Reducing Maternal Mortality through Health Infrastructure: Evidence from Ecuador's Facility Access*

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Abstract

This study addresses the critical issue of maternal mortality in Ecuador, a problem that disproportionately affects developing countries. According to the WHO, maternal mortality remains a challenge in rural areas and among adolescent women. We analyze whether the construction of health facilities between 2012 and 2023 had statistically significant causal effects under standard identification assumptions on the reduction of maternal mortality in Ecuador. To this end, the country's health supply, and national statistical records of live births and general deaths are utilized. We apply the Augmented Inverse Probability Weighting (AIPW) approach proposed by Callaway and Sant'Anna within a staggered adoption difference-in-differences framework. We found that post-treatment estimates provide no systematic evidence of an effect in specifications without controls, indicating a lack of robustness when contexts of heterogeneity between parishes are not adequately addressed. However, once relevant covariates are incorporated, the estimates reveal negative and statistically significant effects at longer durations of exposure to treatment. In these specifications, maternal mortality is reduced by approximately 24% in the periods close to the implementation of the intervention, while in more mature stages of treatment the reductions reach values close to 50%. These findings suggest that the impact of health facilities construction is cumulative rather than immediate and strengthens with longer exposure.

Keywords: *Maternal mortality, health economics, health policy, impact evaluation, augmented inverse probability weighting (AIPW)*.

JEL codes: I15, I18, H43

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Introduction

According to the World Health Organization (2018b), 830 women die daily from preventable causes, 99% of which occur in developing countries, disproportionally affecting rural and impoverished areas, being adolescent women at the highest risk of death. Furthermore, maternal mortality is considered one of the most important indicators for assessing a country's development status, as studies indicate that most of these deaths are preventable and occur in middle- and low-income countries (Say et al., 2014).

Maternal mortality is defined as a woman's death due to pregnancy, childbirth, or the postpartum period (Instituto Nacional de Estadística y Censos (INEC), 2013); it is estimated that between 30% and 40% of maternal deaths could be prevented (Berg et al., 2005; Geller et al., 2014). A study by the World Health Organization (WHO) for the year 2012 found that hemorrhage, indirect deaths, sepsis, hypertension, and embolism are the leading causes of maternal mortality worldwide (Say et al., 2014). Specifically, it has been considered that deaths due to hemorrhage could have been avoided (Geller et al., 2014).

A significant protective factor in preventing deaths in general and maternal deaths is the availability of healthcare facilities. In the case of maternal mortality, especially during childbirth, this is a critical determinant. It significantly reduces emergency response times and ensures the availability of response equipment, operating rooms, medications, and specialized personnel. This importance of access to healthcare facilities during pregnancy has been supported by literature, confirming its effectiveness in preventing maternal and neonatal mortality (Barman et al., 2023; Buser et al., 2021; Figa-Talamanca, 1996; Rosário et al., 2019; Tounkara et al., 2022).

Despite extensive evidence on maternal mortality determinants, causal identification at sub-national levels in Latin America remains scarce. Therefore, we examine whether the opening of healthcare facilities have an impact on the reduction of maternal mortality in Ecuador between 2012 and 2023. We hypothesize that the construction of health facilities led to a causal reduction in maternal mortality in Ecuadorian parishes during 2012 and 2023.

The objective is to demonstrate a causal effect of healthcare facilities construction on the reduction of maternal mortality using an augmented probability weighting (APW)

model. The maternal mortality rate per 100 000 births is considered as the outcome variable, healthcare facilities as the treatment variable.

Hence, this study is structured as follows: In the first section, a literature review is presented, providing evidence related to maternal mortality and its determinants. Next, empirical evidence is presented. Subsequently, the sources of data are presented along with the econometric model and the results obtained. Finally, conclusions and recommendations are proposed.

Literature Review

A substantial boy of literature has examined the causes of maternal mortality, emphasizing, consistently, in the significance of access to timely obstetric care. In this respect, Figa-Talamanca (1996) established distance to healthcare as a primary determinant of maternal survival; which has been duly supported by subsequent research. These findings have been supported by subsequent research. In the same vein, other authors who have emphasized the crucial influence of distance and the decision for institutional childbirth as fundamental variables for maternal mortality (Barman et al., 2023; Buser et al., 2021; Nova Rosario et al., 2019; Tounkara et al., 2022); showing that travel distance and delays in reaching health facilities are a crucial factor that increases maternal risk.

Building on this evidence, scholars argue that the mere existence of healthcare infrastructure or their proximity to people is not sufficient to reduce maternal mortality. It is essential to consider additional factors, such as maternity waiting home strategies, which will not be analyzed in this research but should be mentioned due to their importance.

In this regard, the World Health Organization (WHO) suggests reviewing the availability of water, sanitation, and hygiene services (WASH) in healthcare facilities. These services are fundamental to ensure the effectiveness of care and treatment (World Health Organization, 2015). This proposal is supported by reports on WASH progress for 2020 and 2022 (World Health Organization, 2020a; World Health Organization & United Nations Children's Fund, 2022). In addition, the WHO has issued guidelines to verify the minimum operational requirements of healthcare facilities (World Health Organization,

2020c) in the same context. According to these organizations, there is still much room for improvement in low- and middle-income countries (United Nations Children's Fund (UNICEF) & World Health Organization (WHO), 2020).

In the same context, Paddock determined that access to clean water, healthcare facilities, a complete healthcare team including obstetricians, and the strengthening of communities' awareness are key factors for the success for the reduction of maternal and child mortality (Paddock, 2019). In parallel, the organization of the healthcare facility itself is important when providing care to a woman during the postpartum period (Saucedo et al., 2020).

Therefore, the construction of healthcare facilities and all the logistics involved in their operation must be carefully planned. In this regard, trained and appropriate healthcare personnel are necessary to avoid errors in diagnosis and treatment (Menéndez et al., 2020) and, thus, prevent and reduce the number of deaths.

From a public investment perspective, healthcare infrastructure is indeed part of government budgets. Health spending, in addition to the benefits to people's well-being, has direct economic returns on a country's growth, and vice versa (Barro, 2013; Jamison et al., 2013). This relationship becomes even stronger if state investments are made in preventing key diseases or avoidable deaths to reduce the burden of disease and increase healthy years of life (Khadka & Verguet, 2021).

Extending the benefits beyond, the construction of healthcare facilities for the population have also been shown to have positive effects on subjective well-being (SWB). This measure includes concepts of life satisfaction and happiness (Deb & Okulicz-Kozaryn, 2023). For instance, a study conducted in India demonstrated that SWB decreases when people lack access to education, healthcare facilities, and opportunities to increase their income, particularly in rural areas (Deb & Okulicz-Kozaryn, 2023).

Additionally, investment in infrastructure as part of public spending stimulates the economy to the extent that it can generate greater economic growth, it even potentially reduces the burden of debt for countries (Allen et al., 2013). The direction in which spending is focused is crucial as there are various possibilities for its use, ranging from health promotion efforts that can be consolidated in campaigns to reduce sedentary

behavior; preventive measures such as vaccines; palliative interventions for diseases prevalent in the country or region; and, responses to epidemics that must be addressed.

For instance, in extreme situations such as a pandemic, the existence of healthcare facilities, plus the human factor, and the proper functioning of technological equipment are crucial for achieving better health outcomes, as it was demonstrated during the global COVID-19 emergency (Islam et al., 2020).

Understanding ambulatory care sensitive conditions may channel the spending allocation, as it serves as a good indicator to measure the quality of access to healthcare services and whether unnecessary hospitalizations are being prevented. It does so through an index that includes the time required for care, proper patient management, treatment, and interventions (Muniz Rocha et al., 2021). However, it's not only important to have healthcare facilities but also to use them effectively. For instance, in Ecuador, this process is done through the Reference and Counter-Reference System (Ministerio de Salud Pública del Ecuador, 2013).

At the institutional level, budgets for investment in healthcare facilities, sanitation, and all the necessary resources for their proper management must adhere to public finance regulations (Gruber, 2011). Financing and government actions are necessary to ensure that the right to health is achieved by most of the population.

The concept of universal health has been widely promoted by the WHO and its affiliates. Although it, does not necessarily imply free healthcare, its goal is to expand people's access to healthcare facilities, reduce the financial burden of healthcare payments, and increase access to medicines, vaccines, diagnostics, and other benefits; by also relying in public- private partnerships (Villar Uribe et al., 2021; World Health Organization (WHO), 2020).

It has been highlighted, then, that the issue of access to health is crucial, and the presence of healthcare facilities, especially at the primary level, is fundamental to guarantee the right to health (Sacks et al., 2020). In this respect, the use of available technology, cartography, georeferencing systems, and mathematical models can be applied to measure distances and design evidence-based infrastructure policies (Issahaku Korah et al., 2023), facilitating the implementation and protection of the right to health.

Regarding social dimensions, community engagement is indispensable, especially in culturally and ethnically diverse countries like those in Latin America, where respecting each culture's worldview is essential, but safeguarding the health of all is also critical (Sacks et al., 2020). Individual decisions to seek healthcare are influenced by socio-economic determinants such as religion, place of residence, gender, age, and education level, which must be considered when designing and implementing public health policies (Pintu & Pradip, 2020).

In the case of Ecuador, a middle-income country with issues of inequality and significant cultural diversity, shows results similar to those described regarding subjective well-being (SWB). Health is fundamental to people's well-being and their performance in various activities (Acosta-González & Marcenaro-Gutiérrez, 2021).

Despite this extensive literature, causal evidence at the sub-national level remains limited. This study contributes to the literature by providing novel causal evidence using modern identification strategies.

Empirical approach

The contribution of this research to literature lies in presenting empirical evidence that demonstrates a plausible causality between the outcome and treatment variables. Such studies are often not conducted due to limitations in access to data, as illustrated by a study conducted in Mozambique (Menéndez et al., 2020).While this relationship has been studied before, our research establishes plausible causality between these variables, which adds to the literature and informs the implementation of public health policies. To achieve this, statistical birth and death records from the National Institute of Statistics and Censuses of Ecuador are utilized.

Even when healthcare facilities are equipped and reasonably accessible in terms of distance, other geographical and socioeconomic factors influence the effectiveness of healthcare spending and facility utilization (Serván-Mori et al., 2020). Individual decisions regarding their use also play a crucial role, making maternal education a fundamental barrier that can be overcome, through public policy, and through the information individuals receive when accessing healthcare facilities (Barman et al., 2023; Jakperik et al., 2023; Milkowska-shibata et al., 2020; Sohini et al., 2022). Furthermore, this barrier gets higher in multicultural and multi-ethnic countries like Ecuador, where

diversity in the worldview or culture of mothers, directly influences individual decision and perceptions of life and childbirth (Ruiz et al., 2013).

The previously cited research has employed qualitative methods, observational methods, and quantitative methods, primarily in the form of logistic regression models to explain correlations among study variables such as maternal mortality, infrastructure, education, and others. These methodologies are not typically used to establish causality.

On the other hand, there is also causal inference evidence that supports the importance of health facilities, Ramos et al. (2024) using a difference-in difference Callaway Sant'Anna estimator estimated the impact of opening public hospitals in Mexico. Their study found that the maternal mortality rate decreased by 40% through institutional deliveries.

In the same vein, Nuhu et al. (2023) estimated estimate the impact of technology for maternal and child health in Ghana, using the Augmented Probability Weighting (APW) methodology combined with multivariable modified Poisson and logistic regression models. The program aimed to increase the use of health services in some health facilities in the country. Their study found that the utilization of these services increased by 18 percentage points, 14 percentage points in facility deliveries compared to the control group districts.

For the same country, despite removing financial barriers to antenatal, delivery, and postnatal care, maternal mortality remained high. Osei et al. (2025) evaluates the impact of the fee-exemption policy on maternal health service utilization using pooled nationally representative data and the inverse probability weighting approach. Their findings are an increase in the timely first antenatal care visit, the completion of the number of suggested visits, and institutional deliveries.

The risk of maternal mortality was examined by Alves et al. (2023) in the Bolsa Família program, this is a conditional cash transfer in Brazil that requires beneficiary families to comply with specific health-related conditionalities, including regular medical check-ups. Their research examines women who received the transfer before and during pregnancy. Using a propensity score kernel matching approach, the authors find that the risk of maternal mortality was 18% lower among women who benefited from the program. Although the study does not directly analyze the role of health facilities, access

to such facilities is implicitly fundamental, as compliance with the program's health conditionalities presupposes the availability of healthcare services where beneficiaries can attend mandatory check-ups.

The Ecuadorian case is comparable to the Mexican experience in that both studies use official health facility opening dates, although they differ in the level of analysis, with this study focusing on parishes rather than municipalities. Similarly, while the Ghanaian case employs the same methodological approach, differences in health system organization imply a distinct treatment structure. Evidence from Brazil's Bolsa Família program further underscores the implicit role of health facilities in improving maternal health outcomes.

Methodology

Due to the type of data available, which comes from administrative records, and because the health facility construction intervention was relatively random at the parish level and at different points in time, the econometric approach must explicitly address this context.

Thus, we use the Double Robust (DR) estimator, also known as Augmented Inverse Probability Weighting (AIPW), proposed by Callaway & Sant'Anna (2021). This estimator is indispensable in the causal identification of the Average Treatment Effect on the Treated (ATT), the parameter of interest, or, alternatively, the aggregate ATT for each treatment cohort (group), when we are in presence of staggered treatment.

Under the methodology applied, the parameter of interest, the Average Treatment Effect on the Treated (ATT), is defined for each treatment cohort (group) g and period t:

$$ATT(g,t) = E[\,Y_t(g) - Y_t(0) \mid G = g\,] \quad (1)$$

Where $Y_t(g)$ represents the potential outcome in period t if the parish was first treated in period g, and $Y_t(0)$ is the counterfactual outcome in the absence of treatment. Equation (1) allows us to analyze how the effects of treatment evolve over time for each adoption cohort (group).

The causal identification of (1) relies on a set of assumptions organized into two complementary dimensions. First, the structural assumptions, which ensure the consistency of the empirical design: (i) irreversibility of the treatment, understood as the

impossibility of reversing the treatment condition once a parish receives the intervention, and (ii) random sampling, which assumes independence between observation units.

Second, the identification assumptions that allow the treatment effect to be consistently isolated, related to (iii) non-anticipation, where parishes do not adjust their results before the effective implementation of the treatment, i.e., the behavior of the outcome in pre-treatment periods is not affected by expectations of intervention. (iv) Conditional parallel trends which, adjusted to our context, in the absence of treatment, the expected evolution of maternal mortality would have been similar between the treated parishes and the control group, once conditioned on a set of observable covariates. And finally, (v) overlap, which refers to the fact that for every relevant combination of covariates there is a positive probability of both receiving and not receiving the treatment, which guarantees comparability between treated and untreated units. The above outlines the core identification assumptions required for the identification of (1). For more detail, see Callaway and Sant'Anna (2021).

Given these assumptions, Callaway & Sant'Anna (2021) propose six nonparametric estimators for panel data. However, in this study, $ATT(g,t)$ is modeled by comparing treated parishes (units), assuming compliance with parallel trends conditional on parishes that were never treated. Consequently, without loss of generality, the DR or AIPW estimator is used to identify (2), which combines the advantages of the OR (Outcome Regression) and IPW (Inverse Probability Weighting) methods, allowing for simultaneous integration of both.

This double correction guarantees consistency even if one of the two models is misspecified (but not both), thus providing greater robustness against modeling biases, since it allows for more efficient capture of the heterogeneity of hospital facility construction in Ecuador's parishes over different periods. Formally:

$$\widehat{\mathrm{ATT}_{dr}^{nev}}(g,t;\delta) = \frac{1}{n}\sum_{i=1}^{n}\left[\left(\frac{G_g}{\frac{1}{n}\sum_{i=1}^{n}[G_g]} - \frac{\frac{\widehat{pg}(X_i)C}{1-\widehat{pg}(X_i)}}{\frac{1}{n}\sum_{i=1}^{n}[\frac{\widehat{pg}(X_i)C}{1-\widehat{pg}(X_i)}]}\right)\left(Y_t - Y_{g-\delta-1} - \widehat{m}_{g,t,\delta}^{nev}(X)\right)\right] \quad (2)$$

Where $\widehat{ATT_{dr}^{nev}}(g,t;\delta)$ is the estimator of *Average Treatment Effect on the Treated* conditioned on the covariates (explained in the following section), with respect to the group of parishes that were never treated. G_g takes the value of one if parish i had

a hospital built for the first time $g = 2013,\ldots,2023$; zero otherwise. C is a control group indicator, taking the value of one for parishes that were never treated. $\widehat{p_g}(X_i)$ is the estimated probability of building a hospital in parish i in period g, conditional on covariates X_i. $\widehat{m}^{nev}_{g,t,\delta}(X)$ is the estimator of the expected value of the change in outcomes for parishes never treated, conditional on X_i; that is, it is the regression of the control group. $\overline{G_g}$ is the proportion of units treated in g, and $[\frac{\widehat{p_g}(X_i)C}{1-\widehat{p_g}(X_i)}]$ is the normalization of the control unit weighting, necessary to balance the control group. In this study, $t = 2012,\ldots,2023$ and $\delta = 0$ is set (no anticipation by parishes of the construction of a new hospital is assumed). In summary, the first term finds a valid counterfactual for comparing results in the treated parishes, while the second corrects for residual differences between observed and expected results in the absence of treatment.

Data and Variables

The information used to estimate the econometric model (3) and the covariates used to estimate the impact of health facilities construction on maternal mortality have various sources, as detailed in Table 1.

Table 1. Information Sources

Information	Source	Period
Healthcare services offered	Ministry of Health administrative records (upon request)	August 23, 2024
Live births	Administrative Records- Instituto Nacional de Estadística y Censos (INEC)	2012-2023
Total Deaths	Administrative Records - Instituto Nacional de Estadística y Censos (INEC)	2012-2023

Population	LandScan Oak Ridge National Laboratory	2012-2023
División político-administrativa (DPA)	Instituto Nacional de Estadística y Censos (INEC)	2019
Georeferenced spatial data	Secretaría Técnica del Comité Nacional de Límites Internos (CONALI)/Consejo Nacional Electoral (CNE)	2022

Note: Author's elaboration.

The impact analysis focuses on the construction of public health facilities by the Ministry of Health, which account for 65% of all public facilities in the country and are the driving force behind public health policy. The participation of establishments considered part of the Complementary Health Network (NGOs, SOLCA, Junta de Beneficencia) is marginal, as they represent 4% of the total number of establishments in the country (Ministry of Public Health, 2023).

Likewise, statistical records of live births and general deaths are used. Information was obtained from administrative records for the period between 2012 and 2023. We utilize the date of occurrence rather than the registration date to minimize reporting lag bias. These databases were used to consider the variables of births and maternal deaths. Maternal deaths are those coded with the letter "O" according to the International Classification of Diseases 2010 (ICD-10).

Outcome Variable

The maternal mortality outcome variable was designed in accordance with the specifications of the World Health Organization et al. (2008), which proposes two measures of maternal mortality: (i) the maternal mortality ratio, which represents the risk of maternal death in relation to the number of live births, calculated as:

$$MMR = \frac{\text{N° of Maternal Deahts}}{\text{N° of live births}} * 100\,000$$

Where MMR (Maternal Mortality Ratio) is calculated as the total number of maternal deaths per 100 000 live births, during the same period. The second measure is (ii) the maternal mortality rate, calculated as (Wilmoth et al., 2012):

$$\text{MMRate} = \frac{\text{N° of Maternal Deahts}}{\text{Woman year lived at ages } 15-49} * 100\,000$$

Where MMRate (Maternal Mortality Rate) reflects not only the risk of maternal mortality, but also the women's fertility level (Wilmoth et al., 2012). The first approximation of maternal mortality is the most common in literature and it is a national indicator as well (Anderson et al., 2016; Jayachandran et al., 2010; Wilmoth et al., 2012), therefore we use the first definition.

From this perspective, once the above has been stated, we approximate our outcome variable measured by MMR per i in each period t. In addition, we convert this variable by applying the natural logarithm, a transformation that is useful for reducing the high variation of this variable, following the work of Jayachandran et al. (2010) and Anderson et al. (2016). However, when applying a monotonic transformation, we must consider the implications this may have on the causal identification of the treatment effect.

Roth & Sant'Anna (2023) show that the parallel trends assumption, which is key to causal identification in difference-in-differences, is insensitive to monotonic transformations of the outcome variable under three scenarios: random assignment of treatment, stationarity of the distribution of Y (0) across groups, or a combination of both. In this study, the construction of health centers can be considered approximately random between treated and untreated parishes, so it is reasonable to maintain the validity of the parallel trends assumption even when the maternal mortality ratio (MMR) is transformed into logarithms.

Additionally, McConnell (2024) warns that under logarithmic transformations, the estimator $\widehat{ATT}$ may show sign changes when there are significant initial differences in the average levels of the outcome between groups, although this result is derived solely from canonical DID, where the author proposes the use of matching techniques as a strategy to

mitigate this probl(Callaway & Sant'Anna, 2021)ethodology of (Callaway & Sant'Anna, 2021) is appropriate, as it allows for the incorporation of propensity scores to reduce systematic differences between treated and untreated parishes, strengthening the validity of the causal estimator.

Covariates

In identifying equation (3), the specification is closely related to determining which covariates are necessary for a correct estimate. These allow us to determine which parish in the control group serve as a more accurate counterfactual for estimating the effects of treatment within the propensity score. In this regard, different covariates were specified to adjust (3) with respect to the context of health center construction and maternal mortality.

The total population within the polygons of each parish was included as the main covariate, given that it is a key determinant in the decision to build health infrastructure. Additionally, variables associated with the sociodemographic characteristics of mothers (proportion of mothers with primary education, single, married, mestizo, and in the age range of 15 to 36 years) were incorporated to control for unobservable heterogeneity between treatment units. These variables were constructed by multiplying the average number of mothers observed throughout the entire time horizon by the population corresponding to each parish in year t, thus allowing relevant demographic variations over time to be captured.

Results

Table 1 presents the average ATT results for each cohort for the outcome variable, natural logarithm of the maternal mortality ratio (MMR), using the Doubly Robust (AIPW) estimator by Callaway & Sant'Anna (2021) under different control specifications, classifying them with and without the inclusion of the year 2020 in the estimation. Under this methodology, there are several ways to aggregate the estimated effects for each cohort to obtain an average estimator of the treatment impact.

For our study, the aggregation is constructed using the simple average of the $ATT(g,t)$ estimators across cohorts and post-treatment periods. Specifically, each cohort-time effect receives the same weight, without additional weightings for the size of the treated group or the duration since the adoption of the treatment. This choice is appropriate in contexts with temporal heterogeneity and treatment staggering, as it

prevents early cohorts or larger groups from dominating the aggregate estimate, facilitating a transparent and comparative reading of the effects over time.

We observe substantial heterogeneity in the estimated effects depending on when the treatment was applied, both in terms of statistical significance and direction, suggesting that the effectiveness of the intervention varies between cohorts and depends on the specific context of each parish. For the specifications including the year 2020, it can be observed that, without the inclusion of controls (1), only the year 2013 has a significant effect; however, the other cohorts show a positive sign, which was not expected in our study, and furthermore, these results are not significant. In specification (2), with the inclusion of controls that attempt to model the conditions under which a parish could be subject to treatment, no point in the treatment shows a consistent significant effect. For specification (3), the controls are much more robust to both variables, the treatment and the control, where we specify more broadly the number of mothers of childbearing age at each moment t, where we find a greater number of years with negative treatment effects, in particular, the estimated ATT for 2017 maintains a negative and highly significant coefficient (-0.304**), demonstrating that the construction of health facilities in this period resulted in an efficient decrease in the MMR per parish.

However, the exogenous shock of the COVID-19 pandemic significantly altered health service provision, which directly affected the outcome variable, as well as the functioning of the health service provision and access system (Roberton et al., 2020; World Health Organization, 2020b). Consequently, the inclusion of this period could introduce a heterogeneous bias in the estimation, compromising the fundamental assumption of causal identification of this methodology: the validity of parallel trends between the treated and control groups.

Having explained the rationale for excluding 2020 from our main specification, specifications (4), (5), and (6) respond differently to the results presented above. Similarly, for the results under specification (4), controls are excluded from the estimation, where, in general, it is worth mentioning that the standard errors decrease significantly compared to the model with 2020 included. The significance of the effect of health facility construction shows the same dynamics, with only 2013 having a negative and significant magnitude (-0.240**).

After controlling unobservable heterogeneity within the individual trends of each parish, a more consistent dynamic is observed between control and treatment groups in terms of overall cohort effects.

In specification (5), we find a significant and negative effect for two specific points in time, where for 2014, the construction of health facilities is associated with an approximate 26.6% reduction in the maternal mortality ratio (MMR) for the corresponding cohort, compared to the control group, demonstrating high effectiveness in the application of the treatment. For 2017, a negative and significant effect is also observed, where the estimated coefficient of −0.221 indicates that the intervention is associated with an approximate 22% reduction in the maternal mortality ratio, similarly showing an effective reduction in maternal mortality for those belonging to this cohort.

For the last specification (6), under the application of much more robust controls in terms of maternal mortality due to the number of mothers of childbearing age within each parish, we find results like the previous ones, although with smaller standard errors, demonstrating that the inclusion of these covariates better controls the estimate. As in (5), the years 2014 and 2017 show negative and significant effects on treatment. Specifically, the estimated average ATT value for the cohort treated in 2014 is -0.245, which translates into an approximately 24.5% decrease in the maternal mortality ratio. For 2017, the construction of health facilities reduces the maternal mortality ratio approximately by 34.8%. These results are consistent with the estimates obtained under the inclusion of covariates. On average, the construction of health facilities reduced maternal mortality in these two periods.

Table 2. Mean ATT results by cohort

Cohort	Dependent Variable: ln(MMR)					
	With 2020			Without 2020		
	(1)	(2)	(3)	(4)	(5)	(6)
2013	-0.231**	-0.325	-0.319	-0.240**	-0.333	-0.323
	(0.110)	(0.257)	(0.275)	(0.116)	(0.264)	(0.279)
2014	0.003	-0.156	-0.139	-0.107	-0.266**	-0.245**
	(0.113)	(0.121)	(0.112)	(0.093)	(0.116)	(0.097)
2015	0.350	0.320	0.264	0.280	0.251	0.201
	(0.377)	(0.276)	(0.332)	(0.318)	(0.218)	(0.278)
2016	-0.046	-0.047	-0.077	-0.047	-0.051	-0.077
	(0.099)	(0.050)	(0.070)	(0.097)	(0.051)	(0.069)
2017	0.091	-0.169	-0.304**	0.048	-0.221*	-0.348**
	(0.116)	(0.124)	(0.150)	(0.112)	(0.115)	(0.140)
2018	0.655	0.684	0.759	0.774	0.798	0.883
	(0.496)	(0.514)	(0.542)	(0.594)	(0.609)	(0.637)
2019	0.116	0.227	0.005	0.120	0.222	0.009
	(0.078)	(0.261)	(0.158)	(0.078)	(0.259)	(0.158)
2022	-0.024	-0.002	-0.011	-0.024	-0.002	-0.011
	(0.057)	(0.009)	(0.009)	(0.057)	(0.009)	(0.009)
Controls 1		X			X	
Controls 2			X			X

Note: The estimator used to obtain these results is Doubly Robust (DR) or Augmented Inverse Probability Weighting (AIPW). Covariates included at the parish level in the specification of controls (1) are: total population and average proportions of women who gave birth in each year t, classified according to marital status (unmarried), educational level (secondary education), ethnicity (indigenous), and age range (15 to 35 years). The specification of controls (2) incorporates: total population, average proportions of women who gave birth in each year t, segmented by educational level (primary education), marital status (single and married), ethnicity (mestizo), and alternative age ranges (15–19 and over 36 years). Approximate standard errors by Bootstrap and adjusted by clusters at the parish level, in parentheses. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In terms of reviewing the parallel trends assumption for the results presented above, this is shown graphically in Appendix 1, where the dynamic effects of the treatment for each cohort were obtained for each cohort. In this regard, event-study graphs 2A and 5A, for the 2014 and 2017 cohorts, respectively, provide consistent empirical evidence in favor of the conditional parallel trend assumption, a key condition for the causal validity of the estimator. For these two cases, the coefficients for the pre-treatment period are statistically indistinguishable from zero and do not exhibit a systematic trend prior to the start of treatment, i.e., no persistent increasing or decreasing pattern is observed in the *ATT(g,t)* estimators before year g. This suggests that, in the absence of treatment, the evolution of the MMR in the treated units would have followed a similar trajectory to that of the comparison group.

Additionally, the absence of anticipatory effects in the dynamics of the effects reinforces the causal interpretation of the results. In contrast, starting in the year of treatment, a persistent change in the post-treatment coefficients is observed, which systematically moves away from zero and exhibits consistent dynamics over time. This temporal discontinuity between the pre- and post-periods reinforces the interpretation that the estimated effects respond to the treatment and not to previous structural differences between groups.

In summary, the stability of the pre-treatment coefficients and the absence of divergent trends provide graphical evidence in support of the conditional parallel trends assumption. This evidence is consistent with the estimated treatment effects.

Table 3. Dynamics ATT's per period

Exposition	ATT
-9	-0.009 (0.006)
-8	-0.015 (0.018)
-7	0.007 (0.023)
-6	0.015 (0.024)
-5	1.452 (1.363)
-4	-0.370 (0.490)

-3	0.294 (0.446)
-2	-0.295 (0.410)
-1	-0.238 (0.203)
0	0.254 (0.260)
1	-0.248*** (0.089)
2	-0.115 (0.161)
3	-0.144 (0.116)
4	-0.260** (0.112)
5	-0.362*** (0.107)
6	-0.338*** (0.124)
7	0.049 (0.248)
8	-0.308** (0.125)
9	-0.517* (0.280)
10	-0.841 (0.749)

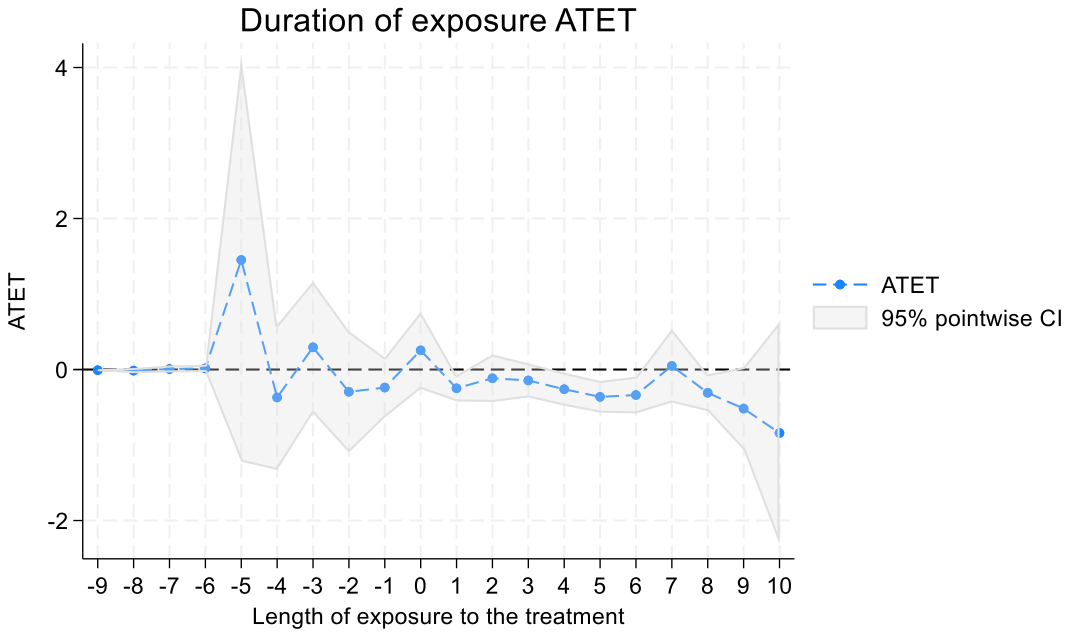
Nota. Standard errors in parenthesis. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table 3 summarizes the dynamic estimators of the average treatment effect on the treated (ATT) based on the number of periods elapsed since the construction of sanitation facilities. For the periods prior to the intervention (exposure -9 to -1), most of the estimated coefficients are small, statistically insignificant, and close to zero, which supports the validity of the parallel trends assumption and suggests the absence of pre-treatment effects.

For the post-treatment periods, the estimated effects become negative and statistically significant at various points in time depending on exposure to the intervention. In particular, the estimated coefficient for period 1 (−0.248) implies an approximate 24% reduction in the MMR. This effect intensifies in subsequent periods, reaching reductions of close to 26% in period 4, 36% in period 5, 33% in period 6, 30% in period 8, and 51% in period 9 with relative statistical significance. These results suggest that the impact of health facilities construction is not immediate but accumulates

over time, consistent with a gradual process of consolidation of access and effective use of health services. Similarly, these statements are graphically validated in Figure 1, which shows this downward trend in maternal mortality rates for the purposes of health facilities construction according to duration of exposure.

Graph 1. Dynamic ATT due to treatment exposure



Note. The figure shows the $ATT\ (g,\ t)$ estimators aggregated by duration of exposure to treatment. The 95%-point confidence intervals are constructed from robust cluster-adjusted standard errors. The inference is performed on a point-by-point basis for each period; a coefficient is considered statistically significant when its confidence interval does not contain the value zero.

Conclusions

This study analyzed the causal effect of healthcare facility construction on maternal mortality at the parish level, using the natural logarithm of the maternal mortality ratio (MMR) as the dependent variable and applying the Doubly Robust estimator (AIPW) proposed by Callaway & Sant'Anna (2021) in a context of staggered treatment adoption. Empirical evidence shows clear temporal heterogeneity and heterogeneity between treatment moments, which justifies the use of methodologies that address these implications to avoid potentially biased estimates. Overall, the results suggest that the effectiveness of healthcare infrastructure is not homogeneous over time and that it depends critically on the moment of implementation and the context in which it is developed.

The aggregate results by cohort show that, excluding 2020, which was affected by an exogenous shock associated with the COVID-19 pandemic, negative and statistically significant effects emerge for the groups treated in 2014 and 2017, particularly under specifications with more robust controls. Given that the dependent variable is in logarithms, these estimated coefficients are interpreted as percentage reductions in the maternal mortality ratio, implying that the construction of health facilities reduced maternal mortality by approximately 25% for the 2014 cohort and between 22% and 35% for the 2017 cohort, depending on the specification. The consistency of the results across different control structures validates the robustness of the findings and suggests the substantive impact of the construction of health facilities in these specific periods.

Cohort-specific event studies provide graphical evidence in support of the conditional parallel trends assumption, a fundamental requirement for causal identification. In particular, for the 2014 and 2017 cohorts, pre-treatment estimates are statistically indistinguishable from zero and show no systematic trends prior to treatment.

Finally, dynamic analysis by duration of exposure showed that the impact of treatment is not immediate, but rather accumulates progressively over time, with increasingly greater reductions in MMR as the number of periods of exposure increases. This process is consistent with a gradual process of consolidating access to maternal health services and improvements in the efficiency of care. Overall, the results suggest that investment in health infrastructure is an effective public policy for reducing maternal mortality, if it is evaluated in conjunction with its temporal dynamics, heterogeneity of effects, and the contexts in which it is implemented.

Disclosure

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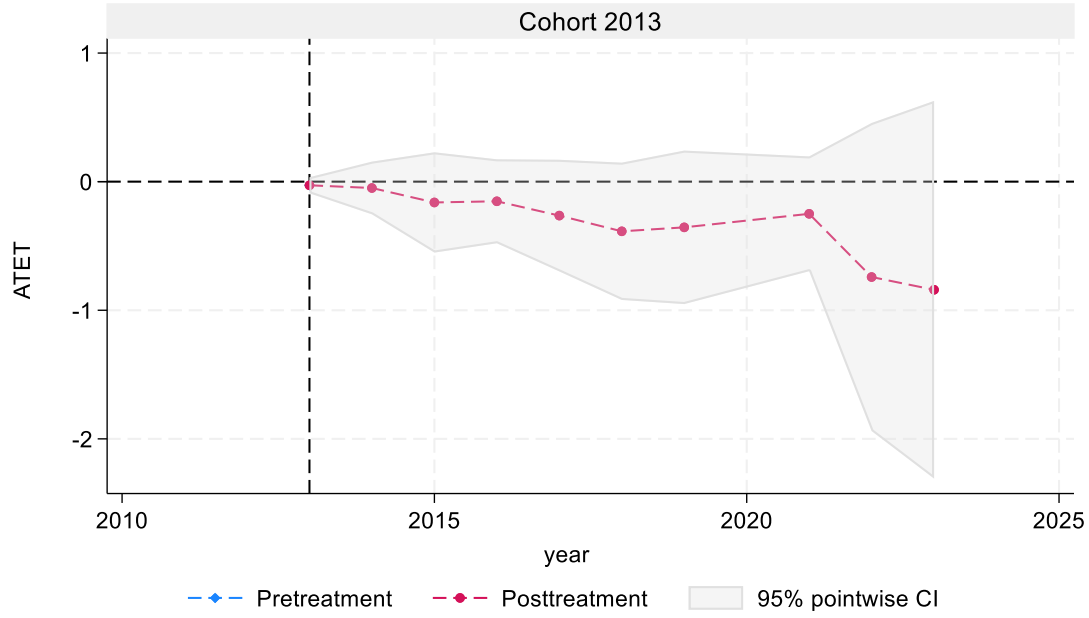
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Appendix 1

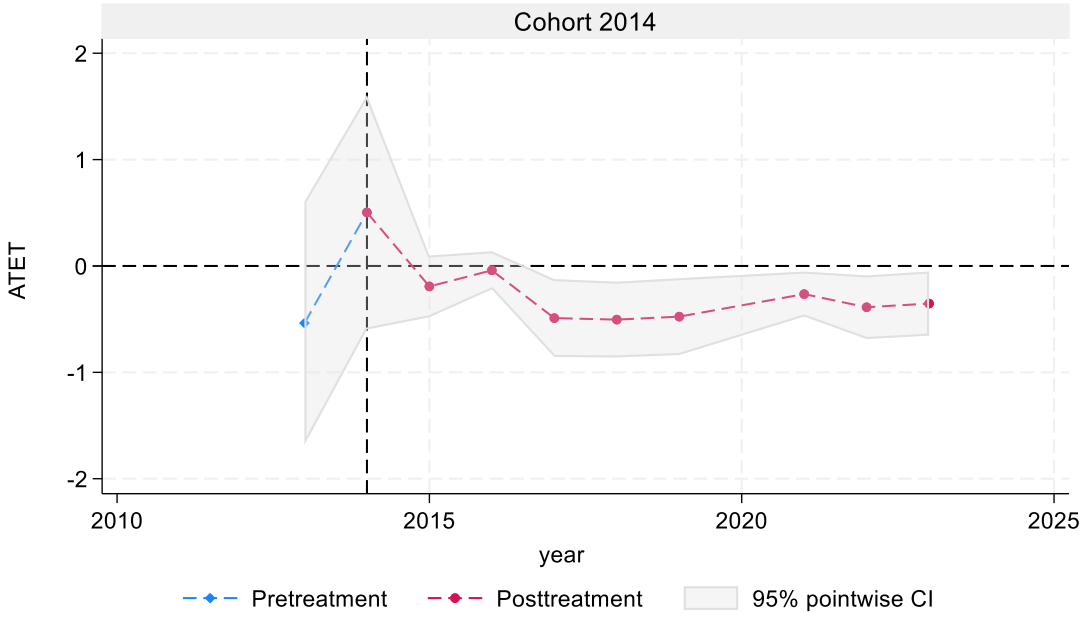
This section graphically shows the dynamic effects of hospital facility construction for each cohort g at each point in time t. In general, the effect is considered significant if the confidence interval does not include the value zero. To support the assumption of parallel trends, the coefficients estimated before treatment must show insignificant dynamics; therefore, such confidence intervals must include zero, which means that the differences between the pre-treatment trends in the maternal mortality ratio (MMR) for parishes that did not have hospital services built and parishes that did see this intervention are similar.

Graph 1A. Event study of the effect of treatment on MMR – 2013 cohort



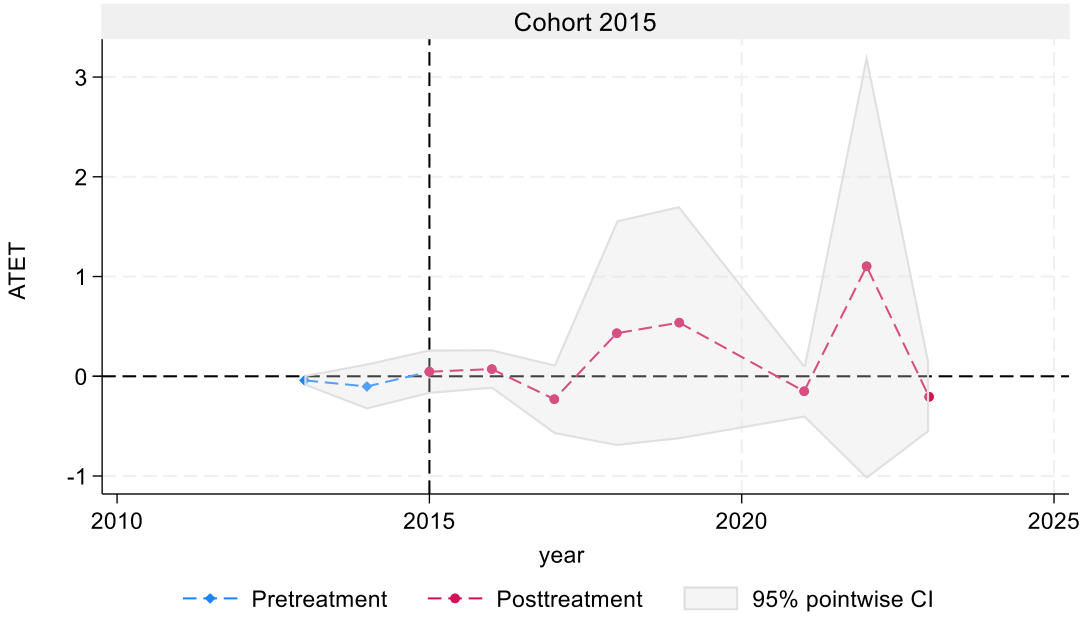
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 2A. Event study of the effect of treatment on MMR – Cohort 2014



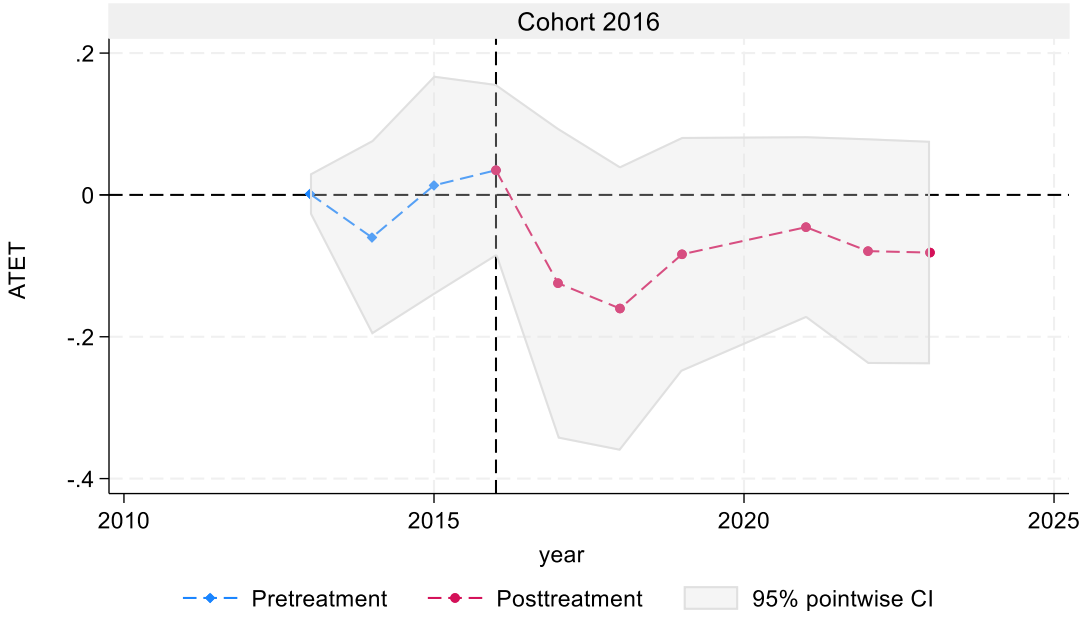
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 3A. Event study of the effect of treatment on MMR – Cohort 2015



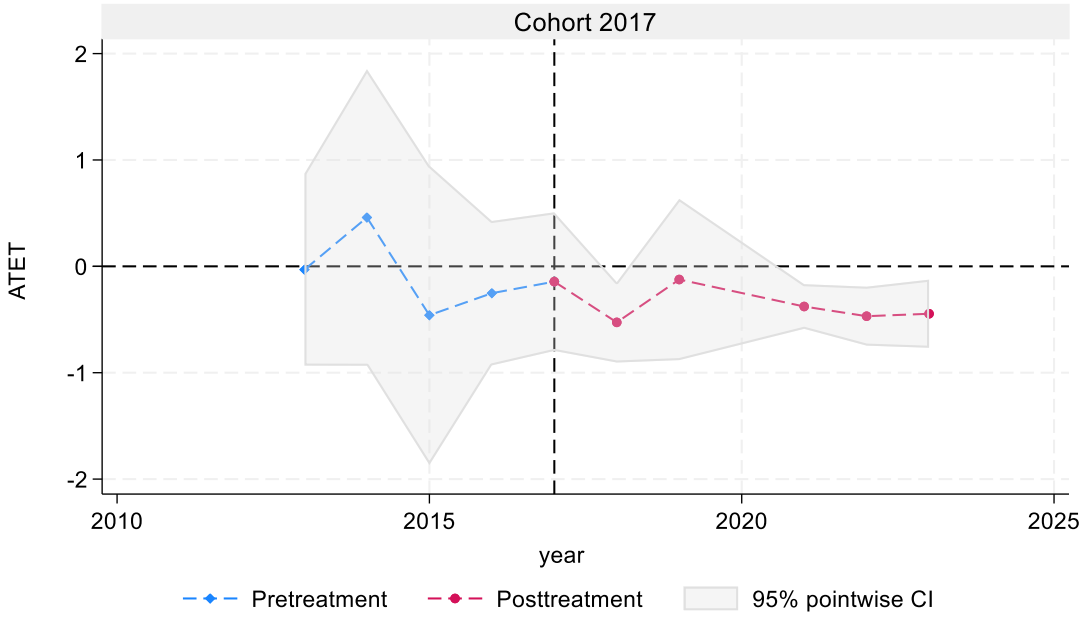
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 4A. Event study of the effect of treatment on MMR – Cohort 2016



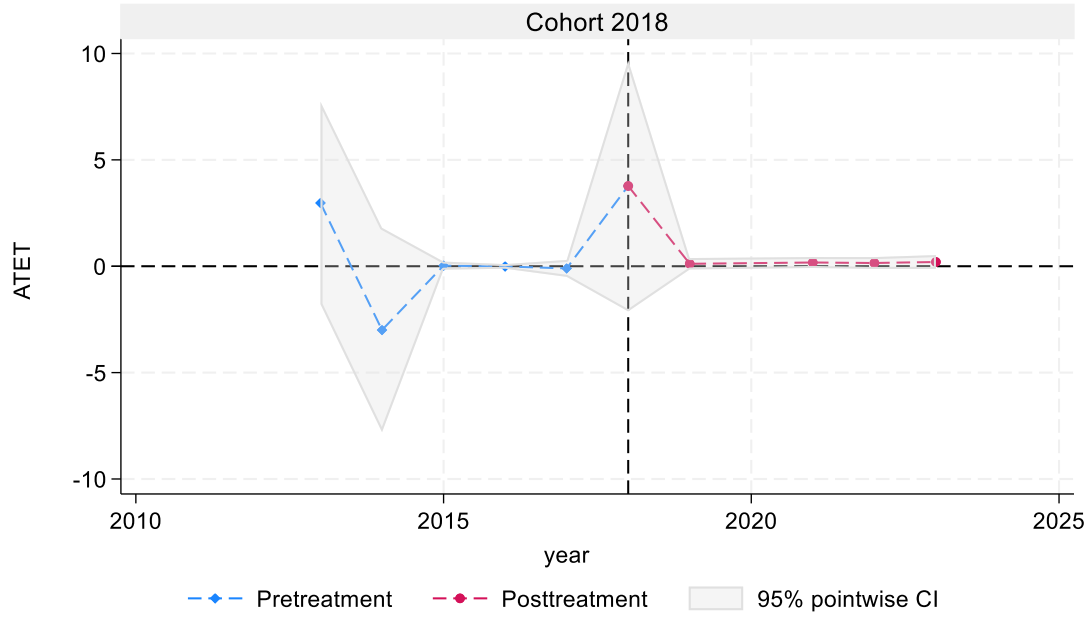
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 5A. Event study of the effect of treatment on MMR – Cohort 2017



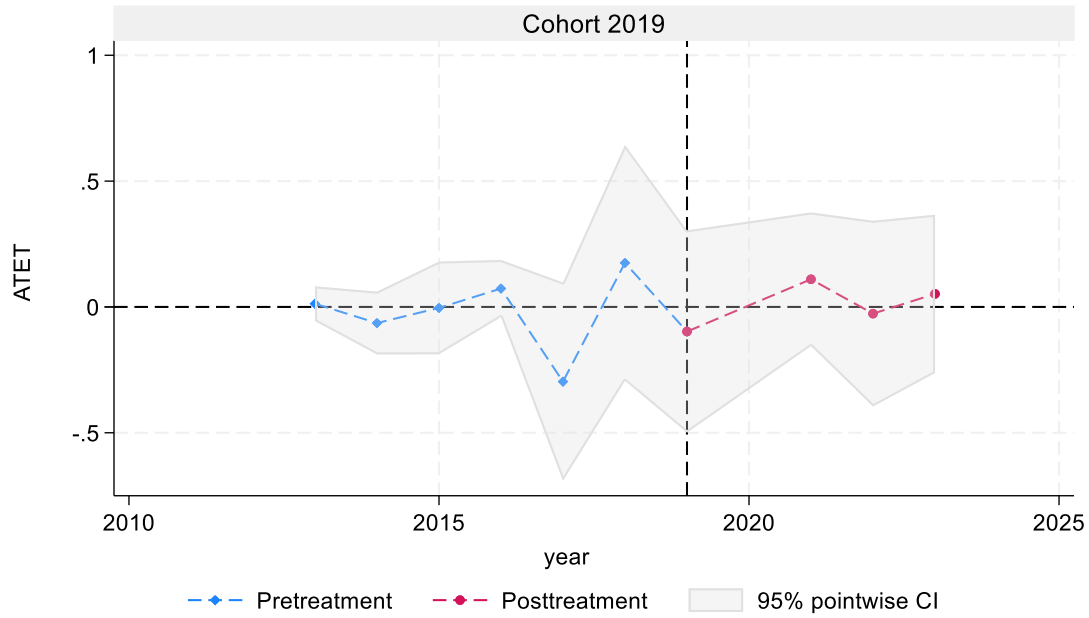
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 6A. Event study of the effect of treatment on MMR – Cohort 2018



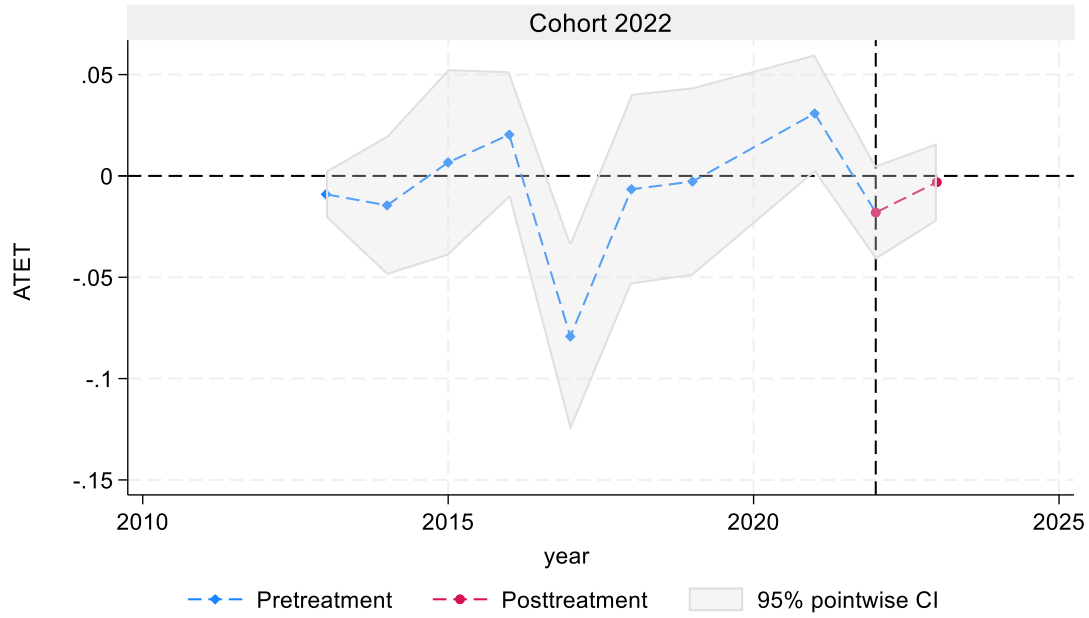
Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 7A. Event study of the effect of treatment on MMR – Cohort 2019



Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.

Graph 8A. Event study of the effect of treatment on MMR – Cohort 2022



Note. The graph corresponds to an event study that reports the estimators $ATT\ (g,\ t)$ under specification (6), normalized with respect to the base period prior to treatment. The inference is performed on a point-by-point basis for each period, using robust standard errors adjusted by cluster.