality, primary school completion, adulthood labor market outcomes and farm productivity. We find that the vaccination campaign significantly reduced the child mortality rate. The result also shows an increase in primary school completion. In adulthood, the vaccinated cohorts are significantly more likely to be employed and earn higher agricultural yields.

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1 Introduction

There is a considerable body of evidence indicating that early childhood socioeconomic circumstances have consequences that last a lifetime (Currie and Vogl, 2013; Almond et al., 2018; Case et al., 2005; Flores et al., 2020; Heckman et al., 2013; Gertler et al., 2014), partly because of the formative nature of childhood. Thus, programs targeting children have the potential to enhance human capital building, health, and economic outcomes in addition to providing immediate benefits. However, with a few notable exceptions (Nandi et al., 2020; Atwood, 2021), has not considered the impact that large public programs that specifically target child health will have in the long-run.

In this paper, we evaluate the short, medium, and long-run effects of a national immunization program in Burkina Faso that, in a period of three weeks, covered the majority of a cohort of children who were five years old or younger. The program was part of a coordinated international effort that sought to expand vaccination coverage in low-income countries. Indeed, vaccines are one of the most cost-effective investments to save lives and increase human capital. Vaccines not only benefit the immunized children, but a high vaccination rate also benefits the next generation by lowering the spread of infections, and thus lowering the burden of the targeted diseases over time. Yet, one in five children globally in 2020 is not vaccinated for life-threatening infectious diseases (WHO, 2021). The vaccination rate is much lower in many developing nations, ranging from 40% to 70% (WHO, 2020).[1]

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 effort. 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 the human capital. Therefore, an effective vaccination program could be an effective childhood intervention, and potentially growth-inducing in the long-run.

Rising vaccine hesitancy in developed nations and continued under-investment in vaccines in developing nations, suggests that the impact of vaccines is still not well understood. 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, 2021). 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 (2021) 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 (2021) 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 adulthood earnings and employment.

[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 12-24 months) in 2020 is 70%; whereas, 46% in Somalia, 47% in Guinea, 51% in Angola, and 54% in Nigeria (World Bank, 2021).

Since there are only a few studies empirically evaluating the positive effect of vaccines, side effects of vaccines– though limited to brief soreness, occasional rash, and infrequent fever– receive much more attention than the life-altering benefits[2]. In this paper, we add to the growing literature on the persistent benefits of early childhood interventions (Currie and Vogl, 2013; Almond et al., 2018; Case et al., 2005; Flores et al., 2020; Heckman et al., 2013; Gertler et al., 2014; Atwood, 2021), and particularly immunization programs, by documenting the effects of a national-level vaccination program on human capital formation and labor market outcomes in a low-income context.

The program, locally known as the "vaccination commando program (VCP)" was implemented in 1984 in Burkina Faso. It provides a unique natural experiment to evaluate the impact of a national-level vaccination program. In 1983, the national vaccination rate was only 17 percent (Unicef et al., 2007; Kessler et al., 1987). The same year, a military regime led by Thomas Sankara came into power after a coup. Observing the colossal failure of the existing expanded program in immunization (EPI), the regime initiated the VCP, which vaccinated over one million children against measles, yellow fever, and meningitis in a two-week campaign. As a result of the VCP, the vaccination rate in Burkina Faso increased from 17 percent to 77 percent in a few months. 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).

We utilize the sudden implementation of the VCP through deploying military and without mentionable change in Burkina Faso's health system as a quasi-experiment. We measure the impact of VCP 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 year-old or younger would have been eligible to receive all early childhood vaccination. In contrast, older individuals would not theoretically be eligible for the childhood vaccination.

We focus on two child health outcomes– under-two (i.e., infant) and under-five child mortality rate. We find that the vaccination leads to a significant decline in infant and child mortality. Clemens et al. (1988) and Koenig et al. (1990) in Bangladesh find similar results that measles vaccination reduces child mortality. Nandi et al. (2019) find measles vaccination leads to better health outcomes in Ethiopia, India, and Vietnam. Contrary to our findings, Bloom et al. (2011) find vaccination has no impact on children's height and weight in the Philippines. Our study is much broader in its scope compared to these studies. We study the impact of national-level vaccine intervention, while these studies use relatively small-scale interventions.

We also explore how vaccination affects children's educational outcomes. We use an indicator of educational attainment– primary school completion. We find vaccination leads to a significant rise in the likelihood of primary school completion. Our results confirm those of several studies which find positive effects of vaccination programs on grade attainment in South Africa (Anekwe et al., 2015), Ethiopia and Vietnam (Nandi et al., 2019), and India (Nandi et al., 2020).

[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

Finally, we inquire how the vaccination affects the treated cohorts' labor market outcome in adulthood. We find that vaccinated cohorts are significantly more likely to be employed and earn higher agricultural yields per hector. Atwood (2021) found a similar result for the measles vaccine in the United States where the labor market is well established. Whether vaccines have an impact on labor market outcomes in developing countries with more frictions in the labor markets remains an open question that we address.

This study makes two major contributions to the literature. First, we evaluate nationwide vaccination programs: while there are several studies on the impacts of vaccination, most focus 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[3]. Our study is part of a fast-growing body of research that focuses on understanding the long-term returns of large health interventions (Atwood, 2021; Nandi et al., 2020). Second, our results demonstrate that vaccines can have a strong and positive effect in the long-run even in environments where the labor market is less than perfect.

The rest of the paper is organized as follows. In Section 2, we highlight the VCP context and lay out the details of the VCP. We discuss our data sources and variables used in Section 3, and our method in Section 4. We discuss our results and placebo tests in Section 5. Finally, we conclude the paper in Section 6.

2 Program Description

More than half of all deaths of children under five years in Burkina Faso were directly attributed to vaccine-preventable diseases (Bellamy, 1998). To improve the situation, Burkina Faso established its Expanded Program on Immunization (EPI) in 1980 to administer vaccines against measles, meningitis, and yellow fever to infants and children. Only 25,000 of the half a million children under age two were vaccinated in 1981 Bellamy (1998). Lack of vaccines and ineffective transportation of the immunizer personnel were cited for the low coverage. Vaccination Commando (VC) was established in 1984 to address the failure of the EPI. In a 15 days campaign between November 25^{th} and December 10^{th} of 1984, Burkina Faso vaccinated over 1 million children against measles, yellow fever, and meningitis. The VC campaign covered 68-75% of the previous unimmunized children and saw an increase in the national vaccination coverage from 17% to 77%. Consequently, the number of reported measles cases fell sharply after the VC program (See Figure 1).

The vaccination Commando (VC) aimed to vaccinate children between the ages of 9 months to six years against measles and those between the ages of one to fourteen against both meningitis and yellow fever (Kessler et al., 1987). The government took both demand and supply-side initiatives to achieve its objective. The government raised health awareness for vaccination through a nationwide campaign using multiple mediums: radio and television, circulated educational leaflets in several

[3]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 the 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.

dialects, displayed posters, organized contests, staged theaters, and artists sang special songs to create awareness for the program. The government procured vaccines from the world market with funds from WHO, UNICEF, and several national governments on the supply side. The Ministry of health provided a refresher course for the health workers, temporarily assigned workers to ensure adequate staffing, and issued new vaccination cards. Besides, the government established multi-sectoral vaccination committees in every province to mobilize community support and participation. On top of that, the militaries were deployed to facilitate transportation logistics.

3 Data Sources and Descriptive Statistics

We use four sources of data: the demographic and health survey (DHS) data (child mortality), data from the national censuses (5% sample of 1985, 1996 and 2006), data from the permanent agricultural survey, and reports from the Ministry of Health on immunization. We use the 1993 round of the DHS to calculate child and infant mortality. The census data serve two purposes. First, we use the data to calculate education and labor market outcomes. Second, using the full census of 1985 and report on the number of children immunized in each province in December 1983 to calculate the vaccination rates per province. Finally, we use the agricultural data (see Kazianga and Wahhaj (2017)) to calculate agricultural productivity.

Table 1 Table 1 shows descriptive statistics of the Demographic Health Survey and the Burkina Faso General Population and Housing Census data. We present the sample size, mean and standard deviation (SD) of the total sample in columns (1)-(3). We also subdivided the VCP intensity into two groups– below average and above average are reported in columns (4)-(6) and (7) - (9), respectively. We categorized the entire sample of individuals who were born between 1966 and 1983 into three birth cohorts– 1966-1971, 1972-77, and 1978-83. Only the birth cohort 1978-83 was eligible for measles vaccination, and thus became the treated cohort. About 43 percent of our sample belongs to the treated cohort, 30 percent of the sample belongs to the first control group, the individuals born between 1972-1977, and the remaining 26 percent belongs to the second control group of individuals born between 1966-1971.

We also report the measles vaccination rate in the total sample and across the two categories in the Census data; the entire sample has a measles vaccination rate of about 65 percent, whereas the vaccination rate for the below-average and above-average intensity regions is 45 and 82 percent, respectively. About 58 percent of the sample is identified as Muslim, and 51 percent is female; only 15 percent of the sample completed primary school. We also created the dummy variable for working, and 44 percent of the Census data identified working in one sector.

Table 2 gives the summary statistics of the 2010 to 2012 panel of the permanent agricultural survey of the ministry of agriculture of Burkina Faso; the total sample is presented in columns 1 through 3, and columns 4 through 6 present the summary of the below-average vaccine rate, and columns 7 through 9 present the summary of the above average vaccine rate. The mean vaccination rate for the total sample is about 59 percent, below average is about 44 percent, and above average is 81 percent. About 32 percent of our sample belongs to the treated cohort, 35 percent of the sample belongs to the first control group, the individuals born between 1972-1977, and the remaining 38 percent belongs to the second control group of individuals born between 1966-1971.

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. Mortality outcome includes both infant and child mortality. Child mortality is a dummy variable that takes the value of one if the parent reported the death of a child under age five, while infant mortality takes the value of one if the parent-reported death of a child under age two. 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 Figure 2 - 4.

We use labor market outcomes in adulthood to measure the long-term effect of the increased vaccination. We focus on two outcomes: labor force participation and agricultural yield. Labor force participation is a dummy variable if that takes one if the child participate in labor force in adulthood. The agricultural yield measures the total value of agricultural output produced in a year. We present the trends in these variables in Figure 5 - 6.

4 Empirical Strategy

We measure the impact of VCP 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 year-old or younger would have been eligible to receive all early childhood vaccination. In contrast, older individuals would not theoretically be eligible for the childhood vaccination. We start with the following continuous treatment intensity TWFE specification:

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

where Y_{ijk} is the outcome of interest of individual i in cohort j in province k, I_k is the treatment intensity (the percentage of children vaccinated in December 1984) in province k, VCP_j is a dummy variable indicating whether the individual belong to a cohort exposed to the vaccination commando program, and η_k and γ_j represent province and cohort fixed effects, respectively. 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 of 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.

Recent research, see (Callaway et al., 2021) and references therein, have demonstrated that two-way fixed effects estimates can be severely biased when treatment effects change over time within treated units. Identification of the treatment effect requires a stronger assumption than the parallel trend assumption needed in the case of binary treatment. Therefore, we conduct a series of robustness checks by adopting a binary treatment that compares the provinces whose vaccination rates are below the national median and those with higher vaccination rates[4].

[4]In our specific case, we assume that provinces with lower vaccination rates can serve as a good counterfactual for

5 Results

In this section, we present the short-term and long-term impacts of VCP. We focus on health and educational outcomes to measure short-term impact, whereas we use labor force participation and agricultural productivity in adulthood to measure long-term impact.

5.1 Short-term Outcomes: Mortality

In the absence of vaccination, a large fraction of child mortality is attributed to vaccine-preventable diseases. As a result, the VCP should significantly reduce child mortality. We look at two mortality outcomes based on children's age: under-two (i.e., infant) and under-five child mortality.

5.1.1 Infant Mortality

Table 3 presents the impact of VCP on infant mortality based on equation (1). The dependent variable is the under-two child mortality rate in rural Burkina Faso. Columns (1) and (2) in the table contain the estimated coefficient ($\hat{\beta}_1$) on the interaction of the treatment cohort dummy, VCP_j (i.e., Cohort of birth 1978-83=1), and treatment intensity, I_k (i.e., province level measles vaccination rate). Here, the treatment cohort dummy variable (VCP_j) indicates whether the individual belongs to a cohort exposed to the vaccination commando program. Treatment intensity (I_k) is the percentage of children vaccinated in December 1984 in province k. Columns (3) and (4) use high vaccination rate.

All columns of table 3 include province and year-of-birth fixed effects capturing spatial and time variation in outcome. Even columns include additional controls such as ethnicity and gender. We cluster the standard errors at the province level as treatment assignment happens at the province level. We present the standard errors in parentheses. The estimations are based on the rural sample of 1993 Demographic and Health Survey (DHS) of Burkina Faso.

The results in Table 3 suggest that VCP has significantly reduced infant mortality. The treatment effect in column (1) is negative and statistically significant. For example, the coefficient in column (1) is -0.07, indicating that a one percent increase in vaccination rate leads to seven percentage points lower infant mortality. The coefficient is identical in column (2) with additional controls. Column (3) of Table 3 shows the treatment effect for high vaccine intensity. The result shows that high vaccination intensity has a statistically significantly larger negative effect than the low vaccine intensity. The coefficient is identical in column (4) with additional controls. The coefficient in column (4) is -0.04, indicating that a high vaccination intensity leads to a four percentage points lower infant mortality than low vaccination intensity.

5.1.2 Child Mortality

Table 4 presents the impact of VCP on under-five child mortality based on equation (1). The dependent variable is the under-five child mortality rate in rural Burkina Faso. The results in Table 4

those with higher vaccination rates if the evolution of the outcomes of interest at lower vaccination rates would have been the same.[Describe in more details– constant marginal response across groups, given dosage, etc.

suggest that VCP has significantly reduced under-five child mortality. For example, the coefficient in column (2) indicates that a one percent increase in vaccination intensity leads to seven percentage points lower under-five child mortality. Column (4) of Table 4 shows that vaccination high vaccination intensity has a larger negative effect than the low vaccination intensity. The coefficient in column (4) is -0.05, indicating that a high vaccination intensity leads to a five percentage points lower child mortality than low vaccination intensity.

5.1.3 Mortality Placebo Results

In this subsection, we conduct a falsification exercise to examine the validity of our estimation approach. Specifically, we re-estimate equation (1) using older cohorts who 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. As the VCP only affected the cohort of birth 1978-83, this placebo exercise should produce no effects of the VCP on mortality outcomes for the falsely unexposed cohort. Table 5 and 6 reports the results based on this placebo test.

The outcome variable in table 5 is the infant mortality rate and in table 6 child mortality rate in rural Burkina Faso. The estimated effects are statistically insignificant at a 5-percent significance level. Therefore, the placebo exercise supports our estimation approach and shows that our estimation using equation 1 is not picking up spurious effects on mortality.

5.2 Short-term Outcomes: Education

In the previous section, we show that the VCP leads to a lower child mortality rate, indicating that the treated cohort has better health. The improved health outcome of the vaccinated children may also lead to better educational outcomes. In this section, we explore how VCP affects children's educational outcomes. We focus on primary school completion. Children in Burkina Faso usually start their primary school at age six and complete it at age 12.

5.2.1 Primary Completion

Table 7 presents the impact of VCP on primary school completion based on equation (1). The estimations are based on the 1996 and 2006 rounds of General Population and Housing Censuses of Burkina Faso. Columns (1) and (2) in the table contain the estimated coefficient ($\hat{\beta}_1$) on the interaction of the treatment cohort dummy, VCP_j (i.e., Cohort of birth 1978-83=1), and treatment intensity, I_k (i.e., province level measles vaccination rate). Similarly, Columns (3) and (4) show estimated coefficients for high treatment intensity.

The results in Table 7 suggest that VCP has significantly increased primary school completion. The treatment effect in column (1) is positive and statistically significant. The coefficient is identical in column (2) with additional controls such as religion and gender. The result suggests that a one percent increase in vaccination rate leads to five percentage points higher primary school completion. Column (4) of Table 7 shows that high vaccination intensity leads to a two percentage points higher primary school completion than low vaccination intensity.

5.2.2 Primary Completion Placebo Results

We conduct a falsification exercise to examine the validity of our primary school completion results. In this exercise, we re-estimate equation (1) using the cohort of birth 1972-77 as the exposed cohort. As the VCP only affected the cohort of birth 1978-83, this placebo exercise should produce no effects of the VCP on primary school completion for the unexposed cohort. The estimations are based on 1985, 1996, and 2006 rounds of General Population and Housing Censuses of Burkina Faso. Table 8 reports the results based on this placebo test. The estimated effect in column (4) is close to zero and statistically insignificant at a 5-percent significance level. Therefore, the placebo exercise supports our estimation approach and shows that our main primary school completion results are not picking up spurious effects.

5.3 Long-term Outcomes: Labor Market Outcomes

Along with short-term outcomes such as health and educational outcomes, we also explore the long-run impacts of the VCP. We study the labor market outcomes of the treated cohort when they become adults. We look at two labor market outcomes— labor force participation and agricultural productivity.

5.3.1 Labor Supply

Table 9 presents the impact of VCP on Labor supply. As we find in the previous section that the treated cohort has a higher likelihood of primary school completion; they are likely to continue education longer. As a result, they will participate in the labor force at a later age. To capture this fact, we define labor supply as an indicator that equals one if an individual is working or studying and zero otherwise. The estimations are based on the 1996 and 2006 General Population and Housing Censuses of Burkina Faso. Columns (1) and (2) in the table contain the estimated coefficient ($\hat{\beta}_1$) on the interaction of the treatment cohort dummy, VCP_j (i.e., Cohort of birth 1978-83=1), and treatment intensity, I_k (i.e., province level measles vaccination rate). Similarly, Columns (3) and (4) show estimated coefficients for high treatment intensity.

The results in Table 9 suggest that VCP has significantly increased labor force participation. The treatment effect in column (1) is positive and statistically significant. The coefficient is identical in column (2) with additional controls such as religion and gender. The result suggests that a one percent increase in vaccination rate leads to six percentage points higher labor force participation rate. Columns (3) and (4) of Table 9 show the treatment effect for high vaccination intensity compared to low vaccination intensity. The results show that high vaccination intensity increases the labor force participation rate by two percentage points compared to low vaccine intensity. However, the coefficients are not statistically significant.

5.3.2 Labor Supply Placebo Results

We conduct a falsification exercise to examine the validity of our labor force participation results. In this exercise, we re-estimate equation (1) using the cohort of birth 1972-77 as the exposed cohort. As the VCP only affected the cohort of birth 1978-83, this placebo exercise should produce no effects

of the VCP on labor force participation for the unexposed cohort. Table 10 reports the results based on this placebo test. The estimated effect in column (4) is close to zero and statistically insignificant at a 5-percent significance level. Therefore, the placebo exercise supports our estimation approach and shows that our main results on labor force participation are not picking up spurious effects.

5.3.3 Agricultural Productivity

Table 11 presents the impact of VCP on agricultural productivity. The outcome variable is the natural log of harvest value per hectare. The estimations are based on the 2010-2012 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso described above, and used in Kazianga and Wahhaj (2017). Columns (1) and (2) in the table contain the estimated coefficient ($\hat{\beta}_1$) on the interaction of the treatment cohort dummy, VCP_j (i.e., Cohort of birth 1978-83=1), and treatment intensity, I_k (i.e., province level measles vaccination rate). Columns (3) and (4) show the estimated coefficients for high vaccination intensity. Even columns include additional controls such as plot owner characteristics (i.e., education, gender, age) and plot characteristics (i.e., toposequence, distance to village).

The results in Table 11 suggest that VCP has significantly increased agricultural productivity. The treatment effect in column (1) is positive and statistically significant. The coefficient is similar in column (2) with additional controls. The coefficient in column (2) is 0.27, indicating that a one percent increase in vaccination rate leads to a 27 percent higher harvest value per hectare. Column (4) of Table 11 shows that the high vaccination intensity has a statistically significant larger positive effect on agricultural productivity than the low vaccination intensity. Compared to the low vaccination intensity, high vaccination intensity leads to a 13 percent higher harvest value per hectare.

5.3.4 Agricultural Productivity Placebo Results

We conduct a falsification exercise to examine the validity of our agricultural productivity results. In this exercise, we re-estimate the equation (1) using the cohort of birth 1972-77 as the exposed cohort. As the VCP only affected the cohort of birth 1978-83, this placebo exercise should produce no effects of the VCP on agricultural productivity for the unexposed cohort. Table 12 reports the results based on this placebo test. The estimated effects are statistically insignificant at a 5-percent significance level. Therefore, the placebo exercise supports our estimation approach and shows that our main results on agricultural productivity are not picking up spurious effects.

6 Robustness Check

As we are using province level vaccine intensity, our result may not capture the true treatment effect if there is large internal migration across provinces in Burkina Faso. Internal migration could be a bigger concern for long-term outcomes. Individual may migrate to other provinces in search of work. As a result, we conduct a robustness check to address concerns of internal migration. In this exercise, we use data on 27 Sub-Saharan African countries over 19 years and synthetic control type 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).

The identification strategy we employ requires aggregate 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) countries 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 over 19 years. We focus on child health and education outcomes to measure the short-term impact and labor market outcomes to measure the long-term impact of vaccination. Child health and educational outcome variables also come from World Bank development indicators. For labor market outcomes, we use data from the Demographic and Health Survey (DHS) for 37 SSA countries (See 7 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.

6.1 Effect of Vaccination on Child Health

At first, we focus on how vaccination affects child health outcomes. We focus on two health outcomes– under-five child mortality rate and prevalence of thinness among 5-9 years. Figure 7 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 7 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 7 Panel (b), we see the confidence bounds for placebo ATTs are not statistically significant at a 10 percent significance level. 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 7 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.

6.1.1 Effect of the Measles Vaccination on Prevalence of Thinness

Now, we turn to our second health outcome, the prevalence of thinness. The data on prevalence of thinness is available from 1975, which gives us nine pre-treatment periods. Figure 8 Panel (a) plots the dynamic treatment effects of vaccination on the prevalence of thinness among children aged 5-9 years. The post-treatment ATTs are negative, which indicates that vaccines reduce the likelihood

of being extremely thin. Six years after the inception of the VC program, it leads to about 23 percent lower prevalence of thinness among children aged 5-9 years. In other words, vaccination leads to significant improvement in health outcomes in Burkina Faso. Nandi et al. (2019) find a similar result for children 11-12 years in Vietnam.

In Figure 8 Panel (b), we show the placebo test result for the prevalence of thinness. We find the fake ATTs fall within the equivalence range with a probability of 0.456. Thus, we can not reject the null that the placebo ATTs are different than the true ATTs. Thus, our identifying assumption hold for this estimation. Panel (c) shows the equivalence test is passed as the minimum range is within the equivalence range. This result provides us evidence that the control and the treatment countries do not have any differential pre-trends.

6.2 Effect of the Vaccination on Primary School Enrollment

In the previous section, we show that the vaccination leads to a better health and lower child mortality. 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.

6.2.1 Effect of the Vaccination on Primary School Completion Rate

We show the dynamic treatment effect of vaccination on children's primary school completion rate in Figure 10 Panel (a). We see the 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.

6.3 Effect of Vaccination on Labor Market Outcomes

The positive health and educational outcomes we find are a relatively short-run benefits of vaccination. 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 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 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 see the vaccinated children are more likely to work and gainfully work in a formal sector.

Figure 11 Panel (a) reports the dynamic treatment effect of vaccination on adults' employment rate. The post-treatment ATTs are positive, which indicates the vaccination increases the likelihood of adult labor force participation. ATT at one year since the treatment started indicates the average rise in the employment rate for the children born in 1985. The result shows that the vaccinated children after six years of the inception of the VC program are about 10 percent more likely to work. Figure 11 Panel (b) shows that the placebo test is satisfied, which indicates that we can not reject the null that the placebo ATTs are different than the true ATTs. However, Figure 11 Panel (c) shows the equivalence test failed as the minimum range is outside the equivalence range. This equivalence result suggests that for some years, the pre-treatment fits are not good.This is not surprising because, unlike other outcome variables in our analysis, we are using sample data (i.e., DHS surveys) to generate aggregate (national) employment rates.

6.3.1 Effect of Vaccination on Formal Employment

Next, we present the dynamic treatment effect of vaccination on adults' formal sector employment rate in Panel (a) of Figure 12. 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 (2021) finds a similar result in the United States for measles vaccination. Figure 12 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 12 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.

7 Conclusion

Measles and other infectious diseases affect millions of people yearly, and Sub-Sahara African countries are no exception. Before 1984, the majority of children's death 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 morbidity and mortality of children. Such under-investment and under-utilization of vaccines could be due in part to a misunderstanding of the overall impact of vaccines. This is not unsurprising given that there are only a few studies that empirically studies 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 program.

In this study, we fill the gap in the literature by studying the effect of a national-level vaccination program on children's health and educational outcomes, and adulthood labor market outcomes.

Besides, we utilize the VCP as a natural experiment to identify the causal effects. Our finding suggests that vaccination significantly increases human capital for the treated cohorts. Vaccination significantly reduces child mortality, improves child health, and increases primary school enrollment and completion. In adulthood, vaccinated cohorts are more likely to be employed and gainfully employed in the formal sector.

Our findings have important policy implications for the role of vaccination in enhancing children's welfare and their human capital in the long run.

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Figures

Figure (1) Measles prevalence over time

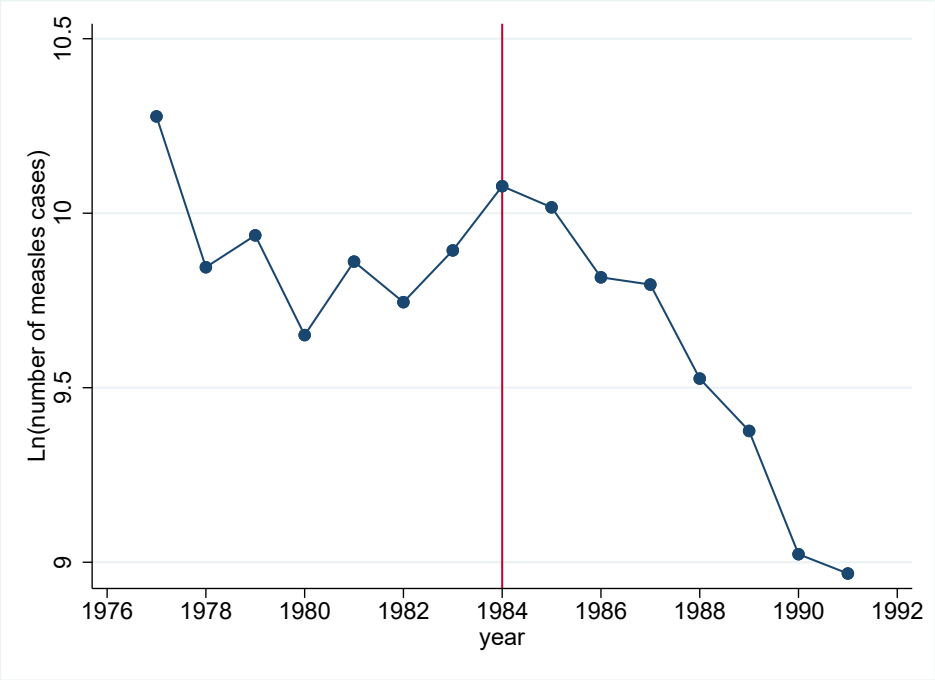
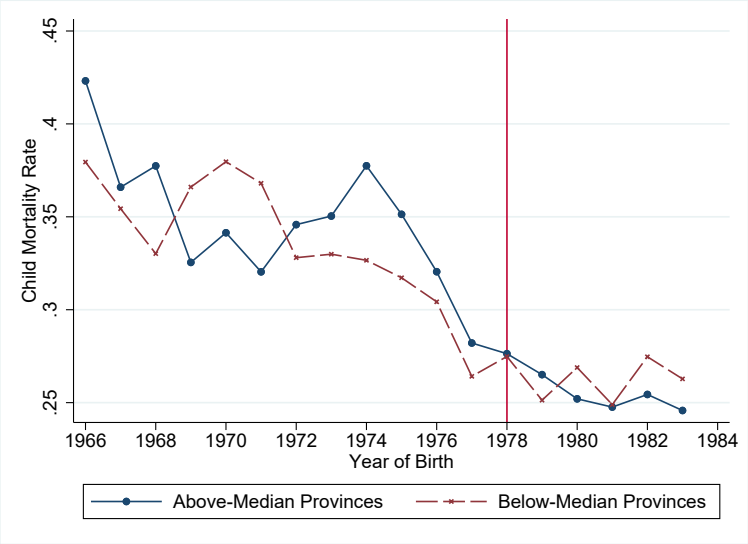
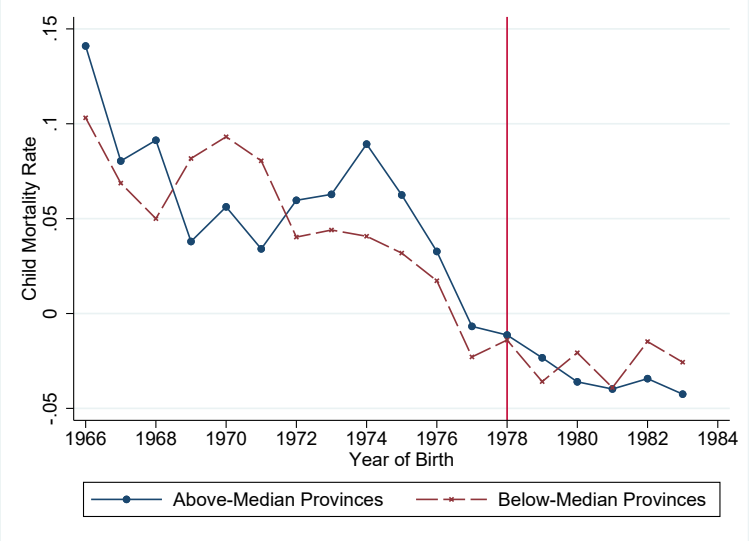


Figure (2) Mortality rate by year of birth from DHS

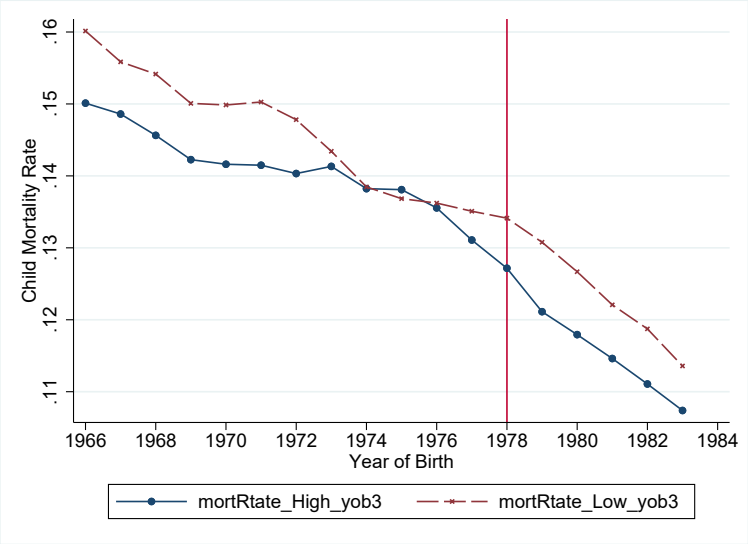


(a) Below and Above Median Vaccination

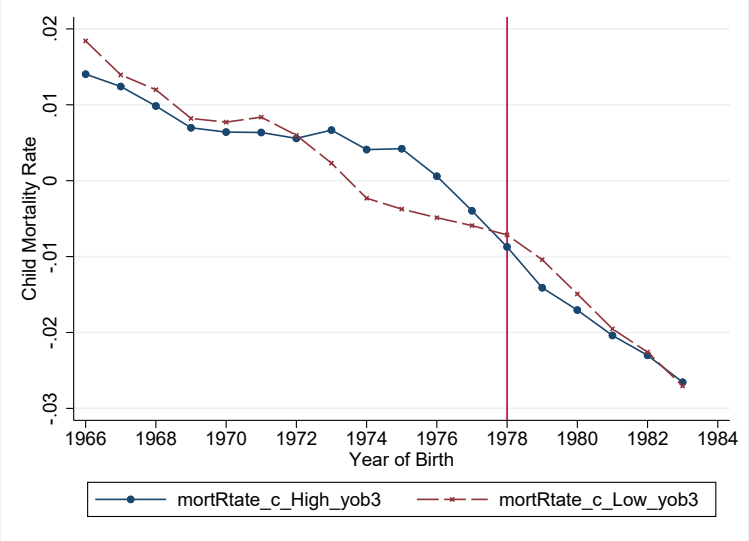


(b) Below and Above Median Vaccination (Centered)

Figure (3) Mortality rate by year of birth From Census

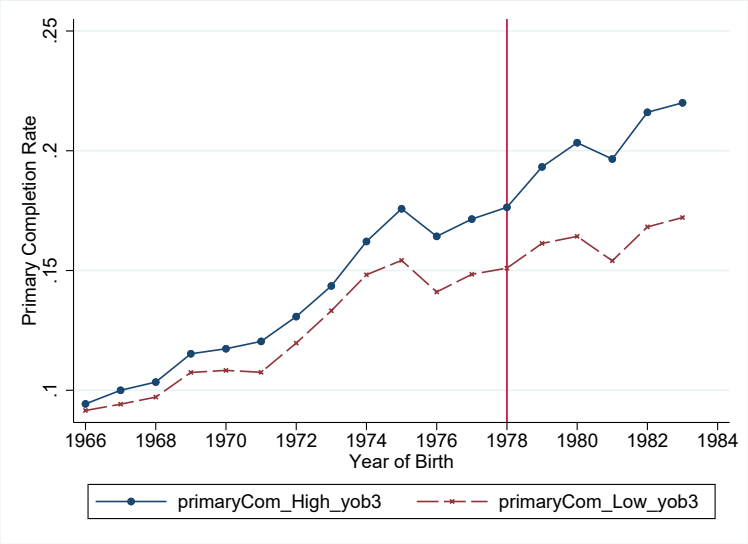


(a) Below and Above Median Vaccination

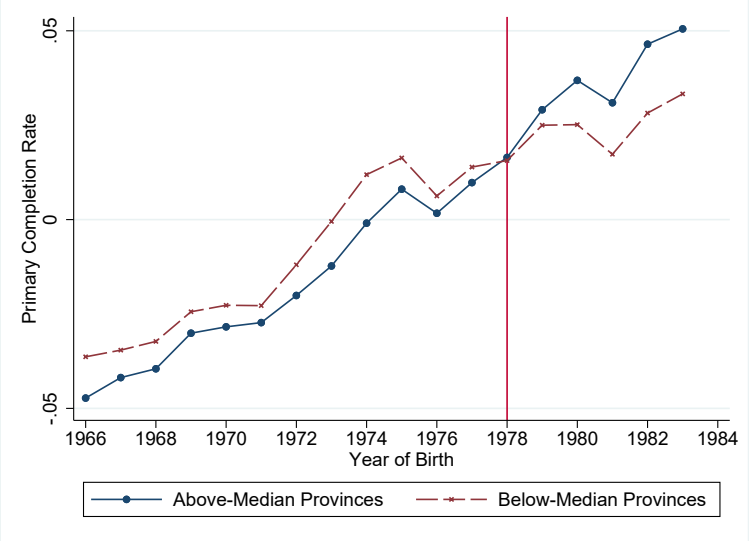


(b) Below and Above Median Vaccination (Centered)

Figure (4) Primary completion rate by year of birth

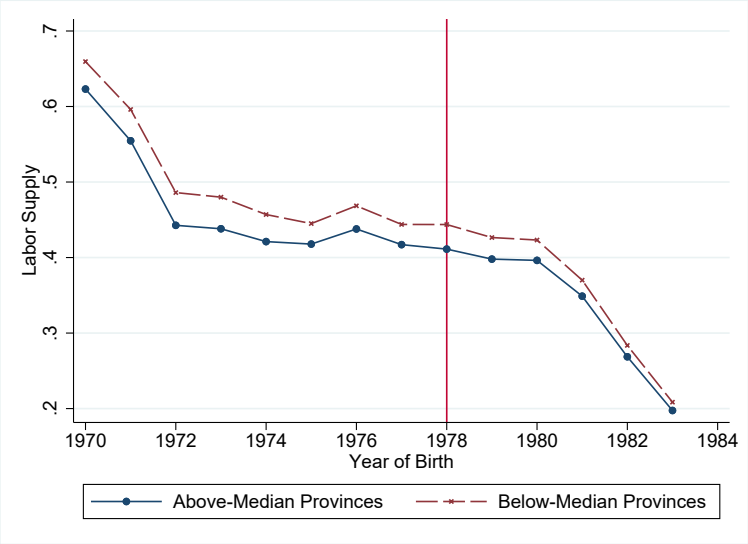


(a) Median Vaccination

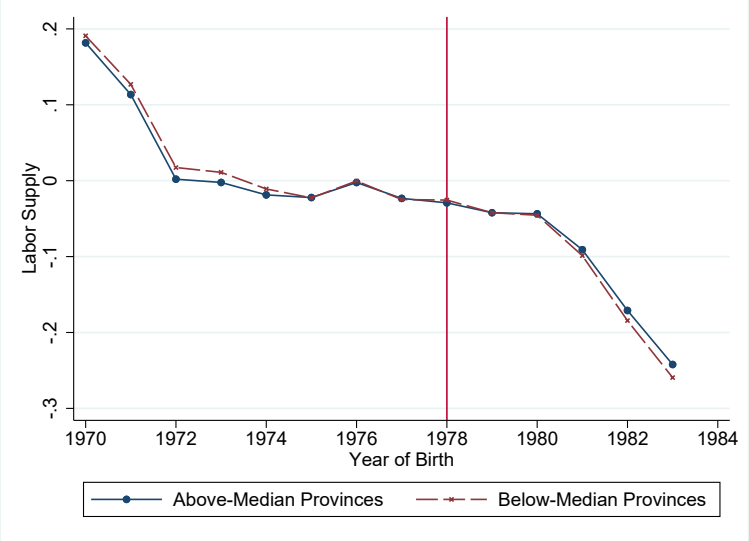


(b) Below and Above Median Vaccination (Centered)

Figure (5) Labor force participation by year of birth

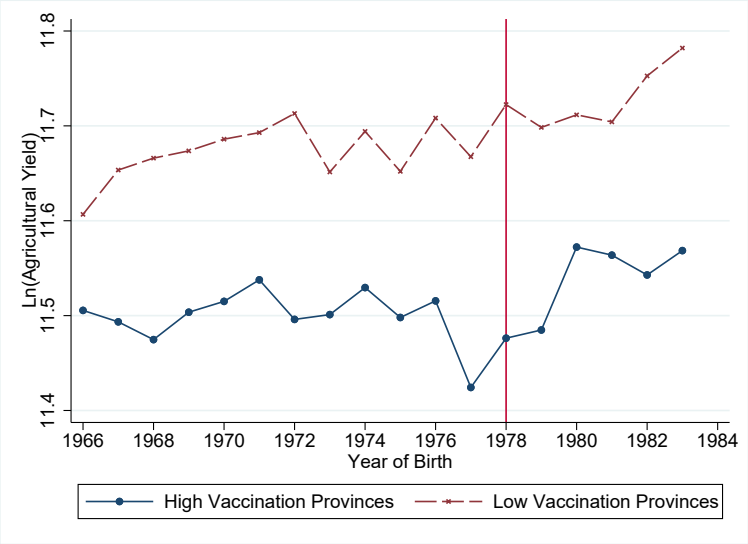


(a) Below and Above Median Vaccination

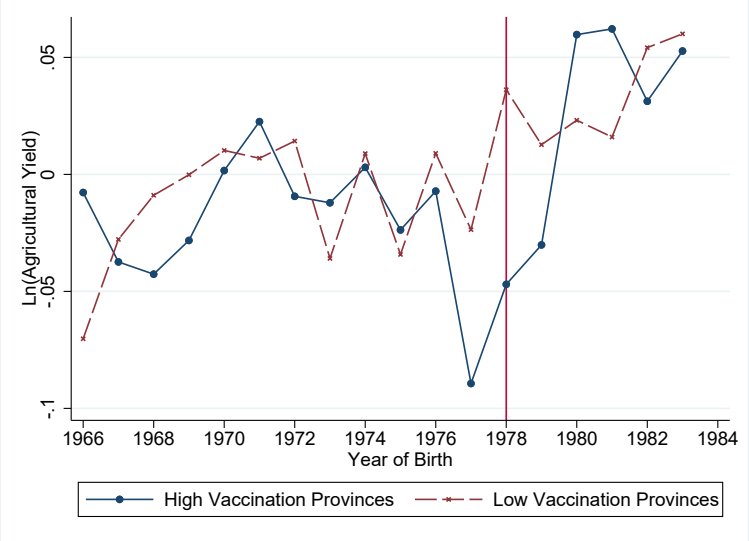


(b) Below and Above Median Vaccination (Centered)

Figure (6) Agricultural Yield by year of birth

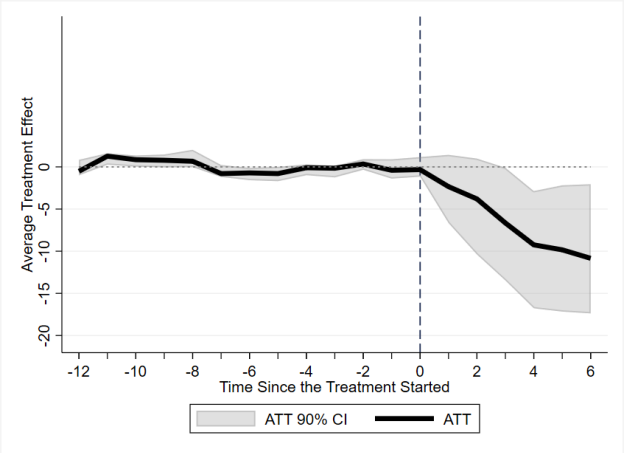


(a) Below and Above Median Vaccination

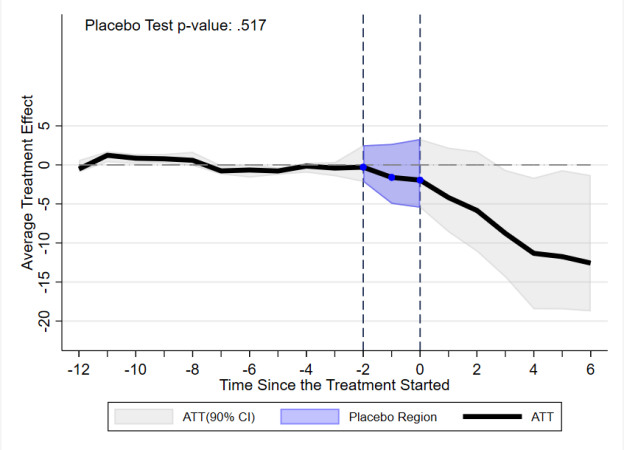


(b) Below and Above Median Vaccination (Centered)

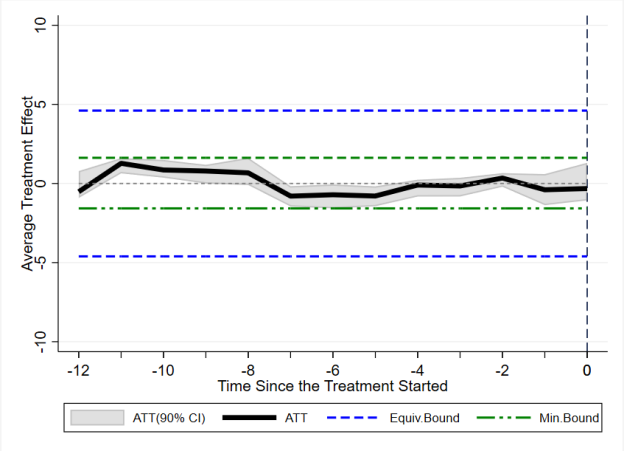
Figure (7) (a) shows the result of mortality rate under five, (b) shows the result for placebo test (c) shows the result of an equivalent test for the mortality rate under five



(a) Mortality rate under five

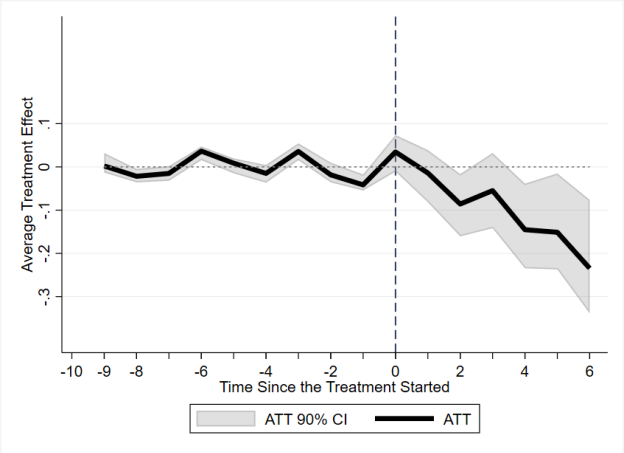


(b) Mortality rate placebo test

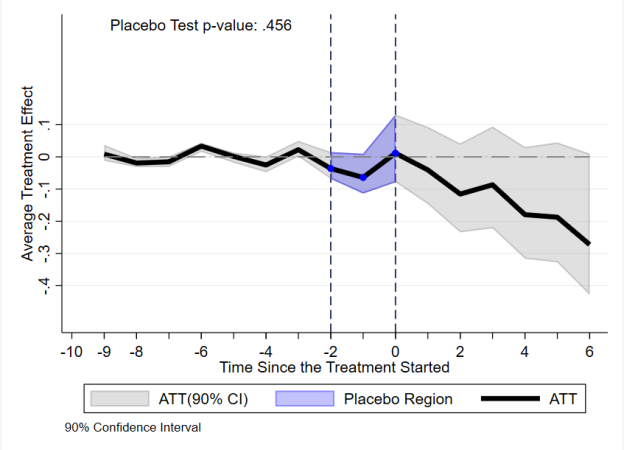


(c) Mortality rate equivalence test.

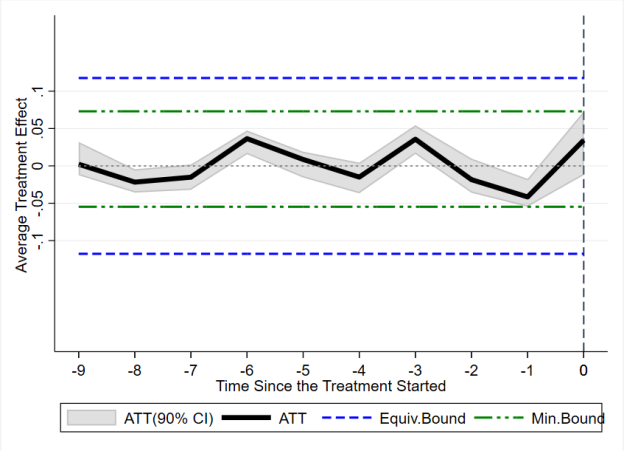
Figure (8) (a) shows the result of BMI less than two s.d, (b) shows the placebo test for BMI less than two s.d (c) shows the equivalent test for BMI less than two s.d



(a) BMI

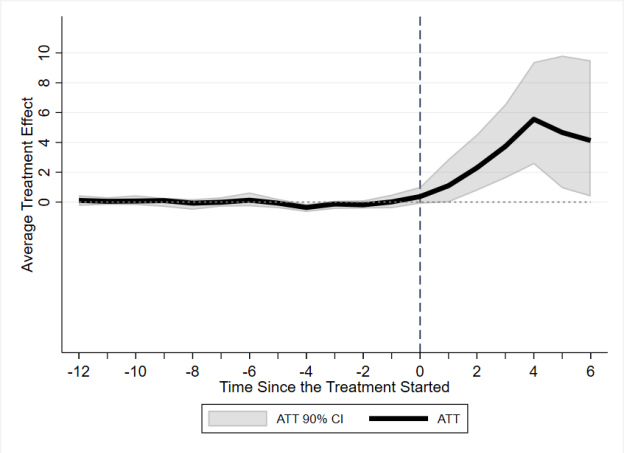


(b) Placebo test for BMI

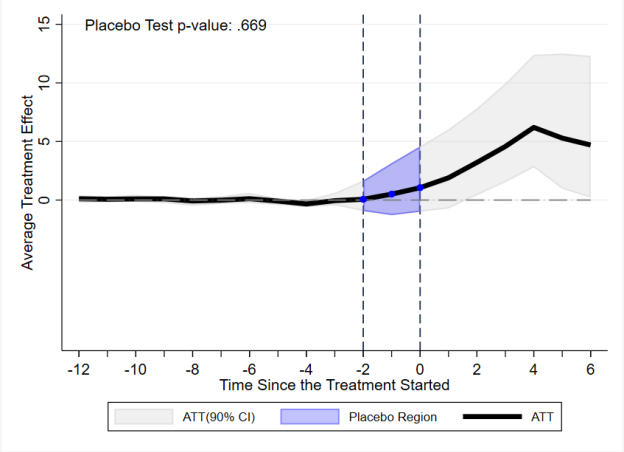


(c) Equivalence test for BMI

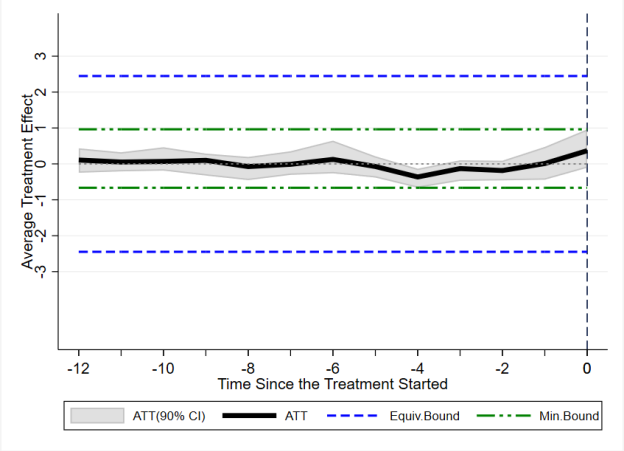
Figure (9) (a) shows the result of primary school enrollment net overall, (b) shows the placebo test for primary school enrollment, (c) shows the equivalent test for primary school enrollment.



(a) Primary school enrollment net overall

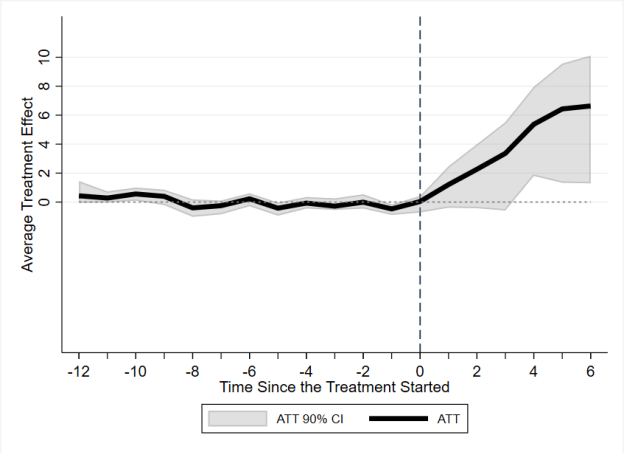


(b) Placebo test for primary school enrollment

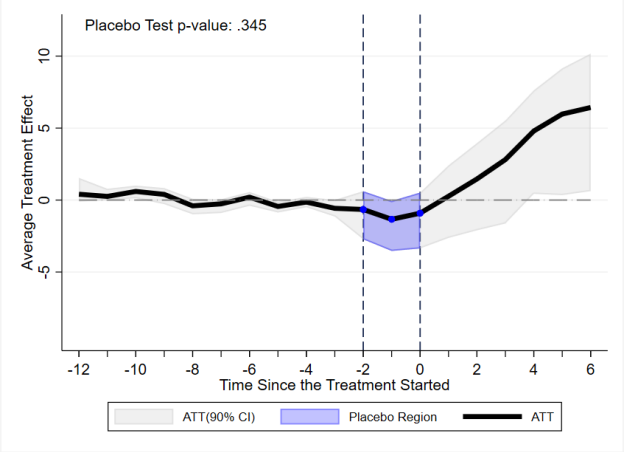


(c) Equivalence test for primary school enrollment.

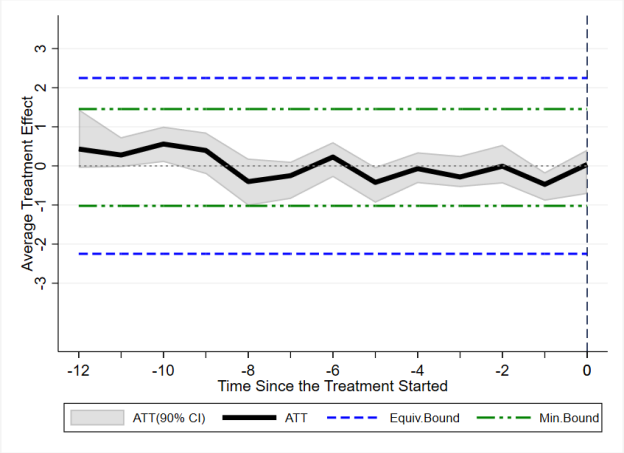
Figure (10) (a) shows the result of primary school completion rate, (b) shows the placebo test for primary school completion rate, (c) shows the equivalent test for primary school completion rate.



(a) Primary school completion rate

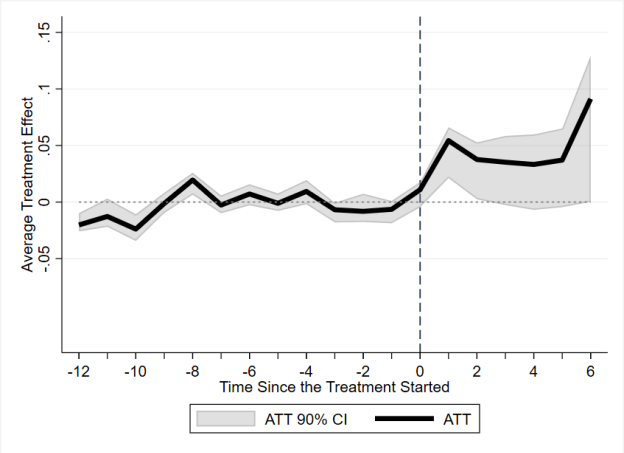


(b) Placebo test for primary school completion rate

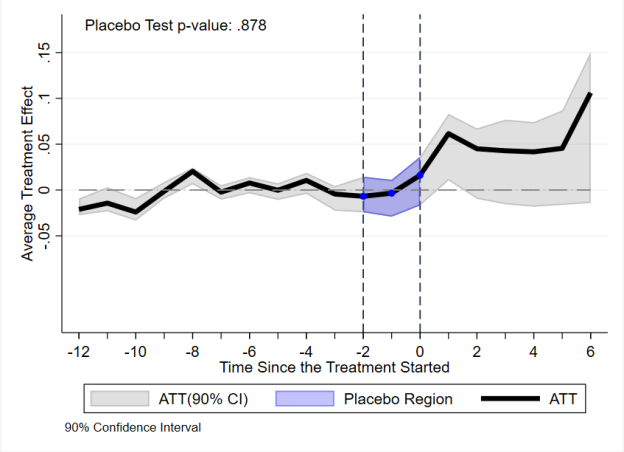


(c) Equivalence test for primary school completion rate.

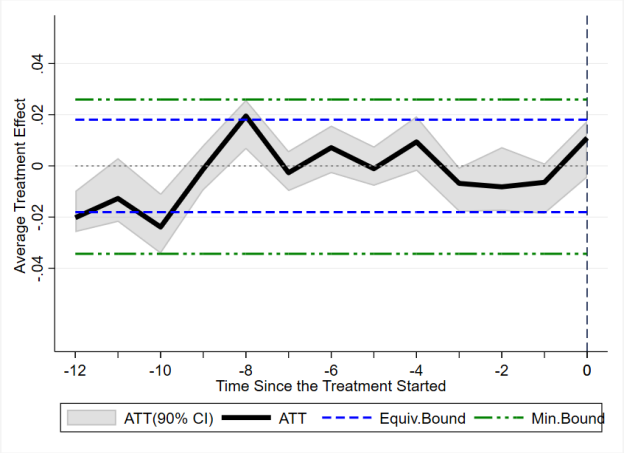
Figure (11) (a) shows the result of employment rate, (b) shows the placebo test for employment rate, (c) shows the equivalent test for employment rate.



(a) Employment rate

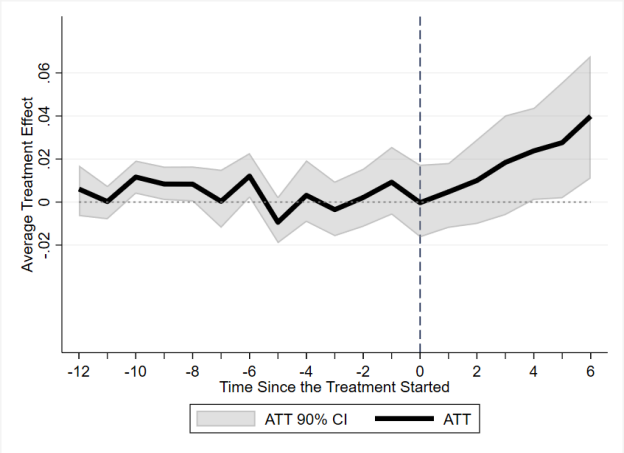


(b) Placebo test for employment rate

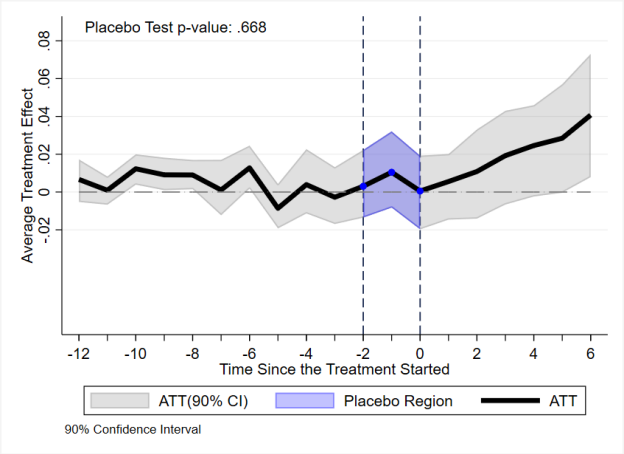


(c) Equivalence test for employment rate.

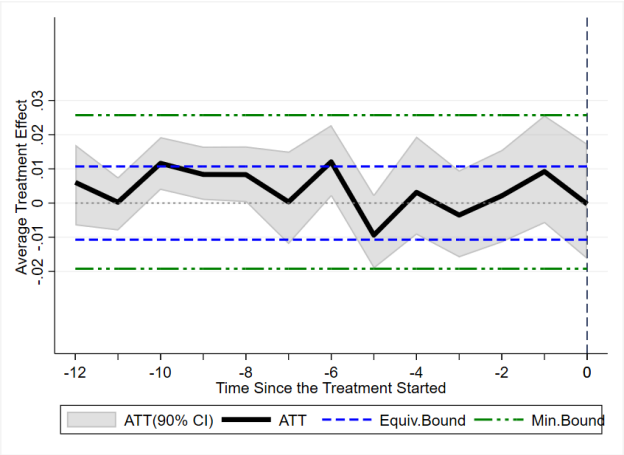
Figure (12) (a) shows the result of formal employment rate, (b) shows the placebo test for formal employment rate, (c) shows the equivalent test for formal employment rate.



(a) Formal employment.



(b) Placebo test for formal employment.



(c) Equivalence test for formal employment.

Tables

Table (1) Descriptive Statistics: Census and Demographic Health Survey

	Full Sample			Below average vaccine rate			Above average vaccine rate		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Census variables									
Cohort of birth 1978-83 =1	941,351	0.43	0.50	463,242	0.44	0.50	478,109	0.43	0.49
Cohort of birth 1972-77 =1	941,351	0.30	0.46	463,242	0.30	0.46	478,109	0.30	0.46
Cohort of birth 1966-71 =1	941,351	0.26	0.44	463,242	0.26	0.44	478,109	0.27	0.44
Measles vaccination rate	941,351	0.65	0.26	463,242	0.45	0.14	478,109	0.85	0.19
Muslim =1	573,191	0.58	0.49	308,378	0.51	0.50	326,698	0.65	0.48
Female =1	941,351	0.51	0.50	463,242	0.51	0.50	478,109	0.51	0.50
Primary completion =1	629,754	0.15	0.36	271,587	0.14	0.30	358,167	0.16	0.37
Working =1	941,351	0.44	0.50	463,242	0.45	0.50	478,109	0.42	0.49
Demographic and health survey variables									
Cohort of birth 1978-83 =1	5,644	0.53	0.50	2,534	0.53	0.50	3,110	0.53	0.50
Cohort of birth 1972-77 =1	5,644	0.33	0.47	2,534	0.33	0.47	3,110	0.33	0.47
Cohort of birth 1966-71 =1	5,644	0.14	0.35	2,534	0.14	0.35	3,110	0.15	0.35
Measles vaccination rate	5,644	0.65	0.25	2,534	0.45	0.15	3,110	0.82	0.18
Mossi =1	5,585	0.56	0.50	2,503	0.39	0.49	3,082	0.70	0.46
Female =1	5,644	0.48	0.50	2,534	0.47	0.50	3,110	0.49	0.50
Infant mortality rate (age 2 years) =1	5,644	0.24	0.43	2,534	0.24	0.43	3,110	0.24	0.43
Child mortality rate (age up to 5 years) =1	5,644	0.29	0.45	2,534	0.28	0.45	3,110	0.29	0.45

Table (2) Descriptive Statistics: Permanent Agricultural Survey

	Full Sample			Below average vaccine rate			Above average vaccine rate		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Permanent agricultural survey (PAS) variables									
Measles vaccination rate	29,817	0.59	0.25	18,150	0.44	0.17	11,667	0.81	0.17
Owner's cohort of birth 1978-83 =1	28,239	0.32	0.47	17,161	0.33	0.47	11,078	0.32	0.47
Owner's cohort of birth 1972-77 =1	28,299	0.35	0.48	17,181	0.34	0.47	11,118	0.35	0.48
Owner's cohort of birth 1966-71 =1	28,623	0.38	0.48	17,402	0.38	0.49	11,221	0.38	0.48
Owner's age	29,817	36.70	5.16	18,150	36.68	5.15	11,667	36.73	5.18
Owner has no literacy =1	29,658	0.74	0.44	18,065	0.73	0.44	11,593	0.76	0.43
Owner is female =1	29,817	0.38	0.49	18,150	0.32	0.47	11,667	0.48	0.50
Topography: flat ground =1	29,817	0.83	0.38	18,150	0.83	0.38	11,667	0.82	0.38
Topography: low ground =1	29,817	0.09	0.29	18,150	0.10	0.29	11,667	0.09	0.29
Topography: sloping ground =1	29,817	0.08	0.27	18,150	0.07	0.26	11,667	0.08	0.27
Plot location: closest to village =1	29,817	0.37	0.48	18,150	0.37	0.48	11,667	0.37	0.48
Plot location: midway =1	29,817	0.55	0.50	18,150	0.55	0.50	11,667	0.55	0.50
Plot location: farthest from village=1	29,817	0.08	0.27	18,150	0.08	0.27	11,667	0.08	0.27
Ln(harvest value in LCU per hectare)	29,761	11.63	1.42	18,112	11.70	1.39	11,649	11.52	1.45

Table (3) Vaccination effects on infant mortality

	(1)	(2)	(3)	(4)
Cohort of birth 1978-83=1 × vaccination rate measles	-0.069**	-0.065**		
	(0.030)	(0.031)		
Cohort of birth 1978-83=1 × High vaccination rate mealses=1			-0.043*	-0.043*
			(0.023)	(0.023)
Constant	0.298***	0.317***	0.298***	0.316***
	(0.029)	(0.029)	(0.029)	(0.029)
Observations	4836	4783	4836	4783
Fixed Effects	Province	Province	Province	Province
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	DHS	DHS	DHS	DHS

Robust standard errors clustered at the province level.

Dependent variable is the infant (age less than 2) mortality rate

Controls include ethnicity and gender

Estimations using the 1993 Demographic and Health Survey (DHS) of Burkina Faso

Table (4) Vaccination effects on child mortality

	(1)	(2)	(3)	(4)
Cohort of birth 1978-83=1 × vaccination rate measles	-0.069**	-0.063*		
	(0.031)	(0.032)		
Cohort of birth 1978-83=1 × High vaccination rate mealses=1			-0.048*	-0.047*
			(0.024)	(0.023)
Constant	0.343***	0.371***	0.343***	0.370***
	(0.029)	(0.034)	(0.029)	(0.033)
Observations	4836	4783	4836	4783
Fixed Effects	Province	Province	Province	Province
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	DHS	DHS	DHS	DHS

Robust standard errors clustered at the province level.

Dependent variable is the child (age less than 5) mortality rate

Controls include ethnicity and gender

Estimations using the 1993 Demographic and Health Survey (DHS) of Burkina Faso

Table (5) Placebo effects on infant mortality

	(1)	(2)	(3)	(4)
Cohort of birth 1972-77=1 × vaccination rate measles	0.135	0.133		
	(0.089)	(0.087)		
Cohort of birth 1972-77=1 × High vaccination rate measles=1			0.032	0.031
			(0.041)	(0.041)
Constant	0.363***	0.352***	0.362***	0.350***
	(0.045)	(0.053)	(0.047)	(0.054)
Observations	2657	2623	2657	2623
Fixed Effects	Province	Province	Province	Province
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	DHS	DHS	DHS	DHS

Robust standard errors clustered at the province level.

Dependent variable is the infant (age less than 2) mortality rate

Controls include ethnicity and gender

Estimations using the 1993 Demographic and Health Survey (DHS) of Burkina Faso

Table (6) Placebo effects on child mortality

	(1)	(2)	(3)	(4)
Cohort of birth 1972-77=1 × vaccination rate measles	0.152	0.149		
	(0.094)	(0.091)		
Cohort of birth 1972-77=1 × High vaccination rate measles=1			0.046	0.044
			(0.045)	(0.045)
Constant	0.404***	0.404***	0.402***	0.402***
	(0.052)	(0.061)	(0.054)	(0.064)
Observations	2657	2623	2657	2623
Fixed Effects	Province	Province	Province	Province
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	DHS	DHS	DHS	DHS

Robust standard errors clustered at the province level.

Dependent variable is the child (age less than 5) mortality rate

Controls include ethnicity and gender

Estimations using the 1993 Demographic and Health Survey (DHS) of Burkina Faso

Table (7) Vaccination effects on primary school completion

	(1)	(2)	(3)	(4)
Cohort of birth 1978-83=1 × vaccination rate measles	0.051**	0.049**		
	(0.020)	(0.022)		
Cohort of birth 1978-83=1 × High vaccination rate measles=1			0.023**	0.021**
			(0.009)	(0.009)
Constant	0.127***	0.261***	0.128***	0.261***
	(0.006)	(0.010)	(0.006)	(0.009)
Observations	403951	389389	403951	389389
Fixed Effects	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	Census	Census	Census	Census

Robust standard errors clustered at the province level.

Dependent variable is the primary school completion rate

Controls include religion and gender

Estimations using the 1985, 1996, and 2006 General Population and Housing Censuses of Burkina Faso

Table (8) Placebo effects on primary school completion

	(1)	(2)	(3)	(4)
Cohort of birth 1972-77=1 × vaccination rate measles	0.023	0.044*		
	(0.016)	(0.023)		
Cohort of birth 1972-77=1 × High vaccination rate measles=1			-0.001	0.002
			(0.008)	(0.012)
Constant	0.094***	0.180***	0.094***	0.180***
	(0.004)	(0.007)	(0.004)	(0.007)
Observations	400761	311436	400761	311436
Fixed Effects	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	Census	Census	Census	Census

Robust standard errors clustered at the province level.

Dependent variable is the primary school completion rate

Controls include religion and gender

Estimations using the 1985, 1996, and 2006 General Population and Housing Censuses of Burkina Faso

Table (9) Vaccination effects on labor supply

	(1)	(2)	(3)	(4)
Cohort of birth 1978-83=1 × vaccination rate measles	0.056**	0.057**		
	(0.025)	(0.027)		
Cohort of birth 1978-83=1 × High vaccination rate mealses=1			0.016	0.016
			(0.013)	(0.014)
Constant	0.590***	0.637***	0.590***	0.637***
	(0.007)	(0.018)	(0.008)	(0.018)
Observations	411947	411947	411947	411947
Fixed Effects	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	Census	Census	Census	Census

Robust standard errors clustered at the province level.

Dependent variable is an indicator of labor supply decision that equals 1 if working or studying, and zero otherwise

Controls include individual characteristics: age, gender, and religion

Estimations using the 1996 and 2006 General Population and Housing Censuses of Burkina Faso

Table (10) Placebo effects on labor supply

	(1)	(2)	(3)	(4)
Cohort of birth 1972-77=1 × vaccination rate measles	-0.023	-0.043		
	(0.017)	(0.026)		
Cohort of birth 1972-77=1 × High vaccination rate mealses=1			-0.003	-0.000
			(0.009)	(0.013)
Constant	0.495***	0.771***	0.495***	0.771***
	(0.010)	(0.026)	(0.009)	(0.026)
Observations	422451	334507	422451	334507
Fixed Effects	Province	Province	Province	Province
Fixed Effects	Year	Year	Year	Year
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	Census	Census	Census	Census

Robust standard errors clustered at the province level.

Dependent variable is an indicator of labor supply decision that equals 1 if working or studying, and zero otherwise

Controls include individual characteristics: age, gender, and religion

Estimations using the 1985, 1996, and 2006 General Population and Housing Censuses of Burkina Faso

Table (11) Vaccination effects on agricultural productivity

	(1)	(2)	(3)	(4)
Birth cohort 1978-83=1 × vaccination rate measles	0.290***	0.266***		
	(0.097)	(0.078)		
Birth cohort 1978-83=1 × High vaccination rate mealses=1			0.114*	0.129**
			(0.065)	(0.059)
Constant	11.549***	5.664*	11.612***	12.867***
	(0.028)	(3.109)	(0.012)	(0.070)
Observations	17561	17470	17561	17470
Fixed Effects	Household	Household	Household	Household
Fixed Effects	Year	Year	Year	Year
Fixed Effects	Crop	Crop	Crop	Crop
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	PAS	PAS	PAS	PAS

Robust standard errors clustered at the province level.

Dependent variable is the natural log of harvest value per hectare

Plot owner characteristics: education, gender, age; plot characteristics: toposequence, distance to village

Estimations using the 2010-2012 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso

Table (12) Placebo effects on agricultural productivity

	(1)	(2)	(3)	(4)
Birth cohort 1972-77=1 × vaccination rate measles	-0.079	-0.071		
	(0.126)	(0.133)		
Birth cohort 1972-77=1 × High vaccination rate mealses=1			-0.004	0.031
			(0.084)	(0.090)
Constant	11.623***	11.098***	11.601***	12.771***
	(0.037)	(3.457)	(0.017)	(0.079)
Observations	19046	18952	19046	18952
Fixed Effects	Household	Household	Household	Household
Fixed Effects	Year	Year	Year	Year
Fixed Effects	Crop	Crop	Crop	Crop
Fixed Effects	YOB	YOB	YOB	YOB
Other controls	None	Yes	None	Yes
Data Source	PAS	PAS	PAS	PAS

Robust standard errors clustered at the province level.

Dependent variable is the natural log of harvest value per hectare

Plot owner characteristics: education, gender, age; plot characteristics: toposequence, distance to village

Estimations using the 2010-2012 panel of the Permanent Agricultural Survey of the Ministry of Agriculture of Burkina Faso

Appendix

A Robustness Check: Internal Migration

A.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 A.1).

In Table A.1, 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 A.1). 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 mortal-

Table (A.1) Descriptive Statistics

	Burkina Faso			Other SSA Countries		
	All	Bofore	After	All	Bofore	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)	(7.57)	(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

Note: In this table, we present the mean and standard deviation of the variables. The standard deviations are in parentheses.

ity 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.

A.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)[5]. 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:

$$Y_{it}(0) = f(X_{it}) + h(U_{it}) + \epsilon_{it} \tag{2}$$

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 $\hat{\delta_{it}}$, $\hat{ATT} = \frac{1}{|M|}\sum_{(i,t)\in M}\hat{\delta}_{it}$. Similarly, the ATT at a period s since the treatment started $\hat{ATT}_s = \frac{1}{|S|}\sum_{(i,t)\in S}\hat{\delta}_{it}$ in which

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

$S = \{(i,t) \mid D_{i,t-s} = 0, D_{i,t-s+1} = D_{i,t-s+2} = \ldots = D_{i,t} = 1\}$. 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:

$$Y_{it} = \delta_{it} D_{it} + L_{it} + x_{it}\beta + \eta_i + \gamma_t + \epsilon_{it} \tag{3}$$

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 estimate L by solving the minimization problem.

$$\hat{L} = \min_{L} \frac{1}{\mid A \mid} \sum_{(i,t) \in A} ((Y_{it} - L_{it})^2 + \lambda_L \|L\|) \tag{4}$$

where $A = \{(i,t) | D_{it} = 0\}$ 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

$$\hat{\delta}_{it} = Y_{it}(1) - \hat{Y}_{it}(0) \tag{5}$$

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.

*Health and Farm Labor Productivity

- Agricultural production function: we express the production function as

$$F(L, A) \tag{6}$$

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

$$L = \theta(H)\,\mathcal{L}(H) \tag{7}$$

- Effect of improving health (vaccination) on farm production Using 6 and 7, the partial derivate of H on production is

$$\frac{\partial F\left(L,A\right)}{\partial H}=\left(\mathcal{L}(H)\frac{d}{dH}\theta(H)+\theta(H)\frac{d}{dH}\mathcal{L}(H)\right)\frac{\partial}{\partial\xi_1}F(\xi_1,A) \tag{8}$$

  where $\xi_1=\theta(H)\times\mathcal{L}(H)$

- Observed variables and estimable changes With our data, we observe $\mathcal{L}$, but not θ. In fact, we can even estimate $\frac{\partial\mathcal{L}(H)}{\partial H}$. This the DID estimate when we use total labor (or labor per hectare) applied on the farm as dependent variable.

- Interpretation of our results In our regressions, we find $\frac{\partial\mathcal{L}(H)}{\partial H}=0$, thus the effect of health on production reduces to:

$$\frac{\partial F\left(L,A\right)}{\partial H}=\left(\mathcal{L}(H)\frac{d}{dH}\theta(H)\right)\frac{\partial}{\partial\xi_1}F(\xi_1,A) \tag{9}$$

  That is, our results show that the vaccination effects work by making farm labor more effective (or improving the quality of farm labor) without changing the quantity.