Unequal Beginnings: Health Reform and Prenatal Care Disparities in Colombia

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Abstract

This paper investigates the impact of two major health reforms in Colombia—the 2011 Law 1438 and the Unification of Benefits Plans implemented between 2009 and 2012—on disparities in prenatal care utilization and birth outcomes. Colombia's managed competition system ensures universal coverage through mandatory enrollment in either a contributory scheme for formal workers or a subsidized scheme for low-income, informal-sector populations. Using individual-level data on births and fetal deaths from 2008 to 2015, I find that the reforms narrowed the prenatal care gap between insurance schemes by 3 to 4%, with effects varying across rural contexts. Instrumented logistic models predict that prenatal visits increase the probability of normal weight and length at birth, with effects of up to 5 percentage points. A municipality-level panel data analysis further suggests that one additional prenatal visit lowers fetal mortality from specific causes by up to 3%. Lastly, higher insurer concentration decreases care utilization in the contributory scheme but improves it in the subsidized scheme. A back-of-the-envelope calculation suggests that the treatment effect of the reforms is associated with an annual social value of approximately $290 million USD. These findings offer novel evidence on the interaction between insurance design, policy reform, and preventive care in a regulated competition framework.

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1 Introduction/ Research Question

I aim to explore how the expansion of healthcare, market design, and insurer power affect the availability and use of prenatal care in Colombia. I will focus on studying two policy decrees implemented from 2008-2012 in the Colombian healthcare system, quantifying the effect they had on the utilization of prenatal care among rural populations and low-income individuals throughout the country. Specifically, the research asks: How does the institutional and structural expansion of the Colombian healthcare system influence utilization of preventive services and health outcomes in underserved populations and regions?

2 Introduction and Institutional Background

The Colombian healthcare system, established by Law 100 of 1993, operates under a managed competition model designed to achieve universal coverage and reduce disparities in healthcare access. Before its implementation, less than a quarter of Colombians had health insurance, and the poor faced significant barriers to accessing healthcare, including high out-of-pocket expenses. I will provide an outline of the relevant ways in which the Law 100 modified healthcare access in Colombia. Specifically, I will focus on the introduction of a dual system of contributory and subsidized schemes, funded by payroll contributions and government subsidies, allowing individuals to pick their insurer.

2.1 Colombian Health Insurance Design

The Colombian Healthcare system, which is a managed competition model, was established in 1993 by the Law 100. Prior to 1993, coverage was such that less than 4% of the population had insurer choice. Although public hospitals were supposed to primarily serve the poor and provide free medical treatment to uninsured people, only 20% of admissions to public hospitals corresponded to the population in the poorest quintile and 91% of the poorest hospitalized patients faced out-of-pocket expenses (Interamerican Development Bank, 2010).

The "welfare" story gets even more heterogeneous when considering the realities faced by the population in rural areas: in 2017, 50 years of armed conflict had led to the second highest amount of internally displayed people in the world (UN News, 2017), weak institutions, lack of access to services and poor infrastructure, an inaccessible geography, among others. While many health indicators have improved since the 1993 creation of the healthcare system, individuals in rural areas continue to face multiple health disparities when compared to their urban counterparts: (1) teenage pregnancy is twice as high in rural areas; (2) infant mortality was around 30% higher in rural areas by 2015 and did not decrease in rural areas from 2010-2015; and (3) human capital associated to medicine was also significantly lower in rural areas. In 2016, doctor density in rural areas was 13.2 per 10,000 inhabitants, falling short of the 31.9 doctors per 10,000 inhabitants in urban areas (Plan Nacional de Salud Rural, 2018).

The Law 100 of 1993 was part of a movement of socially-progressive policies that followed the establishment of a Social Rule of Law through the 1991 Constitution. The Law 100 created a Social Security system under which both a pension and a healthcare system were established, and there was a policy intent to reduce disparities in access to basic services. The healthcare system established aim to achieve universal coverage through mandatory enrollment. To achieve this, the system was divided into a contributory scheme (CS) and a subsidized scheme (SS).

The contributory scheme covers around 50% of the population (even though it was aimed to cover 60% of the population by 2010), namely all employees, self-employed individuals and pensioners who have a monthly income equal to or greater than the minimum salary and contribute to the system through a 12% payroll contribution. The national minimum salary is a legally mandated wage floor set annually through negotiations between the government, employers, and labor unions, aimed at ensuring a basic standard of living for workers. The subsidized scheme covers people whose income is less than the minimum salary and also vulnerable individuals such as internally displaced people (IDP), orphans, indigenous communities and other ethnic minorities. These individuals do not contribute financially to the system, unlike those in the contributory scheme, and they enroll by completing an affiliation form where they choose an insurer (EPS) that works within their municipality. Thus, the system is funded by tax contributions from individuals in the contributory system, as well as both fiscal and parafiscal contributions from the State.

It is important to highlight that there are two groups of individuals that do not fall under either scheme, which comprise around 7.5% of the country's population across the period of study. Firstly, there is a group of individuals that fall under the special scheme, which consists of certain public servants in the defense, education, and energy sectors. By 2022, 4.2% of the population belonged to the special scheme. Secondly, there are individuals who are not registered in the Social Security system and are thus effectively uninsured.

According to a poll conducted by the National Administrative Department of Statistics (DANE) in 2013, 26% of the uninsured individuals are in the process of enrollment, and 31 % of uninsured individuals claim that either (1) there is too much paperwork, (2) they are not interested in getting insured, or (3) they were unaware that they had to do so. By 2013, 3.4% of the population was uninsured, and by December 2022, this percentage dropped to 0.8% (Ministry of Health, 2022). My paper will drop the uninsured population and those in the special scheme for the analysis of prenatal care evolution in rural areas and when studying the impact of policies changing the provisions of health services across insurance schemes.

Individuals across both main schemes have the right to pick their insurer, choosing from a variety of Health Promotion Entities (EPS) with different provider networks. All enrollees are recipients of a basic Benefits Plan. From 1993 to 2007, individuals in the contributory scheme had access to a more comprehensive universal plan. After a transition period from 2008-2012, the Benefits Plans for both schemes were unified. EPS are responsible for managing healthcare delivery, which involves contracting with healthcare providers (IPS) and ensuring that individuals receive the covered medical services. The intent behind allowing individuals to choose their insurer is to foster competition among EPSs, incentivizing them to improve the quality and efficiency of the offered services. Unlike the US healthcare system, insurers do not compete over (1) premiums; (2) coinsurance rates ; or (3) copays since these are set by the government and are homogeneous across all EPS and IPS. More specifically, insurance premiums are zero (not to be confused with payroll contributions in the CS), and co-insurance rates and copays in the CS are standardized by the government making them a function of the individual's income. This implies that insurers compete with each other through their network breadth and quality of the service provided.

2.2 Vertical Integration and Healthcare Expansion

In the Colombian healthcare system, vertical integration has been a significant topic of debate and regulation, particularly influenced by laws such as Law 1122 of 2007. This law explicitly addressed the issue of vertical integration by limiting the extent to which EPS (Health Promotion Entities) could provide services through their own network of IPS (Health Service Providers). Specifically, the law mandated that EPS could not offer more than 30% of health services through their own facilities, requiring them to contract with external IPS for the majority of services. This law also enforced that 60% of health services from the SS should be contracted with public hospitals.

Since there are no insurance premiums, insurers receive capitation payments from the government, adjusted for risk. More specifically, the government fixes a Unitary Payment for Capitation (UPC) at the beginning of each year, which corresponds to the transfer the government makes to insurers to finance the treatments covered under the Health Benefits Plan (HBP). This payment is intended to cover the cost of healthcare services, regardless of the actual services provided to the individual, and is thus adjusted for three factors: (1) age; (2) sex ; and (3) region. As a result, any efficiencies achieved through vertical integration do not directly translate into lower premiums or greater market share, since insurers do not compete on price. Instead, these efficiencies may lead to improvements in the quality of care, for instance by freeing up resources to focus on preventive measures, as well as standardizing procedures given the constraints of the fixed UPC payment system. The unique structure of insurer competition in the Colombian healthcare system, and the fact that lack of insurance coverage is not the main source of regional asymmetries, implies that quality and accessibility of health services are important dimensions in which the healthcare system design impacts health outcomes.

In this context, it is relevant to understand how the expansion (and contraction) of the healthcare system has affected the geographic and social asymmetries of key health indicators across the territory. Considering the incentives to vertically integrate is fundamental for understanding the channels through which insurance dynamics affect regional variations in health outcomes. Aside from the restrictions on vertical integration, the State also has the ability to intervene or terminate insurers when they fail to meet quality standards, financial solvency requirements, or when they engage in practices that jeopardize patient safety and access to services. The National Health Superintendency (Supersalud) is the government agency responsible for overseeing and regulating the country's healthcare system, ensuring that healthcare providers, insurers, and other entities comply with the laws and policies governing healthcare delivery. This regulatory power enables the government to enforce accountability and promote practices that encourage insurers to operate in a manner that prioritizes the health and well-being of enrollees. Over the last 20 years, over 100 insurers, varying over market power, have been terminated by the State. For instance, in 2015, SaludCoop, an insurer with 20% of all enrollees in the system, was terminated by the State. More recently, in 2022, CafeSalud, who had around 4% of enrollees, was also terminated.

While the State has managed transfers of enrollees differently on each occasion, it has been customary for enrollees to be transferred to an incumbent insurer for a set period of time, and after this, they can switch to their insurer of preference within their insurance scheme.

3 Focus and Literature Review

The Colombian healthcare system offers a unique case to examine the interplay between insurance design, policy interventions, and preventive care access. Despite progress since the introduction of Law 100 in 1993, significant gaps in access persist, particularly in rural areas and for populations under the subsidized scheme. These gaps are especially evident in preventive services like prenatal care, which have both immediate and long-term implications for health outcomes.

This paper focuses on two critical policy interventions aimed at addressing these disparities: the expansion of the services to rural areas under Law 1438 of 2011 and the Unification of the Health Benefits Plans. The 2011 Law sought to strengthen the healthcare system by prioritizing services like prenatal care and addressing systemic health inequities. Meanwhile, the gradual unification of benefits from 2008 to 2012 aimed to reduce barriers to specialized care for individuals under the subsidized scheme, aiming to close the gap between the contributory and subsidized schemes.

3.1 Focus on Preventive Care in Rural Areas

From both an Industrial Organization (IO) and Micro-Development perspective, there has been limited focus on the effects of insurance dynamics on rural preventive care access in developing countries. Prenatal care is a particularly compelling aspect of preventive care because it helps reduce the need for costly medical interventions, starting from gestation and extending to later treatments such as complicated deliveries, neonatal intensive care utilization, and long-term management of preventable conditions like low birth weight, developmental delays, and maternal complications. Predicted poor health outcomes for vulnerable populations, conditional on low resources for disease treatment, can be improved if quality preventive care is provided. While this paper does not aim to quantify the quality of prenatal care, it assumes that, given its low cost and substantial benefits compared to its counterfactual (no or low monitoring of pregnancy), it offers a high return on investment. The expansion of prenatal care is also politically significant, as it signals that a society cares about the survival and well-being of its citizens.

3.2 Focus on Law 1438 of 2011

The expansion of health services (2011 Law), establishing preferential attention for prenatal services across the country will be one of my two policies of interest in studying the effects of insurance dynamics on preventive care access.

The law, passed by Congress, was established with the general intent of strengthening the healthcare system. Among the primary goals of this law were: (1) reducing prevalence in perinatal, maternal, and infant morbidity and mortality, (2) decreasing the incidence of public health-related diseases, (3) lowering the incidence of chronic non-communicable diseases and, more generally, diseases that are precursors to high-cost health events, (4) reducing the prevalence of communicable diseases, including immunopreventable diseases, and (5) ensuring effective access to healthcare services (Ministerio de Salud, 2011).

3.3 Focus on the Unification of the Health Benefits Plans (HBP)

The second policy I am interested in studying in regards to healthcare expansion is the unification of the Health Benefits Plans across both schemes. From 1993 to 2008, the subsidized scheme Benefits Plan excluded over 2,000 medications, procedures, and specialized health services that the contributory scheme affiliates had access to. In 2008, the Constitutional Court, through Sentence T-760, declared the disparities in Health Benefits between the two schemes unconstitutional, asserting that the significant access barriers faced by individuals in the subsidized scheme violated the State's constitutional obligation to ensure the right to health equally for all citizens. The Court ordered the State to "adopt a program and a schedule for the gradual and sustainable unification of the Benefits Plans of the contributive scheme and the subsidized scheme by February 2009, taking into account: (i) the population's priorities based on epidemiological studies, (ii) the financial sustainability of the coverage expansion and its financing through the UPC and other funding sources provided for under the current system (Colombian Constitutional Court, 2008)."

In 2009, the State, through the Commission of Health Regulation (CRS), presented a schedule for the gradual unification of health benefits across the contributive and subsidized schemes. This process was carried out through a series of agreements that extended the unified Health Benefits Plan to different age groups, achieving complete unification before

2013 through the following schedule:

1. Agreement 04 of 2009: Unified the plans for children aged 0 to 12 years.

2. Agreement 011 of 2010: Extended the unification to children and adolescents under 18 years old.

3. Agreement 027 of 2011: Unified the plans for adults aged 60 and older.

4. Agreement 032 of 2012: Completed the unification by including adults aged 18 to 59 years.

After the unification of the Health Benefits Plans, affiliates in the subsidized scheme gained access to the expanded range of services, no longer required Health Secretary authorizations for specialist visits or follow-ups, and could receive direct referrals from the ER to specialists in cases like pediatrics and obstetrics, bypassing general practitioners. Patients also gained access to hospitalizations in Intensive Care Units (ICUs) and continuity of diagnosis and treatment from specialists under the insurers (EPS).

The investment required to achieve the unification corresponded to an important share of the Colombia's health budget. According to the Ministry of Health (2012), there was a monthly budget of 120,000,000,000 COP (27.5 Million USD in 2025) allocated to the Unification of the Health Benefits Plans which, when annualized, corresponded to 12.6% of the total health budget in 2012. This occurred in a context where the rapid expansion of the subsidized population placed massive pressure on public finances. As Lamprea and García (2016) point out, by 2011, "68% of the funds used to finance the subsidized scheme came from public sources," mostly through national transfers to local governments, while only 25% came from payroll taxes, and municipalities themselves contributed just 1%. From 2003 to 2009, health expenditures for the subsidized scheme averaged 1.1% of GDP annually, despite payroll taxes for the contributory scheme reaching 2.2%. This fiscal architecture reveals the underlying tension between the policy ambition of universal access and the structural fragility of its financing model. As such, this policy implied an important financial effort with the intent of increasing healthcare access and outcomes for poor and vulnerable individuals.

Given the gradual nature of this policy, I will study its effect on the dynamics of access to prenatal care across both schemes.

3.4 Literature Review

Focusing on Colombia, papers like Serna and McNamara (2024), and Gamba (2023) have examined the effects of different healthcare payment models, including fee-for-service and capitation contracts, established from 2010 to 2015 on different health outcomes (e.g., C-sections and birth outcomes). These studies leverage variations in insurer-hospital payment structures and policy changes, such as government regulations allowing extended dependent coverage for young adults under parental insurance.

Likewise, studies that have focused on understanding the impact of vertical integration on health in Colombia, (Serna, 2024) have focused on its effect of health market outcomes – namely utilization, contract type choice (capitation or fee-for service), and impact on prices.

According to a Healthcare IO literature review done by NBER (2023), most of the healthcare economics papers regarding vertical integration in healthcare markets consider integration between types of providers: e.g., primary care practitioners and hospitals; or primary care practitioners and specialists. There is also a very small literature analyzing the effects of integration between insurers and providers.

When studying regulated competition markets, like Colombia's, most papers have focused on studying Medicare within the US Healthcare System. These papers have focused on understanding the effects of (1) subsidies, (2) risk-adjustment transfers, and (3) contract generosity. Ellis and Layton (2014) and Geruso and Layton (2017) provide a conceptual framework for understanding the implications of ex-ante and ex-post risk-adjustment transfers.

Through my paper, I aim to offer a novel perspective on how insurance structure and policy design interact with geography and market concentration to shape the distributional effects of two reforms, as well as subsequent health outcomes. By examining the impact of policies aimed at expanding healthcare coverage, such as the 2011 Law and the Unification of the Benefits Plans, I seek to understand how these reforms have addressed asymmetries in care access. This analysis contributes to the broader discussion on healthcare equity, extremely present in Colombia's political arena, adding nuance to the effects of some of the most important policy interventions in regulated competition markets like Colombia's.

4 Model

In this section I discuss the models I plan to implement to study the effect of institutional policies on (1) the utilization of prenatal services and on (2) health outcomes at birth. I will also develop a (3) panel data, municipal-level model relating fetal mortality to prenatal care.

When focusing on (1), I will consider two standard different difference-in-differences (DiD) models (one for each institutional policy), using prenatal visits as the dependent variable. The treatment effect will be given by the interaction of a dummy variable for the year-month combination when the policy was enacted, and a categorical variable containing information for insurer scheme or rurality category. I will include municipality and year-fixed effects in these models. Additionally, I will consider a staggered difference-in-differences (DiD) model for the Unification of Benefits Plans policy, exploiting the implementation of the treatment at different time periods for different age groups. To implement this model, I consider a special parallel trends assumption, which bases the control group not only on never-treated units, but also on not-yet treated units.

To conduct the analysis on (2), I will consider different DiD–Instrumental Variable (DDIV) models using three different health outcomes at birth as the dependent variable. More specifically, I will be using weight at birth, length at birth, and gestation time (length from conception to birth) as the dependent variables. Since I want to study the effect of prenatal visits on these health outcomes while accounting for potential endogeneity, I will instrument prenatal visits using the policy-driven variation in treatment exposure captured by the Difference-in-Differences (DiD) framework. Specifically, I will use the interaction term $\mathbb{1}_{\{t \geq x\}} \times Treated_i$ as the instrument for prenatal visits, leveraging the exogenous shift in access to prenatal care induced by the insurance reform. Notice that this approach implies using the DiD equation in (1) (with prenatal visits as the dependent variable, and a health reform as treatment) as the first-stage for the reduced form regression with health outcomes as the dependent variable. This follows the standard DDIV structure, where the first stage estimates the effect of the policy on prenatal visits, and the second stage uses the predicted values to estimate their causal effect on birth outcomes. Since $Post \times Treated$ serves as a natural instrument under the assumption that the policy change is exogenous to individual unobserved characteristics, an additional instrument Z_{it} is not necessary unless there are concerns about instrument strength or confounding. This approach allows me to identify the causal impact of prenatal visits while controlling for selection bias and omitted variable concerns within a quasi-experimental framework. [0]

The analysis on (3) will aim to relate fetal deaths associated to particular diseases with prenatal at the municipality level. Specifically, I will run a panel data, fixed-effects model, relating yearly mortality rate in a municipality by a specific illness (by ICD-10 Code) and insurance scheme to the average number of prenatal visits in that municipality. I will include year-fixed effects and department fixed-effects in this models.

4.1 Prenatal visits as Dependent Variable and Institutional Policy as Treatment

With the four sources of data I plan to use, I use a difference-in-difference model to study the effect of specific policy decrees in the Colombian healthcare system, controlling for insurer scheme, rurality type, market concentration, and demographic characteristics. Key events include:

1. 2011 Law, establishing preferential attention for prenatal services across the country.
2. Unification of the Health Benefits Plans (HBP) done across a gradual schedule, spreading treatment out temporally for different age groups.

The basic DiD model for both policies will follow the specification below:

$$\log(\mathrm{Y}_{it}) = \beta_0 + \beta_1 \mathrm{Vulnerable}_{it} + \beta_2 \left[\mathbb{1}_{\{t\geq x\}} \times \mathrm{Vulnerable}_{it}\right] + \boldsymbol{X_{it}} + \gamma_m + \delta_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the number of prenatal visits, $Vulnerable_{it}$ represents a dummy for rural areas (for the 2011 Law regression) or a dummy for belonging to the subsidized scheme (for the Unification of the Benefits Plans regression), $\boldsymbol{X_{it}}$ controls for demographics, and $\mathbb{1}_{\{t\geq x\}}$ comprises an indicator variable for observations recorded past time period x, which will depend on the date of the implementation of each specific policy. γ_m will comprise municipality fixed effects and δ_t year fixed effects. Notice that i represents the individual and t the year of observation. In the specific models to each treatment, which are explained below, additional controls (like market concentration) and interaction terms will be considered.

[0] A canonical example of this approach is Duflo (2001), who measures the impact of Indonesian school construction on both adult labor market outcomes and educational attainment.

In my models, I will mostly use the log of the number of prenatal visits as the outcome of interest. Beyond the interpretability of coefficients, I will do so because I am particularly interested in increases in prenatal visits among individuals with low prenatal care, relative to those who already have high levels of access – eg. the effect of attending to a fourth prenatal visit on birth outcomes instead of just three is assumed to be higher than the effect of attending a tenth time instead of just nine.

4.1.1 Model Implemented for Law 1438 of 2011

Recall that the Law 1438 of 2011 established preferential attention for prenatal services across the whole territory, aiming to improve the quality of the service provided in rural areas. Thus, when applying Equation 1 to this policy, the term $Vulnerable_{it}$ will be a categorical variable of the form $Rural_{it}$, representing different categories of rurality. Additionally, since the law was passed on January 19th of 2011, and my data has information about outcomes at the year-month level, I decided to let $x = 2011$ regarding the time indicator variable in Equation 1. As such, the model I implemented follows the identification below:

$$\begin{aligned}\log(\mathrm{Y}_{it}) = \beta_0 &+ \beta_1 \mathrm{NonUrban}_i + \beta_2 \mathrm{Contributory}_{it} + \beta_3 \mathbb{1}_{\{t \geq 2011\}} \times \mathrm{NonUrban}_i \\ &+ \beta_4 \mathbb{1}_{\{t \geq 2011\}} \times \mathrm{Contributory}_{it} + \beta_5 \left[\mathrm{NonUrban}_i \times \mathrm{Contributory}_{it}\right] \\ &+ \beta_6 \left[\mathbb{1}_{\{t \geq 2011\}} \times \mathrm{NonUrban}_i \times \mathrm{Contributory}_{it}\right] + \gamma_m + \delta_t + \epsilon_{it}\end{aligned} \tag{2}$$

where i represents the individual and t the year of observation, $NonUrban_i$ represents a dummy variable assigned by the type of municipality where the parturient women reside (eg. it is 0 for women in urban areas), and $Contributory_{it}$ represents a dummy variable for the contributory insurance scheme (eg. it is 0 for women in the subsidized scheme).

Firstly, it is important to note that the main coefficient of interest in this regression is β_3, as it captures the treatment effect of the policy, namely the causal impact of the Law 2011 on prenatal visits. Specifically, it captures the difference between changes in prenatal care usage for women in rural and urban areas after the implementation of this law.

Notice that unlike Equation 1, I choose to interact $NonUrban_i$ and $\mathbb{1}_{\{t \geq 2011\}}$ with $Contributory_{it}$. This is because of the overlap in treatment of the Unification of the Benefits Plans for Minors and the Law 2011. By including $Contributory_{it}$ in this regression, I can separate the causal effect that the insurance scheme changes could have had in the access to prenatal visits. Additionally, it allows me to better identify the policy change, isolating how the combined impact of rural residency and contributory insurance status interacts with the implementation of the Law 2011. This helps distinguish whether changes in access to prenatal visits are primarily driven by the policy shift, the insurance structure, or their interaction.

Additionally, the dummy variable $NonUrban_i$ in Equation 2 can be very easily tweaked to consider different types of rurality, given by the National Planification Department's (DNP) levels of rurality: urban, intermediate level, rural and scattered rural areas. To do this, I can simply split up the variable $NonUrban_i$ into three dummies (and set one as baseline) that consider Rurality type (namely transform $NonUrban_i$ into a categorical variable $Rural_{it}$). Notice that this will be done in the models for the Unification of the Benefits Plans below.

4.1.2 Model Implemented for Unification of the Benefits Plans

Recall that the Unification of the Benefits Plans was done gradually, firstly for teenage minors in January of 2010, and later for adults aged between 18-60 years old in July 2012. Through the unification of the Health Benefits Plans, affiliates in the subsidized scheme gained access to a range of services previously just available to the individuals in the contributory scheme.

The motivation for analyzing the Unification of the Benefits Plans stems from its potential role in reducing the percentage of women in the subsidized scheme receiving low levels of prenatal care, particularly in contrast to the contributory scheme, following its full implementation in 2012.

When applying Equation 1 to this policy, the term $Vulnerable_{it}$ will be a dummy variable of the form $Contributory_{it}$, assigning 1 for enrollment to the contributory health scheme and 0 for enrollment to the subsidized health scheme. For the teenage mother identification, the law was passed on January of 2010, so I let $x = 2010$. Importantly, the data in this model is restricted to mothers who were 12-17 years old at the time of delivery. As such, the model I implemented to study the effect of the Unification of the Health Benefits for teenage mothers is:

$$
\begin{aligned}
\log(\mathrm{Y}_{it}) = \beta_0 + \beta_1 \mathrm{Contributory}_{it} + \sum_{i=2}^{4} \beta_i \mathrm{Rural\_type}_i + \beta_5 \mathbb{1}_{\{t \geq 2010\}} \times \mathrm{Contributory}_{it} \\
+ \sum_{i=2}^{4} \beta_{4+i} \left[\mathbb{1}_{\{t \geq 2010\}} \times \mathrm{Rural\_type}_i\right] + \sum_{i=2}^{4} \beta_{7+i} \left[\mathrm{Contributory}_{it} \times \mathrm{Rural\_type}_i\right] \\
+ \sum_{i=2}^{4} \beta_{10+i} \left[\mathbb{1}_{\{t \geq 2010\}} \times \mathrm{Rural\_type}_i \times \mathrm{Contributory}_{it}\right] + \gamma_m + \delta_t + \epsilon_{it}
\end{aligned}
\tag{3}
$$

where i represents the individual, t the year of observation, and m the municipality of observation. $Rural\_type_i$ is a categorical variable that takes the value 2 if the mother resides in an intermediate level area, takes the value 3 if the mother resides in a rural area, and takes the value 4 if the mother resides in a scattered rural area. We omit the variable from the equation when it equals 1 (birthing mother lives in urban areas) to avoid perfect multicollinearity. Like in Equation 1 and Equation 2, I include municipality and year-fixed effects.

The idea of interacting rurality categories with the time dummy and the health insurance scheme dummy follows the same rationale as in Equation 2: better isolate and identify the treatment effect of the policy for individuals living in different areas of the country. However, another key argument for the inclusion of the rurality variables is that teenage pregnancy is significantly more prevalent in rural areas than in urban areas. For teenage mothers, 35% of births correspond to women residing in rural areas, whereas for adult mothers this share is 24%.

Notice that the main coefficient of interest in Equation 3 is β_5, as it captures the causal impact of the Unification of the Benefits Plans for Teenagers on prenatal visits.

Similarly, I conducted another identification for the Unification of Health Benefits for adult mothers. In this identification, $Vulnerable_{it}$ will also be a dummy variable of the form $Contributory_{it}$, assigning 1 for enrollment to the contributory health scheme and 0 for enrollment to the subsidized health scheme. For the adult mother identification, the law was passed on July of 2012, so I let $x = July - 2012$, or 07/12. As such, the model I implemented to study the effect of the Unification of the Health Benefits for adult mothers is:

$$
\begin{aligned}
\log(Y_{it}) = \beta_0 &+ \beta_1 \mathbb{1}_{\{t \geq 07/12\}} + \beta_2 \text{NonUrban}_i + \beta_3 \text{Contributory}_{it} + \beta_4 HHI_{mt} + \beta_5 \left[\mathbb{1}_{\{t \geq 07/12\}} \times \text{Contributory}_{it}\right] \\
&+ \beta_6 \left[\mathbb{1}_{\{t \geq 07/12\}} \times \text{NonUrban}_i\right] + \beta_7 \left[\text{NonUrban}_i \times \text{Contributory}_{it}\right] + \beta_8 \left[HHI_{mt} \times \text{Contributory}_{it}\right] \\
&+ \beta_9 \left[HHI_{mt} \times \text{Rural}_{it}\right] + \beta_{10} \left[\mathbb{1}_{\{t \geq 07/12\}} \times HHI_{mt}\right] + \beta_{11} \left[\text{NonUrban}_i \times \text{Contributory}_{it} \times \mathbb{1}_{\{t \geq 07/12\}}\right] \\
&+ \beta_{12} \left[\text{NonUrban}_i \times \text{Contributory}_{it} \times HHI_{mt}\right] \\
&+ \beta_{13} \left[\text{NonUrban}_i \times \text{Contributory}_{it} \times \mathbb{1}_{\{t \geq 07/12\}} \times HHI_{mt}\right] + \gamma_m + \delta_y + \epsilon_{it}
\end{aligned} \tag{4}
$$

where i represents the individual, t the month of observation, y the year of observation, and m the municipality of observation. Notice that this regression is ran at the month level since the treatment allows for a more precise identification at this level. Additionally, this regression includes HHI_{mt} which stands for the Herfindahl-Hirschmann Index (HHI), a measure of insurer concentration in the healthcare market, at the municipality-month level for each of the two insurance schemes. The rationale for including HHI as a regressor will be explained in section 5.3, however, the structure of the HHI data at the month-municipality level strengthens the proposition of running this regression at the month level, not at the year level. It is worth noting that the interaction between HHI_{it} and both $NonUrban_{it}$ and $Contributory_{it}$ will give a good understanding of how a more concentrated market affects outcomes in vulnerable areas in the country. We can quantify this effect through β_9 and β_{10}.

Notice that just like in the model for teenage mothers Equation 3, β_5 is the main coefficient of interest of Equation 4 as it captures the causal impact of the Unification of the Benefits Plans for Adults on prenatal visits. Just like in Equation 2, $NonUrban_i$ can be easily tweaked into $Rural\_type_i$ used in Equation 3 to narrow the interaction of the categories of rurality with insurance scheme, insurer market concentration, and the Health Benefits Unification policy. However, since this policy does not directly target rurality categories and rather it targets inequalities in healthcare across insurance schemes, the rurality dummy will be deemed sufficient for the model.

4.1.3 Staggered DiD for Unification of the Benefits Plans

My second approach aimed at capturing the treatment effect of the policy by calculating an overall treatment effect, not just a treatment effect for each of the different age groups. To do so, I implemented Callaway and Sant'Anna (2021) Difference-in-Differences model with Multiple time periods. I will outline the basics of this model, which captures treatment effects in Difference in Difference Designs with multiple periods.

In this framework, several key components are defined to identify and estimate treatment effects:

- $Y_{it}(0)$: The untreated potential outcome for unit i in period t. This is the outcome that would be observed in the absence of treatment.
- $Y_{it}(g)$: The potential outcome for unit i in period t if it were treated starting in period g.
- G_i: The time period when unit i first receives treatment. Units are grouped by their treatment adoption period, making G_i the defining group characteristic.
- C_i: An indicator variable for whether unit i belongs to the never-treated group ($C_i = 1$).
- D_{it}: An indicator variable for whether unit i is treated in period t, with $D_{it} = 1$ if treated and $D_{it} = 0$ otherwise.
- X_i: A vector of pre-treatment covariates for unit i.
- Y_{it}: The observed outcome for unit i in period t, defined as:

$$Y_{it} = \begin{cases} Y_{it}(0), & \text{if } D_{it} = 0 \\ Y_{it}(g), & \text{if } D_{it} = 1 \end{cases}$$

The methodology assumes no anticipation effects, meaning that treatment in future periods does not influence current outcomes. Additionally, it relies on the assumption of staggered treatment adoption, where once treated, a unit remains treated in all subsequent periods.

The model employs two versions of the parallel trends assumption, based on never-treated units and on not-yet treated units. Mathematically, it is defined as follows:

1. **Based on Never-Treated Units:** For any group g and post-treatment period $t \geq g$, the change in untreated potential outcomes for the treated group is assumed to follow the same trend as that of the never-treated group:

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid G = g] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid C = 1].$$

This requires a sufficiently large and comparable never-treated group to serve as the control.

2. **Based on Not-Yet-Treated Units:** Alternatively, for $t \geq g$, the change in untreated potential outcomes for the treated group is assumed to follow the same trend as that of not-yet-treated groups:

$$\mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid G = g] = \mathbb{E}[Y_t(0) - Y_{t-1}(0) \mid D_s = 0, G \neq g, s \geq t].$$

This uses units that have not yet received treatment as the comparison group, leveraging more data at the expense of assuming more homogeneity across groups.

A core parameter in this framework is the group-time average treatment effect defined as:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G = g]. \tag{5}$$

This represents the average effect of treatment for the group treated in period g, observed in period t. When there are only two periods and two groups, this reduces to the standard ATT in the canonical DiD setup.

Given the large number of group-time effects in multi-period designs, the authors created a way to aggregate these estimates for interpretability:

- **Overall Treatment Effect:** The overall treatment effect across all treated groups is given by:

$$\theta_{OS} = \sum_{g=2}^{T} \theta_S(g) P(G = g),$$

where $\theta_S(g)$ is the average effect for group g, weighted by the proportion of units treated in g.

- **Dynamic Treatment Effects:** To study treatment effect dynamics, the effects can be aggregated by elapsed time since treatment (e):

$$\theta_D(e) = \sum_{g=2}^{T} 1\{g + e \leq T\} ATT(g, g+e) P(G = g \mid G + e \leq T).$$

As in (1) - (4), it is clear that Y_{it} will be the number of prenatal visits (which will be logged when running the staggered DiD). I will consider the teenage mothers group (g = 1) to be group 1 and the adults group (g=2) to be group 2. Following the policy design, I set the treatment date for the minors (t=1) to be January 2010, whereas the treatment date for adults (t=2) is July 2012.

Notice that in (3) and (4), the treatment group contains the women in the subsidized scheme, minors and adults respectively. The control group for (3) and (4) contains the individuals in the contributory scheme belonging to the age group of this regression. However, for the staggered DID, I will define my parallel trends assumptions by basing the control group on not-yet-treated units. This implies that at period 1, where teenage minor mothers in the subsidized scheme become benefited by the Unification of the Benefits Plans, the control group consists not of all women in the contributory scheme, but also of those women in the subsidized scheme that are adults.

Using this model will allow for a more precise estimate of the causal effect of the Unification of Health Benefits on prenatal visits by formally considering its staggered nature with all the observations present in the dataset.

4.2 Health Outcomes as Dependent Variables and prenatal Visits as Endogenous Regressor — DDIV Approach

To study the causal effect of prenatal visits on birth outcomes (birth weight, length at birth, and gestational age), I implement a Difference-in-Differences Instrumental Variables (DDIV) model. This approach exploits exogenous variation in access to prenatal care introduced by two institutional policy changes—Law 1438 of 2011 and the Unification of Benefits Plans—to instrument for prenatal visits, addressing endogeneity concerns due to unobserved maternal characteristics that may influence both prenatal care utilization and birth outcomes.

The general DDIV model follows a two-stage structure. In the first stage, I estimate the effect of each policy on prenatal visits using a standard difference-in-differences (DiD) regression (similar to Equation 1 in section 4.1, but with prenatal visits as the dependent variable). In the second stage, I estimate a logit model to capture the probability of a normal birth outcome given the predicted number of prenatal visits from the first stage. A complementary reduced form regression directly estimates the intent-to-treat (ITT) effect of each policy on birth outcomes.

The first stage equation is given by:

$$\begin{aligned} S_{it} &= \gamma_0 + \gamma_1 Vulnerable_i + \gamma_2 \left(\mathbb{1}_{\{t \geq x\}} \times Vulnerable_i\right) \\ &\quad + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \eta_{it} \end{aligned} \tag{6}$$

where S_{it} represents the number of prenatal visits for mother i in period t. The variable $\mathbb{1}_{\{t \geq x\}}$ is a policy-specific indicator for the post-policy period (2011 for Law 1438, and either 2010 or 2012 depending on age group for the Unification of Benefits Plans). The term $Vulnerable_i$ indicates either rural residence (for the 2011 Law) or affiliation with the subsidized scheme (for the Unification of Benefits Plans). The vector of covariates $\boldsymbol{X_{it}}$ controls for maternal age at the time of birth and educational attainment, while municipality and year fixed effects are captured by δ_m and λ_t, respectively. The coefficient γ_2 captures the policy-induced increase in prenatal visits for the treated group.

The second stage equation, estimating the causal effect of prenatal visits on birth outcomes using a logit model, is:

$$\begin{aligned} \log\left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)}\right) &= \beta_0 + \beta_1 \hat{S}_{it} + \beta_2 \mathbb{1}_{\{t \geq x\}} + \beta_3 Vulnerable_i \\ &\quad + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \epsilon_{it} \end{aligned} \tag{7}$$

where Y_{it} is a binary variable indicating whether the birth outcome is normal (1) or not (0). The fitted number of prenatal visits $\hat{S}_{it}$ from the first stage serves as the endogenous regressor. The coefficient β_1 estimates the log-odds increase in the probability of a normal birth outcome associated with an additional prenatal visit.

Finally, the reduced form equation estimates the direct effect of the policy on birth outcomes:

$$\begin{aligned} \log\left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)}\right) &= \theta_0 + \theta_1 \mathbb{1}_{\{t \geq x\}} + \theta_2 Vulnerable_i + \theta_3 \left(\mathbb{1}_{\{t \geq x\}} \times Vulnerable_i\right) \\ &\quad + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \nu_{it} \end{aligned} \tag{8}$$

where θ_3 captures the intent-to-treat effect of the policy on birth outcomes. Notice that Y_{it} will capture the probability of a normal birth outcome (normal weight, normal length, or normal gestation time).

This general framework applies to both institutional policies. In the following subsections, I specify how $Vulnerable_i$ and $\mathbb{1}_{\{t \geq x\}}$ are defined for each policy context.

4.2.1 DDIV Model for Law 1438 of 2011

The Law 1438 of 2011 established mandatory improvements in prenatal care across Colombia, prioritizing rural areas. In this setting, I define $Vulnerable_i$ as an indicator for whether a mother resides in a rural area, and I define $\mathbb{1}_{\{t \geq x\}}$ as an indicator for observations recorded in or after the year 2011.

The first stage equation is:

$$\begin{aligned} S_{it} = {} & \gamma_0 + \gamma_1 \text{Rural}_i + \gamma_2 \text{Contributory}_{it} + \gamma_3 \left(\mathbb{1}_{\{t \geq 2011\}} \times \text{Rural}_i\right) \\ & + \gamma_4 \left(\mathbb{1}_{\{t \geq 2011\}} \times \text{Contributory}_{it}\right) + \gamma_5 \left(\text{Rural}_i \times \text{Contributory}_{it}\right) \\ & + \gamma_6 \left(\mathbb{1}_{\{t \geq 2011\}} \times \text{Rural}_i \times \text{Contributory}_{it}\right) + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \eta_{it} \end{aligned} \tag{9}$$

The second stage equation follows:

$$\log\left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)}\right) = \beta_0 + \beta_1 \hat{S}_{it} + \beta_2 \text{Contributory}_{it} + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \epsilon_{it} \tag{10}$$

The reduced form equation is:

$$\begin{aligned} \log\left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)}\right) = {} & \theta_0 + \theta_1 \text{Rural}_i + \theta_2 \text{Contributory}_{it} + \theta_3 \left(\mathbb{1}_{\{t \geq 2011\}} \times \text{Rural}_i\right) \\ & + \theta_4 \left(\mathbb{1}_{\{t \geq 2011\}} \times \text{Contributory}_{it}\right) + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \nu_{it} \end{aligned} \tag{11}$$

This setup ensures that the fitted logit model captures the probability of normal birth outcomes while adjusting for relevant policy interventions.

4.2.2 DDIV Model for Unification of Benefits Plans

The Unification of Benefits Plans equalized health services between the contributory and subsidized schemes. This policy was implemented gradually: first for teenage mothers (aged 12-17) in January 2010, and later for adult mothers (aged 18-60) in July 2012. Through this reform, affiliates in the subsidized scheme gained access to a broader range of services, aligning their benefits with those available to affiliates in the contributory scheme. In this context, I define $Vulnerable_i$ as an indicator for whether a mother is affiliated with the contributory scheme. This reflects the fact that before the unification, mothers in the contributory scheme already had access to the full benefits package, meaning they form the control group.

Model for Teenage Mothers (12-17 years old) For teenage mothers, the treatment date is set to January 2010, so the time dummy $\mathbb{1}_{\{t \geq x\}}$ equals 1 from 2010 onward. The first stage equation estimating the effect of the Unification of Benefits Plans on prenatal visits for teenage mothers is:

$$
\begin{aligned}
S_{it} = {} & \gamma_0 + \gamma_1 \text{Contributory}_i + \gamma_2 \text{NonUrban}_i + \gamma_3 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{NonUrban}_i \right) + \gamma_4 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{Contributory}_i \right) \\
& + \gamma_5 \left(\text{NonUrban}_i \times \text{Contributory}_i \right) + \gamma_6 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{NonUrban}_i \times \text{Contributory}_{it} \right) \\
& + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \eta_{it}
\end{aligned} \tag{12}
$$

The corresponding second stage equation, estimating the effect of prenatal visits on birth outcomes for teenage mothers, follows:

$$
\begin{aligned}
\log \left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)} \right) = {} & \beta_0 + \beta_1 \hat{S}_{it} + \beta_2 \text{Contributory}_{it} + \beta_3 \text{NonUrban}_i \\
& + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \epsilon_{it}
\end{aligned} \tag{13}
$$

The corresponding reduced form equation, capturing the intent-to-treat effect of the Unification of Benefits Plans on birth outcomes for teenage mothers, is:

$$
\begin{aligned}
\log \left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)} \right) = {} & \theta_0 + \theta_1 \text{NonUrban}_i + \theta_2 \text{Contributory}_{it} + \theta_3 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{Contributory}_{it} \right) \\
& + \theta_4 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{NonUrban}_i \right) + \theta_5 \left(\text{NonUrban}_i \times \text{Contributory}_{it} \right) \\
& + \theta_6 \left(\mathbb{1}_{\{t \geq 2010\}} \times \text{NonUrban}_i \times \text{Contributory}_{it} \right) + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \nu_{it}
\end{aligned} \tag{14}
$$

Model for Adult Mothers (18+ years old) For adult mothers, the treatment date is set to July 2012, so the time dummy $\mathbb{1}_{\{t \geq x\}}$ equals 1 from July 2012 onward. The first stage equation estimating the effect of the Unification of Benefits Plans on prenatal visits for adult mothers is:

$$
\begin{aligned}
S_{it} = {} & \gamma_0 + \gamma_1 \text{Contributory}_i + \gamma_2 \text{NonUrban}_i + \gamma_3 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{NonUrban}_i \right) + \gamma_4 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{Contributory}_i \right) \\
& + \gamma_5 \left(\text{NonUrban}_i \times \text{Contributory}_i \right) + \gamma_6 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{NonUrban}_i \times \text{Contributory}_{it} \right) \\
& + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \eta_{it}
\end{aligned} \tag{15}
$$

The corresponding second stage equation, estimating the effect of prenatal visits on birth outcomes for adult mothers, follows:

$$
\begin{aligned}
\log \left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)} \right) = {} & \beta_0 + \beta_1 \hat{S}_{it} + \beta_2 \text{Contributory}_{it} + \beta_3 \text{NonUrban}_i \\
& + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \epsilon_{it}
\end{aligned} \tag{16}
$$

The corresponding reduced form equation, capturing the intent-to-treat effect of the Unification of Benefits Plans on birth outcomes for adult mothers, is:

$$
\begin{aligned}
\log \left(\frac{\mathbb{P}(Y_{it} = 1)}{\mathbb{P}(Y_{it} = 0)} \right) = {} & \theta_0 + \theta_1 \text{NonUrban}_i + \theta_2 \text{Contributory}_{it} + \theta_3 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{Contributory}_{it} \right) \\
& + \theta_4 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{NonUrban}_i \right) + \theta_5 \left(\text{NonUrban}_i \times \text{Contributory}_{it} \right) \\
& + \theta_6 \left(\mathbb{1}_{\{t \geq 07/2012\}} \times \text{NonUrban}_i \times \text{Contributory}_{it} \right) + \boldsymbol{X_{it}} + \delta_m + \lambda_t + \nu_{it}
\end{aligned} \tag{17}
$$

This split-by-age-group approach reflects the gradual implementation of the Unification of Benefits Plans and allows for a more precise identification of policy effects within each age group. In both cases, the coefficient on the interaction term—γ_4 in the first stage, θ_3 in the reduced form, and indirectly contributing to β_1 in the second stage—captures the differential policy effect on prenatal visits and birth outcomes for mothers in the contributory scheme compared to mothers in the subsidized scheme, with all other observable factors controlled for.

4.3 Panel Data at the Municipality-Year Level with Fetal Deaths as Dependent Variable and prenatal Care as Independent Variable

I will conduct a panel data analysis relating fetal mortality associated with particular diseases to average prenatal care levels at the municipal level. When considering fetal diseases, I will classify them through ICD-10 Diagnostic Codes, a medical classification list by the World Health Organization (WHO), which contains codes for diseases, signs and symptoms, abnormal findings, and external causes of diseases.

To calculate the incidence ratio of deaths by each specific illness, I calculate the ratio between the deaths associated with a particular illness and the total number of births plus the total number of deaths registered in that municipality per year. This implies

$$\text{Mortality}_{ijt} = \frac{\text{Deaths}_{ijt}}{\text{Deaths}_{ijt} + \text{Deaths}_{-j,it} + \text{Births}_{it}}$$

where j indexes the illness/cause of death by ICD-10 code, i indexes the municipality, and t indexes the year of observation. Then, at the municipality level, I regress the calculated index on average prenatal visits, controlling for insurance scheme ($Contributory_{it}$) and rural municipalities ($NonUrban_{it}$), as well as year-fixed effects and department fixed effects. Formally, I estimate the following model:

$$\begin{aligned}\text{Mortality}_{ijt} = {} & \beta_0 + \beta_1 \text{MeanPrenatalVisits}_{it} + \beta_2 \text{Contributory}_{it} + \beta_3 \text{NonUrban}_i \\ & + \gamma_i + \delta_t + \epsilon_{ijt}\end{aligned} \tag{18}$$

The coefficient of interest is β_1, which captures the relationship between average prenatal visits in a municipality and the incidence ratio of fetal mortality for a specific disease. Municipality fixed effects γ_i account for time-invariant differences between municipalities, while year fixed effects δ_t account for shocks common to all municipalities in a given year.

Notice that the coefficient of interest in this model is β_1, which will be estimated through multiple regressions to quantify the causal effect of prenatal care on mortality at the municipal level. From the ICD-10 Codes indexed by j, non-illness related causes like abortions will be excluded from the analysis. Likewise, generic ICD-10 codes that don't capture a death cause preventable through prenatal care, will not be deemed suitable for the analysis. Section 5.2 will further elaborate on the structure and utilization of ICD-10 codes.

This municipal-level panel model will thus aim to relate the prevention or reduction of the incidence of particular illnesses to prenatal care, aiming for a high specificity degree that a generic DiD approach would not capture.

5 Data

(a) The Vital Statistics database (EEVV) containing individual-level data on births, prepared by the National Administrative Department of Statistics (DANE). The data is available from 1998 to 2022 and contains over 30 variables regarding demographic and insurance information for the mother, information on prenatal visits, information on some relevant health outcomes at birth, as well as some information on the father. It contains information regarding the area of residency of the mother at the time of birth at the municipality level. There are 33 departments (including the capital city, Bogotá), and 1116 municipalities with reported observations.

(b) The Fetal Deaths database (EEVV-Fetal Deaths) containing individual-level data on fetal deaths, prepared by the National Administrative Department of Statistics (DANE). The data is available from 1998 to 2022 and contains information regarding the cause of death of the fetus, classified by International Statistical Classification of Diseases and Related Health Problems (ICD-10) codes, demographic and insurance information for the mother, as well as information regarding the area of residency of the mother at the time of birth at the municipality level. I will also utilize an ICD-10 code crosswalk to match the disease to its name.[1]

(c) The "CUBOS" data, which are multiple sets of public data aggregated at the same level (sex, age, diagnosis code, income level, city/town of residence, insurer, and year). There are multiple CUBOS, ranging from Insurance Affiliation Information, Statistics about Enrollees, Information about Providers, etc. Access to each of the CUBOS is granted after attending an online orientation course. I will work with the Cubos Affiliates Data, which contains the number of enrollees for each insurer (EPS) and each scheme for each month, at the municipality level.

(d) Colombian Location data (equivalent to US-MSAs), mapping municipalities to rural and urban characterizations. The National Planification Department (DNP) has constructed a crosswalk mapping municipalities to rural/urban categories (will be explained further in this section).

[1]ICD-10 P-codes and Q-codes were retrieved as a CSV from an open-source software platform called OpenSAFELY, developed at the Bennett Institute for Applied Data Science at Oxford University. This data can be accessed through: ICD-10 Chapter XVI and ICD-10 Chapter XVII.

5.1 Vital Statistics Dataset

I will be using the DANE Vital Statistics (EEVV) dataset to study the impact of the expansion of healthcare on (1) preventive care access and (2) will then expand the analysis to health outcomes. The unit of observation within these records is the live birth, offering a wealth of information about the birth event itself, the newborn, and the parents. The only preventive service available for study is the number of prenatal visits that preceded each birth, whereas health outcomes include weight, length and gestation duration. These variables are not continuous, and are rather divided into discrete categories based on predefined thresholds. When studying health outcomes, it will be particularly important to find a model that accurately captures the nature of the data and also account for potential confounding factors, including socioeconomic status and maternal age to overcome endogeneity concerns.

I summarized the basic statistics of the Vital Statistics Dataset in Table 1, Table 2, and Figure 1. Table 1 presents a glossary of the most important variables in the dataset and describes the distribution of their values.

Additionally, EEVV has a specific categorization regarding location of birth and residential area of the mother. For each location of birth and residential area, there are three possible categorizations based on territorial characteristics:

1. Municipal Center: Refers to the main urban area or administrative center of a municipality, typically being the most developed part of a municipality, with better infrastructure, public services, and access to healthcare and education.

2. Populated Center: This term refers to smaller settlements within the municipality, such as townships, villages, or other organized communities. Concretely, it is defined as a concentration of at least twenty (20) contiguous, neighboring, or adjoining households located in the rural area of a municipality or departmental subdivision.

3. Dispersed Rural Area: This refers to sparsely populated, rural areas. Formally, it encompasses the area between the census boundaries of municipal centers (cabeceras municipales) and populated centers (centros poblados), extending out to the municipal boundary. This area is characterized by a dispersed arrangement of homes and agricultural operations.

A weakness of this categorization, especially when focusing on urban/rural divisions, is that the territorial division is done for statistical purposes, rather than policy purposes, since they are reliant on administrative boundaries rather than population density (DNP, 2014). By considering the interaction between population density and population, the DNP categorization is able to address the idea of varying levels of urbanization, recognizing that not all rural areas are purely agricultural nor are urban areas fully industrialized. For instance, under DANE's categorization, a low-density municipal center may still be classified as "urban" if it has the required infrastructure, whereas a high-density settlement could remain "rural" if it lacks such infrastructure. The main purpose of this classification is to accurately understand the different degrees at which the population has grown differently throughout the territory. Thus, I included the constructed by the DNP, which divides all municipalities into four categories regarding levels of rurality: (1) cities and agglomerations (urban), (2) intermediate level, (3) rural, and (4) scattered rural areas.

Figure 1 contains the average number of prenatal visits for the four DNP rural categories from 2008-2015. Table 2 contains information on total number of births and their breakdown by health scheme and rurality in raw numbers.

5.2 Fetal Deaths Dataset

I will be using the Fetal Deaths Dataset to perform a municipal-level analysis on the evolution of fetal mortality associated with different diseases. The analysis will be conducted at the (1) municipal level for (2) specific medical conditions for the following reasons:

1. **Data Concerns Regarding Fetal Death Reporting at the Department Level:** When conducting an analysis of the trend of fetal deaths, there is a significant increase in the total number of fetal deaths per year reported, while reported births remained stable over this period. More specifically, there was a 54% increase in the number of reported fetal deaths from 2008 to 2015, whereas there was an 8% decrease in reported births from 2008 to 2015. This would suggest that infant mortality increased by 65% over this 7-year period, which is inconsistent with the reported 80% reduction in infant mortality rate by the National Department of Statistics (DANE, 2020). This increase in reported fetal deaths was consistent across insurance schemes (contributory and subsidized), and the DANE rurality categories. When further investigating this issue, out of the 311 municipalities that reported fetal deaths in both 2008 and 2015, 94 (around 1/3 of the municipalities) reported an increase of more than 50% in fetal

deaths in 2015 compared to 2008, and 46 (around 1/6 of all municipalities) reported a 200% increase in this period. While excluding the 94 municipalities that reported a 50% increase in fetal deaths yields a more consistent analysis with the infant mortality trends reported by DANE and other health indicators in the Vital Statistics Dataset, I considered this exclusion extremely restrictive, especially when conducting a municipal level analysis relating prenatal care and fetal mortality.

2. **Data Concerns Regarding ICD-10 Categorization :**
After ruling out the possibility of conducting a complete analysis relating the two policies with the number of fetal deaths, I decided to study this dataset through the ICD-10 codes associated to each reported event. Firstly, I decided to drop the observations relating to the ICD-10 Code "P964" which categorizes abortions, as the number of deaths reported under this category are unlikely to be affected by prenatal care. After doing so, I noticed that 67% of all deaths from 2008-2015 were reported under the ICD-10 code "P018", whose description is "fetus and newborn affected by other maternal complications of pregnancy". The number of reported cases in this category doubled from 15,214 in 2008 to 33,907 in 2015, an increase in cases that is higher than the total increase in fetal deaths from 2008 to 2015 (since most of all other categories experienced reductions in reported cases). Given the vague description of the "P018" ICD-10 code, and the high share of deaths that are grouped under it, this category seems to group most fetal deaths that were not attributable to a diagnosed condition. Since excluding this ICD-10 code would result in dropping the vast majority of the observations in the dataset, I determined that the only way to relate prenatal care with fetal deaths would be to do so by doing a diagnosis-level analysis with those observations grouped under ICD-10 codes that match to specific conditions that could be prevented or treated by a physician during the pregnancy.

3. **Advantages of a Diagnosis-Based Mortality Analysis:** While a diagnosis-based analysis might involve significantly fewer observations than an analysis of total fetal deaths, it allows for a more rigorous analysis of how mortality due to specific illnesses has behaved over the years and across insurer type and rurality category. More importantly, a regression can be ran at the municipal level relating prenatal care and mortality rates by a particular illness, controlling for insurer type or rurality category.

5.3 CUBOS Affiliates Data and Herfindahl–Hirschman Index

The CUBOS Affiliates Data contain the number of enrollees for each insurer (EPS) and each scheme for each month from 2009-2015, at the municipality level. Using this information, I will implement the assumption that each pregnant woman who resides in a municipality chooses to enroll in an insurer that is present in their area of residence. This is equivalent to defining health insurer markets at the municipal level. In choosing such insurer, given their insurer scheme, their choice set will be defined by the number of insurers operating within their municipality. Within each municipality, if we consider each woman's choice of insurer and the number of insurers within their choice set, we can define a notion of insurer concentration for their municipality.

Since each woman has a choice of insurer, yet can visit any institution within the insurer's network for prenatal care or for delivering the baby, it could be argued that the definition of health insurer market at the municipal level could be flawed. Given that there is no information about insurer at the individual level for each pregnant woman, we can not test whether their insurer-provider combination matches the insurers in their area of residence. However, since switching health insurers involves and implicit cost for users, and a woman would ideally like to access medical treatment beyond pregnancy visits in a timely manner, it is logical to assume that a woman will decide to insure herself with an insurer that operates within her municipality. In this sense, insurer concentration (and change in insurer concentration) in each municipality could be a determinant of health outcomes related to pregnancy. However, there is no clear intuition hinting at the sign of the effect of insurer concentration on health outcomes, as it could be the case that one insurer in a rural area could provide a more effective service than many, while it could very well be the case that a single insurer would not have any incentive to improve their provided service, given that they do not need to compete for securing more enrollees.

To address this, I calculate the Herfindahl–Hirschman Index (HHI) for municipality-month combinations, by summing the square of the percentage of affiliates enrolled to each insurer under each scheme. HHI ranges from 0 to 10,000. If there is 1 firm that holds 100% of affiliates, its HHI would be $(100)^2 = 10,0000$, indicating a highly concentrated market. Although FTC and DOJ guidelines are updated each year, according to the DOJ's Horizontal Merger Guidelines (2010), an HHI of 1500 or less indicates a low concentration, an HHI between 1500 and 2500 indicates moderate concentration, and an HHI of 2500 or more is considered highly concentrated. For each observation in the Vital Statistics Dataset, I included the HHI in their health insurer market and the change in HHI for the month they gave birth, and I will include these two variables in my model. Then, I include both variables as controls in my DiD models with prenatal visits as the dependent variable for both policies, as well as in the models studying health outcomes (e.g. weight, length, and gestation duration).

6 Results

Before describing the results of the models considered in Section 4, I will first present a set of important facts, backed by descriptive figures and tables that motivate the need for the econometric analysis. These descriptive statistics and visualizations provide a clearer picture of the behavior of the main variables in the dataset over time, allowing the reader to better understand the context behind the research questions and the story the dataset has to tell prior to the formal regression analysis.

Firstly, as shown in Table 2, urban enrollees account for approximately 80% of the population, significantly outnumbering those in rural categories. While urban areas have a higher percentage of enrollees in the contributory scheme, nationwide only 44% of individuals were affiliated with the contributory scheme by 2014. This suggests that a substantial portion of the population in both urban and rural areas is covered by the subsidized scheme, indicating that they either are not formal workers, or they fall below the minimum wage threshold. As such, these social and economic disparities stem from both inter-regional differences—reflecting the urban-rural divide—and intra-regional differences, which are captured by variations in health insurance schemes within each area.

When focusing on preventive care, prenatal visits have increased over time across all areas defined in the DANE dataset. As shown in Figure 3, the cumulative distribution function (CDF) of prenatal visits for each region has shifted to the right from 2008 to 2015, with the urban CDF consistently further to the right than those of Populated Centers and Dispersed Rural areas, which follow a very similar trend over the years. However, when using the DNP classification for rurality, prenatal care in the most rural areas — scattered rural areas — appears to have deteriorated over time. As shown in Figure 1, the average number of visits in scattered rural areas decreased from 4.6 in 2008 to 4.3 in 2015. Furthermore, Figure 4 illustrates that the CDF for scattered rural areas has shifted noticeably to the left, indicating a decline in prenatal care in these low-density areas, even as most other regions experienced improvements.

As explained in Section 4.1, prenatal visits are predicted to have diminishing marginal effects on health outcomes. The impact of an additional visit is expected to be much smaller for women who have already attended more than 10 visits than for those with fewer than 2. Put differently, a key descriptive variable from a policy perspective is the percentage of women with low prenatal care over time. According to the WHO (2016), low prenatal care means having fewer than 4 visits during pregnancy.

Figure 5 shows how this percentage evolved between 2008 and 2015. In 2008, there was a sharp disparity between the two schemes: 21% of women in the subsidized scheme had low prenatal care, compared to just 5% in the contributory scheme. This gap held steady until 2012, when the share of women with low prenatal care in the subsidized scheme began to decline, reaching 17.5% in 2015. In contrast, low prenatal care levels in the contributory scheme remained stable throughout the period, fluctuating only slightly between 5.1% and 4.9%. This stability highlights a very different pattern from what is observed in the subsidized scheme. Given that the time frame of this decline matches the implementation of the Unification of the Benefits Plans for adults, there is an important motivation to quantify the differential effect of the policy, and more specifically, narrow this effect over different areas of the country.

A similar analysis by rurality category shows that Urban, Intermediate, and Rural areas all experienced a steady decline in the share of women with low prenatal care between 2008 and 2015. Interestingly, this decline appears to accelerate in Intermediate and Rural areas after 2012, as shown in Figure 6, suggesting that municipalities in these areas account for a significant part of the improvements described in the previous paragraph. The story is quite different for scattered rural areas, where the share of women with low prenatal care actually increased — rising from 33% in 2008 to 37% in 2015. Both Figure 5 and Figure 6 reinforce the need for interacting rurality types and insurance scheme categories in the models that aim to capture the differential effect of the Law 2011 and the Unification of the Benefit Plans.

To identify key sources of asymmetries in healthcare access across municipalities, I included the Herfindahl-Hirschman Index (HHI), a measure of insurer concentration, in my model for the Unification of the Benefits Plans for adult mothers, as shown in Equation 4. To provide intuition about how insurer concentration varies across the country, Figure 2 plots two maps – one for each insurance scheme – showing the average HHI in each department over the 2009-2015 period. Within each department, I also display the percentage of the population enrolled in the contributory scheme. This percentage is bolded for the five most populous departments: Bogotá D.C., Antioquia, Cundinamarca, Valle del Cauca, and Atlántico.

Interestingly, four of the six departments where more than 50% of the population belongs to the contributory scheme are among these five most populous departments. The map for the contributory scheme, Figure 2a, suggests an inverse relationship between the share of the population enrolled in this scheme and insurer concentration—departments with wealthier populations tend to have more insurers, resulting in lower market concentration. In contrast, southern and eastern departments, which include geographically remote and predominantly rural regions such as the Amazon rainforest and the Orinoco River basin, tend to have lower shares of their population in the contributory scheme and higher insurer concentration within that scheme. The northern departments, although not as rural and remote, also show low levels of contributory scheme affiliation and high levels of insurer concentration in this scheme.

This story would suggest that departments that have most of their population enrolled in the subsidized scheme would have a lower insurer concentration in the subsidized scheme than those who have a higher share of their population enrolled in the contributory scheme. As shown in Figure 2b, this seems to be the case for the northernmost departments, for which insurer concentration is significantly lower in the subsidized scheme than in the contributory. However, for most departments in the southern and eastern regions, insurer concentration levels are also higher in the subsidized scheme compared to those departments that have a significantly lower share of their population in the subsidized scheme.

While this is not surprising when considering that a lower share of the country's population lives in these departments, the effect of insurer concentration on health outcomes and prenatal care is not trivial or obvious from the distribution of country-department population. This motivates the study of the interaction of HHI with rurality categories and insurance schemes suggested in Equation 4.

When shifting the focus to health outcomes, Figures (7) to (9) show the share of newborns with normal weight, length, and gestation time at birth, broken down by insurance scheme and rurality category.[2]

For weight and length, the patterns across insurance schemes largely mirror the trends seen in prenatal care: outcomes, like access to preventive care, are better in the contributory scheme and have improved across both schemes over time. However, the improvement between 2008 and 2015 has been larger in the subsidized scheme. Gestation time, however, follows a different pattern. The share of births with normal gestation time is consistently higher in the subsidized scheme, but this share has declined for both schemes over the period. Since the dataset only captures live births, this trend could partly reflect higher survival rates for premature births in recent years—especially in urban areas—leading to an increase in their recorded numbers.

The patterns across rurality categories are a bit more nuanced. For weight and length, intermediate areas show the highest share of "normal" births, with improvements observed across all areas except scattered rural areas, where the percentage of normal births has declined since 2012. When it comes to gestation time, intermediate and rural areas have the highest shares, both showing relatively stable trends over the 2008-2015 period. Scattered rural areas follow, with a more fluctuating trend. Interestingly, urban areas show a notably lower share of normal gestation births—about 10 percentage points lower than intermediate and rural areas—and this has remained fairly constant over time. This reinforces the interpretation drawn from the differences across insurance schemes.

As I focused on fetal mortality, mortality rates associated to particular diseases have decreased across schemes, however with very different behaviors. Figure 10 plots the mortality rates associated to hypoxia and slow fetal growth across insurance scheme. Over 10% of the reported fetal deaths over this period are associated to Hypoxia and Slow Fetal growth. While the mortality rate associated to hypoxia is higher in the subsidized scheme and experienced a larger reduction in the contributory scheme, the mortality rate associated to slow fetal growth is higher in the contributory scheme and from 2008-2014, and it is lower in 2015. As shown in Figure 11, for both diseases, this rate seems to oscillate more in scattered rural areas, while there seems to be a reduction across Urban, Intermediate and Rural areas. The mortality reported associated with these two diseases is higher in urban

[2] Normal weight is defined as birth weight between 2.5 and 4 kg, normal length refers to newborns measuring between 40 and 59 cm, and normal gestation time ranges from 38 to 41 weeks. Measurements falling outside these ranges are classified as "not normal."

areas than in intermediate and rural areas in 2008, which could be due to higher mortality cause reporting, especially because most of the fetal deaths are grouped under unspecific ICD-10 codes.

Finally, the relationship between hypoxia-related mortality rates and average prenatal visits is negatively sloped across both insurance schemes. As illustrated in Figure 12, municipalities with higher average prenatal visit rates tend to report lower hypoxia-related mortality. When disaggregated by rurality type, Figure 13 shows that this negative relationship holds across urban, intermediate, and rural areas—but not for scattered rural areas, where the pattern is less clear. This aligns with the observation that mortality rates associated with hypoxia and slow fetal growth tend to exhibit greater variability in scattered rural areas compared to other rurality types.

6.1 Results for Law 1438 of 2011

To focus on changes in the number of prenatal visits after the policy's implementation, I regressed the logarithm of prenatal visits on the treatment effect, as presented in the first column of Table 3. This regression includes only the insured population, excluding individuals who are uninsured, belong to a special insurance scheme, or failed to provide insurance information. The regression controls for insurance schemes through the dummy variable *Contributory*, showing that individuals under the contributory scheme receive 27.9% more prenatal visits compared to those in the subsidized scheme. Notably, the interaction between the dummies NonUrban and *Contributory* has a coefficient of -0.06, suggesting a 6% reduction in the effect of belonging to the contributory scheme for individuals in non-urban areas compared to urban areas.

The coefficient for the interaction term Post $\times$ NonUrban is -0.016, indicating a 1.6% increase in the baseline difference in prenatal care utilization between non-urban and urban areas after the policy's implementation. However, this coefficient is not statistically significant at the 10% level.

Given the availability of the DNP categorization of rurality, I regressed the log number of prenatal visits on the interaction terms between Post, *Contributory*, and the categories of rurality. This regression, presented in the second column of Table 3, yielded three key insights.

First, for individuals in the subsidized scheme, utilization of prenatal care is 4% higher in intermediate areas compared to urban areas. This result is likely driven by the longer wait times commonly experienced in large urban centers compared to intermediate territories, which offer similar healthcare technologies but are less congested. However, as shown in Figure 1, the mean number of prenatal visits in urban areas remains higher than in intermediate areas. This suggests that the share of affiliates in the contributory scheme is higher in urban areas than in intermediate ones, potentially offsetting the advantages observed in intermediate regions for the subsidized scheme.

Secondly, the interaction terms in column 2 between the Contributory dummy and both the Intermediate and Rural dummies are negative and statistically significant. Specifically, the coefficient for the Contributory $\times$ Intermediate interaction is -0.14, indicating that, within the contributory scheme, average prenatal visits in intermediate areas are approximately 10% lower than in urban areas. Similarly, in the contributory scheme, prenatal visits in rural areas are 10.7% lower than in urban areas. This pattern suggests a comparable reduction in prenatal visits for individuals in the contributory scheme across both Intermediate and Rural areas.

The third insight comes from analyzing the interaction of the categories of rurality with the time dummy, which aims at estimating the treatment effect for the different rurality groups. Taking Urban as the baseline category, the treatment effect for the Intermediate and Rural areas is insignificant. However, the treatment effect for Scattered Rural areas is significant at the 1% level and it is -0.07, which indicates that prenatal care utilization worsened by 7% in the most rural areas in the country after the 2011 Law was passed. This trend shows an increase in pre-exisiting disparities in healthcare between Urban and Scattered Rural areas, as the coefficient of the Scattered Rural dummy is -0.10, indicating that before the treatment, women in scattered rural areas had 10% lower prenatal care levels that women in Urban areas. In fact, Figure 6 shows that the share of women with low prenatal care increased from 34% in 2008 to 44% in scattered rural territories. This trend contrasts with the reduction in the share of women with low prenatal care observed in urban, intermediate, and rural territories.

This result hints at the failure of this policy in improving access to preventive care to the most rural territories in the country, an effect which is only observable by using the DNP definition of rurality. Given that the contributory dummy and its interaction with the Rurality categories are significant, considering a treatment that targets the differences between care for enrollees across insurance schemes seems pertinent to understand the asymmetries in access to preventive care for individual across the territory. To do so, I will study the Unification of the Benefits Plans outlined below.

6.2 Results for Unification of the Benefits Plans

6.2.1 Results for the Teenage Mothers Model

As outlined in Equation 3, I regress the logarithm of prenatal visits on the treatment for the population aged 12-17 (teenage mothers) using the dataset's definition of non-urban areas as well as the DNP categorization of rurality as controls. These regressions are in columns 1 and 2 of Table 4, respectively. In both cases, the coefficient that captures the treatment is the coefficient of the interaction of Post and Contributory.

In column 1, this coefficient is -0.0297 and in column 2, this coefficient is -0.032, which in both cases is significant at the 5% level. This means that after the Unification of the Health Benefits Plans for teenager mothers, there was a reduction between 3% and 3.26% in the pre-existing difference in prenatal care access between individuals in the contributory and the subsidized scheme. It is important to note that this coefficient was not significant when running the regression for the Law 1438 of 2011.

Just as in the regression for the Law 1438, the Contributory x $NonUrban$ is significant and around 6%. For individuals in the subsidized scheme, prenatal care is 5% higher in intermediate than in urban areas. The direction of the interaction terms of the Contributory dummy and both the Intermediate and Rural dummies are negative (and around -10%) and statistically significant, just like in the model for the 2011 Law. Unlike the regression for Law 1438, the term for Contributory x Scattered Rural is negative and statistically significant, indicating that, within the contributory scheme, average prenatal visits in scattered rural areas are approximately 15% lower than in urban areas. The worsening of prenatal care in scattered rural areas is also captured in this regression through the coefficient of Post and Scattered Rural, which indicates that in the most rural areas in the country prenatal care levels decreased by 9% in Scattered Rural areas after the Unification of the Benefits Plans.

6.2.2 Results for the Adult Mothers Model

Table 5 summarizes the result for the adult population regression. The first column contains the regression outlined in Equation 4, using the dataset's definition of non-urbann areas and without controlling for HHI. The second column uses the DNP's categorizations of rurality, without controlling for HHI. The third column uses the dataset's definition of Non-Urban areas and controls for HHI.

Firstly, I will focus on the treatment effect across all regressions given by the interaction between Post and Contributory. In regressions 1-3, the treatment effect is between -0.026 and -0.0366 all of them significant at the 5% level. This means that after the Unification of the Health Benefits Plans for adult mothers, there was a reduction between 2.6% and 3.6% in the pre-existing difference in prenatal care utilization between individuals in the contributory and the subsidized scheme. Figure 5, hints at the intuition that, after 2012, the percentage of women with low prenatal care decreased in the subsidized scheme and stayed constant in the contributory scheme, suggesting that disparities in access to prenatal care between both schemes were reduced by the treatment.

The coefficient of the Contributory dummy is between 28 % and 41 % in all regressions, supporting the pre-exisiting disparities in prenatal care utilization in both schemes encountered in the Model for Teenage mothers. The interaction between the Contributory dummy and the rurality categories are all negative and significant, strengthening the hypothesis that for the contributory scheme healthcare utilization is better in Urban areas. Notably, the only interaction of the time-dummy *Post* with the rurality categories that is significant is the interaction between *Post* and Scattered Rural, which strengthens two ideas: (1) both policies studied did not effectively reduce the disparities in care across different types of rurality categories and (2) average prenatal care utilization in the most rural areas (Scattered Rural) decreased after the implementation of the policy.

Now, it is important to notice that the regression considered in Column 3 controls for HHI. To interpret the coefficient associated to HHI (which as explained in Section 5.3, is calculated at the municipal-insurer type level) it is important to calculate the average HHI across both schemes. For the contributory scheme, the average HHI is 2089, while the average HHI in the subsidized scheme is 3478. The coefficient of HHI can be interpreted as follows: in the subsidized scheme, a 100 change in HHI, which implies an increase in market concentration, is associated with 0.178% higher levels of prenatal care. However, for the contributory scheme, if you consider a 100 change in HHI, the increase in market concentration is associated with 0.35% lower levels of prenatal care (both in the pre and post period). This negative effect of market concentration on prenatal care utilization is largely influenced by the coefficient between Contributory and HHI. Likewise, this coefficients could be interpreted through the lens of a reduction in market concentration: if the HHI decreases by 100 in the subsidized scheme, then the predicted levels of prenatal care are expected to decrease while in the contributory scheme they are expected to increase.

The findings suggest that insurer concentration has opposing effects across the two health insurance schemes, reflecting fundamental differences in how each scheme operates. In the subsidized scheme, where the average HHI is higher (3478), increased market concentration appears to enhance prenatal care utilization. In this scheme, a higher concentration among insurers may lead to more coordinated care delivery or reduced administrative inefficiencies. This could be due to insurers having greater control over healthcare networks, allowing them to streamline service provision. Conversely, in the contributory scheme, where insurer competition is higher (average HHI of 2089), an increase in HHI results in a decline in prenatal visits. This suggests that increased concentration might reduce competition, leading to worse outcomes — potentially by limiting choices for patients or decreasing incentives for insurers to improve service quality.

Breaking down this effect in the different rurality categories yields the following insight: (1) in urban areas, the effect of HHI on prenatal care depends on the health insurance scheme. In the contributory scheme, an increase in HHI is associated with lower prenatal care levels, whereas in the subsidized scheme, an increase in HHI is associated with higher prenatal care levels. In Intermediate and Rural areas, the effect of HHI on prenatal care is close to 0 and non-significant across both schemes. In Scattered rural areas, it follows that a higher HHI is associated with higher prenatal care levels, and this holds for both schemes. This suggests that the effect of HHI on prenatal care might also be influenced by rurality categories and not only by insurance schemes.

6.2.3 Results for Staggered DiD for Unification of Benefits Plans

To further narrow the treatment effect of the Unification of the Benefits Plans, I ran the Difference-in-Differences model with Multiple time periods outlined in the previous section. In table 16, I summarize the Average Treatment Effect for each group at each time. Here, I consider the "minors" group (g =1) to be group 1, while the "adults" group (g = 2) to be group 2. Similarly, I set the treatment date for the minors (t = 1) to be January 2010, whereas the treatment date for adults (t =2) is July 2012. Here, we care about the periods in which $g \geq t$ for all g, since we want to report the treatment effect for groups that have been treated at period t. Thus, we can notice that the treatment effect for the "minors" group at time 1 is 2.3% and it is 2.84% at time 2. For the adult 2 group, it is 1.45% at time

2. Here, I consider the control group to be ”not treated yet” units, which consists of both never treated units (individuals in the contributory scheme) and not-yet treated units (eg. adults in the subsidized scheme at time 1). This reported result would change if the control group were selected differently.

Lastly, I would highlight that the overall treatment effect was calculated to be 2.28%, as shown in Table 15. This suggests that the policy is associated with a differential increase of 2.28% in prenatal visits in the subsidized scheme compared to the contributory scheme.

6.3 Results for DDIV Models with Health Outcomes as Dependent Variable

As stated in Equations (6)-(8), I use the policy reforms—the Unification of Benefits Plans and Law 1438 of 2011—as instruments for prenatal visits in a Difference-in-Differences Instrumental Variables (DDIV) framework. These policies create exogenous variation in access to prenatal care, allowing me to estimate the causal effect of prenatal visits on the probability of positive birth outcomes while addressing potential endogeneity concerns.

As my dependent variables are binary indicators of birth outcomes, I estimate the second-stage and reduced-form regressions using a logit model. Unlike in a linear probability model (LPM), where coefficients can be directly interpreted as marginal effects, the logit model provides log-odds ratios, making causal interpretation less straightforward. In the second stage, the coefficient on prenatal visits captures changes in the log-odds of a normal birth outcome rather than a direct probability shift. Similarly, in the reduced-form regression, the policy effect represents the log-odds change in birth outcomes due to the policy, not a simple percentage point change. It is important to note that the standard errors presented on the Second-Stage regression tables are not correct because they might be correlated with the error terms in the first stage. This implies that the significance levels of the coefficients presented in these tables are also not correct.

Lastly, the in-sample relationship between prenatal visits and normal health outcomes is captured in Figure 17 through Figure 19. These plots capture the share of newborns with normal health outcomes for each level of prenatal care. For weight and gestation time, this graph shows strong evidence that suggests endogeneity (and supports the IV Model I used): as prenatal visits increase a certain threshold, the share of newborns with normal outcomes starts declining, suggesting that a high number of prenatal visits signals pregnancy related-complications, which could translate into worst health outcomes. However, these figures present another takeaway: for women that don't have low prenatal care levels (more than 4 visits) and also don't have very high levels of care (less than 15 visits), the share of newborns with normal outcomes is almost 20 percentage points higher than for the group of individuals with low levels of care. These graphs motivate the instrumented prediction of normal health outcomes conditioned on prenatal care levels and insurance scheme affiliation.

6.3.1 Results for Law 1438 DDIV

Table 6 contains the second-stage results from the DiD-IV model, which takes the fitted number of prenatal visits from the first stage and estimates their effect on the probability of normal birth outcomes using a logit model. This stage captures the causal impact of additional prenatal visits on birth weight, birth length, and gestational time, with the coefficients reflecting changes in log-odds rather than direct probability shifts. While a causal interpretation of the coefficients can't be drawn, we can conclude, given the coefficients of prenatal visits and the interaction term, whether the probability distribution for each normal outcome is increasing or decreasing in prenatal visits for each health scheme. For the subsidized scheme, the probability distributions of normal weight, length and gestation are increasing in prenatal visits, as all the coefficients in the first row of Table 6 are positive. For the contributory scheme, this does not hold for the three outcomes: for weight and length, the probability distributions of normal health outcomes are increasing in prenatal visits, whereas for gestation time, the probability distribution is not. This result can be summarized as follows: when using the 2011 Law as an instrument, higher levels of prenatal care predict better health outcomes in the subsidized scheme. In the contributory scheme, this holds for weight and length, but not for gestation time, indicating that prenatal care might contribute to better outcomes for certain, but not all observable indicators at birth.

Table 7 presents the reduced-form regression results, which directly estimate the effect of the 2011 Law on birth outcomes. This specification bypasses the first-stage instrument and instead captures the total policy effect on birth outcomes, encompassing both direct effects and any indirect pathways beyond increased prenatal visits. Like the second-stage model, the reduced-form coefficients are in log-odds terms, meaning they reflect relative changes in the likelihood of normal birth outcomes rather than simple percentage point shifts.

6.3.2 Results for Teenage Mothers DDIV

Table 9 captures the second-stage results from the DiD-IV model for minors taking the Unification of Health Benefits Plans as policy, which takes the fitted number of prenatal visits from the first stage and estimates their effect on the probability of normal birth outcomes using a logit model. This stage captures the causal impact of additional prenatal visits on birth weight, birth length, and gestational time, with the coefficients reflecting changes in log-odds rather than direct probability shifts. For the subsidized scheme, the probability distributions of normal weight, length and gestation are increasing in prenatal visits, as all the coefficients in the first row of Table 9 are positive. For the contributory scheme, this does not hold for the three outcomes: for weight , the probability distribution of normal health outcomes is increasing in prenatal visits, whereas for length at birth and gestation time, the probability distributions are not. This result can be summarized as follows: when using the Unification of health benefits for teenage mothers as an instrument, higher levels of prenatal care predict better health outcomes in the subsidized scheme. In the contributory scheme, this holds for weight, but not for length and gestation time, indicating that prenatal care might be less determinant of normal health outcomes for minors than for adults.

To better understand the predicted probabilities of normal outcomes, I plotted the average predicted probability of normal health outcomes conditioned on the number of prenatal visits for both health schemes. These figures consider an average of the probabilities for each municipality weighted on the amount of observations registered. Figure 14(b), plots the predicted share of newborns with normal birth weight, Figure 15(b), plots the predicted share of newborns with normal size at birth, and Figure 16(b), plots the predicted share of newborns with normal gestational time conditioned on prenatal visits.

The graphs for the weighted average predicted probability of normal health outcomes at birth for adult mothers behave as follows:

1. **Weight:** Figure 14(b) indicates that for both schemes, the predicted probability of normal outcomes is increasing in prenatal visits. It also shows that the predicted probability of normal birth weight without any prenatal visits is 85% for the subsidized scheme and 87% for the contributory scheme, suggesting that, in the absence of prenatal care, individuals in the contributory scheme tend to have better birth outcomes. The slope of the subsidized scheme's curve is steeper at lower numbers of prenatal

visits, and it intersects the contributory curve at approximately four prenatal visits. This suggests that the marginal effect of an additional prenatal visit is initially higher in the subsidized scheme compared to the contributory scheme. A possible explanation is that better infrastructure, higher-quality healthcare, and improved maternal support in the contributory scheme may help mitigate the risks of low birth weight more effectively, even before prenatal care interventions take place. Another explanation is that the probability of a successful birth conditioned on low birth weight is higher in the contributory scheme.

2. **Length:** Figure 15(b) indicates that for the subsidized scheme, the predicted probability of normal outcomes is increasing in prenatal visits, whereas for the contributory scheme, it is decreasing. This suggest that the logit model might not capture the impact of prenatal visits on length as the probability of "abnormal" length is very low. Conditioned on low prenatal visits, the predicted probability of normal length is higher for the contributory scheme, and both lines intersect at around 6 prenatal visits. The predicted probabilities of normal length at birth are higher than 98% for all levels of prenatal care across both schemes.

3. **Gestation Time:** For the subsidized scheme, the predicted probability of normal gestation time is increasing on prenatal visits, but for the contributory scheme, it is decreasing. For the adults in the contributory scheme, the decrease in predicted probability as prenatal visits increase is not as high as the decrease for the teenage mothers in the contributory scheme in Figure 16(b) : it is likely the case that prenatal care for adult mothers helps mitigate the bias introduced by women with high-risk pregnancies choosing to attend more prenatal visits. It could also be the case that factors beyond prenatal visits, such as baseline maternal health, and access to early interventions, may be more determinant for gestation time outcomes for individuals in the contributory scheme. In contrast, for the subsidized scheme, prenatal visits seem to play a more critical role in ensuring full-term pregnancies.

6.3.3 Results for Adult Mothers DDIV

Table 8 captures the second-stage results from the DiD-IV model for adults taking the Unification of Health Benefits Plans as policy, which takes the fitted number of prenatal visits from the first stage and estimates their effect on the probability of normal birth outcomes using a logit model. This stage captures the causal impact of additional prenatal visits on birth weight, birth size, and gestational time. For the subsidized scheme, the probability distributions of normal weight and length are increasing in prenatal visits, but for gestation time, its probability of normal outcomes is decreasing in prenatal visits. For this regression, the same is true for the contributory scheme: weight and length are positively influenced by prenatal care, which is not the case for gestation time. Note that these regressions use the unification of the health Benefits Plans for adults as the instrument.

To better understand the predicted probabilities of normal outcomes, I plotted the weighted average predicted probability of normal health outcomes conditioned on the number of prenatal visits for both health schemes. Figure 14(a), plots the predicted share of newborns with normal birth weight, Figure 15(a), plots the predicted share of newborns with normal size at birth, and figure Figure 16(a), plots the predicted share of newborns with normal gestational time conditioned on prenatal visits.

The graphs for the weighted average predicted probability of normal health outcomes at birth for adult mothers behave as follows:

1. **Weight:** Figure 14(a) indicates that for both schemes, the predicted probability of normal outcomes is increasing in prenatal visits. It also indicates that for all levels of prenatal care, the probability of better health outcomes is higher in the subsidized scheme than in the contributory scheme. In the subsidized scheme, the predicted probability of normal weight at 0 visits is around 81%, and at 10 visits, it is around 92%. In the contributory scheme, the predicted probability of normal weight at 0 visits is around 80%, and at 10 visits it is 91%.

2. **Length:** Figure 15(a) indicates that for both schemes, the predicted probability of normal outcomes is increasing in prenatal visits. Conditioned on low prenatal visits, the predicted probability of normal outcomes is higher for the contributory scheme, yet the marginal effect of an additional visit is higher in the subsidized scheme. The predicted probabilities of normal length at birth are higher than 98% for all levels of prenatal care across both schemes.

3. **Gestation Time:** For both schemes, the predicted probability of normal gestation time is decreasing on prenatal visits. For the contributory scheme, the decrease in predicted probability of normal gestation time is higher than in the subsidized scheme. This is likely a result of endogeneity within the sample: women who go to more

prenatal visits are likely to do so since there is an underlying complication that results in an "abnormal" gestation time.

6.4 Results for Panel Data relating Fetal Deaths to Prenatal Care at the Municipality Level

The regression in this section follows the model outlined in Equation 18. I estimate the mortality rate for each disease at the municipal level, defined as the ratio of deaths from that illness in a given year and the sum of the total of deaths and births in the same municipality and year. This illness-specific mortality rate is then regressed on the average number of prenatal visits at the municipal level, along with dummy variables for the insurance scheme and rurality category. To do so, I selected the top five reported causes of death based on ICD-10 codes, excluding two: P018, which groups illnesses under "other" maternal complications, making it too broad and unspecific for analyzing the effect of prenatal visits on mortality, and P964, which categorizes abortions and pregnancy terminations, which are not directly influenced by prenatal care. The four selected causes of death are hypoxia (inadequate oxygen supply to body tissues), placental abnormalities, slow fetal growth, and chorioamnionitis (an infection of the placenta and amniotic fluid). The models using these illnesses are presented in columns 1–4 of Table 12.

Importantly, the coefficient of Average Prenatal Visits is statistically significant and negative for two diseases: Hypoxia and Placental Abnormalities. This indicates that as the average number of prenatal visits increases, the expected mortality rate due to these diseases decreases. Specifically, in the case of Hypoxia, the coefficient is -0.0063, meaning that an additional prenatal visit, on average, would reduce the mortality rate associated with Hypoxia by 0.06 percentage points, holding other factors constant. More intuitively, this says that if the mortality rate associated to hypoxia is 2% for a municipality, an extra prenatal visit is estimated to reduce this rate to 1.94%. Similarly, for Placental Abnormalities, the coefficient is -0.0014, meaning that an additional prenatal visit would lead to a 0.014 percentage point decrease in the mortality rate for this condition, suggesting a protective effect of prenatal care against these complications, yet showing that these protective effect does not extend to other illnesses that might not be preventable or treatable through the channel of prenatal care.

This panel model strengthens the intuition achieved in the DDIV Models with Health

Outcomes as Dependent Variables: prenatal visits show a correlation with specific health outcomes, like weight at birth and reduction of mortality rate by Hypoxia. At the same time, prenatal visits are not correlated to other health outcomes like gestation time and mortality rate by slow growth, which suggests that these outcomes are less likely to be improved through the channel of prenatal care. Given that the expansion of prenatal care for vulnerable groups was achieved for the individuals in the subsidized scheme through the Unification of the Benefits Plans, this policy is likely to have an effect in improving health outcomes.

7 Discussion

This paper employs multiple approaches to study the effect of the 2011 Law and the unification of the Health Benefits Plans—implemented between 2009 and 2012—on prenatal care, with a particular focus on vulnerable populations defined along poverty and rurality dimensions. In the context of the Colombian health insurance system, affiliation type serves as a proxy for income level: individuals in the contributory scheme are generally non-poor, as they are formal workers whose income exceeds the minimum salary, while those in the subsidized scheme are considered poor. Rurality is proxied by the reported area of residence of mothers at the time of birth.

The disparity in access to prenatal care between women in both schemes is significant: women in the subsidized scheme attend 28–40% fewer prenatal consultations than their contributory counterparts in urban areas, and 16–35% fewer in rural areas. Although poor women had access to a free, basic benefits package prior to 2012, the unification of the Health Benefits Plans expanded their access to a broader set of services and removed bureaucratic barriers—such as the need for Health Secretary authorization for specialist visits or follow-up care. Additionally, the 2011 Law established preferential access to prenatal services throughout the country. Taken together, these reforms likely played a key role in improving healthcare utilization among poor women. This rests on the assumption that a major barrier to prenatal care for the poor was the cost of consultations and follow-up appointments—an obstacle that the reforms sought to eliminate.

Prior to 2012, 21% of women in the subsidized scheme showed low prenatal care levels, and were four times more likely to have low prenatal care levels than women in the contributory scheme. After the Unification of the Benefits Plans was completed in 2012, the percentage of women with low prenatal care levels decreased by more than 4 percentage points, whereas the percentage of women with low prenatal care levels in the contributory scheme remained stable. This trend suggests that the expansion of benefits and reduction in access frictions contributed to a narrowing of the gap in prenatal care.

However, these average effects mask substantial heterogeneity across territories. Regression results reveal that the reduction in disparities was not uniform across rurality categories. In fact, in the most remote areas—defined as "scattered rural" in the DNP classification—prenatal care utilization worsened following the reforms. A 7% decline in prenatal visits was estimated after Law 1438, and a 9% decline after the Benefits Plans Unification. These patterns point to a critical shortcoming of the policies: while they successfully expanded access in more accessible rural and intermediate areas, they failed to ameliorate existing inequities in the most isolated regions. This could reflect limitations in healthcare infrastructure, provider availability, or enforcement of entitlements in these zones.

In contrast, intermediate and rural areas (excluding the most dispersed ones) appear to have driven much of the observed improvement. For individuals in the subsidized scheme, these territories even outperformed urban areas in some respects. For example, subsidized enrollees in intermediate municipalities were found to receive 4–5% more prenatal visits than their urban counterparts, possibly reflecting shorter wait times or more effective outreach programs. Still, across all rurality types, those in the contributory scheme consistently showed higher utilization than their peers in the subsidized scheme, reinforcing the persistence of income-based disparities.

Controlling for insurer concentration further reveals systemic differences in how the two schemes operate. In the subsidized scheme, higher market concentration (higher HHI) is associated with increased prenatal care utilization, perhaps reflecting more streamlined service provision in monopolistic or oligopolistic markets. In contrast, in the contributory scheme, higher insurer concentration is associated with worse prenatal care access, possibly due to reduced competitive pressure on insurers to maintain service quality or expand provider networks. These opposing effects underscore the distinct institutional logics of the two schemes and suggest that market structure plays a critical, yet asymmetric, role in shaping maternal health access.

Finally, using logit models predicting the probability of normal health outcomes, this paper finds that prenatal visits are causally associated with improved birth outcomes—particularly birth weight — yet not with others like gestational time. These effects are strongest for individuals in the subsidized scheme, indicating that the marginal benefit of additional care is higher among the poor. Municipality-level panel data models reinforce this conclusion, revealing that increased prenatal visits are associated with lower mortality rates from fetal causes such as hypoxia and placental abnormalities—conditions whose incidence is likely reduced by expanded prenatal care.

Focusing solely on the birth outcomes and mortality rates analyzed in this study—and using conservative international estimates—the treatment effect of a 4% increase in prenatal care utilization is associated with an annual social value of approximately \$290 million USD. This figure combines the estimated prevention of 72 fetal deaths from hypoxia (valued at \$600,000 each using international value-of-life benchmarks[3]), 12,500 avoided low birth weight cases (each estimated at \$14,000 in neonatal care costs[4]), and 2,400 fewer premature births (each averaging \$30,000 in short-term medical costs[5]). While some cost estimates are U.S.-specific, they provide a useful benchmark for the potential scale of economic benefits, especially when adjusted conservatively for international contexts. These figures underscore that even modest improvements in preventive care access can yield substantial social and economic returns.

This paper finds that Colombia's health reforms succeeded in improving access to prenatal care among the poor and narrowing disparities between insurance schemes, particularly in non-scattered rural areas. Yet, these gains remain uneven. Scattered rural territories continue to experience significant barriers to access, and insurer concentration exerts divergent pressures depending on the scheme in question. While prenatal visits do improve health outcomes—particularly among the most vulnerable—there is a need for complementary policies that strengthen infrastructure and accountability mechanisms in the most remote regions. The challenge ahead lies not only in expanding entitlements but in ensuring their realization across all geographies and populations.

[3]Robinson, L.A., Hammitt, J.K., & O'Keeffe, L. (2019). Valuing Mortality Risk Reductions in Global Benefit-Cost Analysis. Journal of Benefit-Cost Analysis, 10(S1), 15–50. https://doi.org/10.1017/bca.2018.26

[4]Russell, R.B., et al. (2007). Cost of Hospitalization for Preterm and Low Birth Weight Infants in the United States. Pediatrics, 120(1), e1–e9. https://doi.org/10.1542/peds.2006-2386

[5]Institute of Medicine (2007). Preterm Birth: Causes, Consequences, and Prevention. National Academies Press. https://www.ncbi.nlm.nih.gov/books/NBK11362/

8 Conclusion

This thesis set out to understand how structural reforms to Colombia's healthcare system—particularly Law 1438 of 2011 and the Unification of the Health Benefits Plans—affected the utilization of prenatal care and maternal health outcomes across regions and populations. Through a combination of Difference-in-Differences, instrumented logit models, and panel models at the municipal level, the analysis finds robust evidence that the Unification of Health Benefits contributed to a measurable increase in prenatal care utilization for women in the subsidized scheme. These increases in utilization are causally linked to improvements in certain birth outcomes: prenatal visits are positively associated with higher probabilities of normal birth weight and length, particularly for individuals in the subsidized scheme. Likewise, higher average prenatal visits at the municipality level predict lower fetal mortality from preventable causes such as hypoxia and placental abnormalities. However, these gains were not evenly distributed: in scattered rural territories—the most remote and institutionally underserved regions—prenatal care utilization worsened following both policy interventions, and mortality outcomes remained more volatile. These results emphasize that national-level access gains may mask persistent or even worsening disparities in more isolated areas.

From an economic perspective, the relevance of these findings lies in the nature of prenatal care as a high-return, low-cost preventive investment. Prenatal care helps reduce the incidence of avoidable and expensive complications—including preterm births, low birth weight, and neonatal mortality—by facilitating early detection of risk factors, timely interventions, and health education. These complications, if left unaddressed, often require costly medical treatments (e.g., NICU admissions) and carry long-term consequences for child development and human capital accumulation. The estimated effect of prenatal visits on outcomes at birth and disease-specific mortality rates supports the view that increased access to prenatal care not only improves immediate health outcomes but likely generates long-term economic returns by reducing the burden on the health system and improving early-life health endowments.

Importantly, the scale of the investment required to implement these reforms was substantial. The unification of the Health Benefits Plans alone represented over 12.6% of Colombia's total health budget in 2012. This occurred in a context where the rapid expansion of the subsidized population placed massive pressure on public finances. As Lamprea and García (2016) point out, by 2011, "68% of the funds used to finance the subsidized scheme came from public sources," mostly through national transfers to local governments, while only 25% came from payroll taxes, and municipalities themselves contributed just 1%. This fiscal architecture reveals the underlying tension between the policy ambition of universal access and the structural fragility of its financing model. The findings presented in this thesis suggest that while this public investment yielded tangible benefits—especially by reducing access disparities between schemes—it did so within a system increasingly reliant on centralized transfers and politically contingent budget priorities.

From a policy design standpoint, the results point to the limits of demand-side reforms—such as insurance benefit equalization—when not complemented by supply-side investments in healthcare infrastructure, provider availability, and transportation networks. Scattered rural territories are characterized by low provider density, weak institutional presence, and high geographical barriers—factors that cannot be addressed solely through expanding nominal entitlements. In such contexts, market design features, like insurer concentration, also have distinct effects. While higher insurer concentration in the subsidized scheme was associated with greater prenatal care utilization, in the contributory scheme, higher concentration was correlated with lower utilization, likely due to weakened competitive incentives. This divergence underscores the importance of aligning competition policy with broader goals of access and equity in regulated healthcare markets.

More broadly, this thesis contributes to the economics literature on healthcare access in developing countries by documenting how insurance structure and policy design interact with geography and market concentration to shape the distributional effects of reform. In a system as fragmented as Colombia's—where individuals can choose among competing insurers, but where real options are unevenly distributed—the institutional details of reform matter. As many middle-income countries pursue universal health coverage within managed competition frameworks, the Colombian case offers key lessons: expanding formal coverage is necessary, but insufficient; targeting infrastructural and institutional bottlenecks is crucial to ensure equity in actual access and outcomes.

Data Availability

I provide data and code for replicating the results of this paper in this GitHub Repository[6].

[6] This repository is available at: https://github.com/pablotorresrey/colombiaprenatalvisits

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10 Figures

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Table 1: Variables of Interest Present in Births and Fetal Deaths Datasets

Name	**Distribution in Dataset**
Insurance Type	0 (Subsidized) - 56% 1 (Contributory) - 44%
Rurality Type	Urban – 78.1% Intermediate – 13.8% Rural – 5.4% Scattered rural – 2.8%
Weight at Birth	1 (< 1 kg) – 0.4% 2 (1.0–1.49 kg) – 0.7% 3 (1.5–1.99 kg) – 1.6% 4 (2.0–2.49 kg) – 6.1% 5 (2.5–2.99 kg) – 26.3% 6 (3.0–3.49 kg) – 42.3% 7 (3.5–3.99 kg) – 19.0% 8 (> 4 kg or more) – 3.4%
Length at Birth	1 (< 20 cm) - 0.0004% 2 (20-29 cm) - 0.1% 3 (30-39 cm) - 1% 4 (40-49 cm) - 40.7% 5 (50-59 cm) - 57.8% 6 (60-69 cm) - 0.01%
Gestation Time	1 (< 22 weeks) – 0.0% 2 (22–27 weeks) – 0.4% 3 (28–37 weeks) – 18.5% 4 (38–41 weeks) – 80.4% 5 (> 42 weeks) – 0.4%
Prenatal Consults	0 consultations – 2.7% 1-4 consultation – 18.5% 5 consultations – 12.2% 6 consultations – 16.7% 7 consultations – 16.8% 8 consultations – 17.1% 9 consultations – 9.4% 10 consultations – 4.6% 11+ consultations – 1.5%
ICD-10 (Disease) Code	P018 (Other Complications) - 67% P200 (Hypoxia) - 8.1 % P95 (Unspecified cause) - 8.1% P014 (Ectopic pregnancy) - 2.6 % P059 (Slow Fetal Growth) - 1.7 %

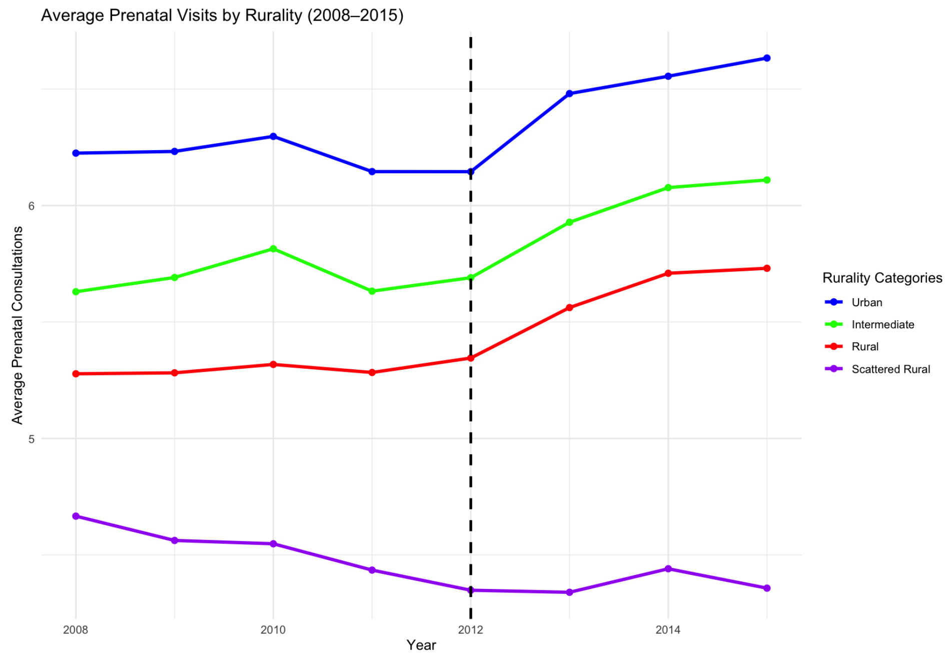


Figure 1: Average Prenatal Visits for each rurality category

Table 2: Total Number of Events by Affiliation and Residential Area (2008–2014)

Year	**Total Events**	**Affiliation**		**Residential Area**		
		Contributory	**Subsidized**	**Urban**	**Populated Centers**	**Dispersed Rural**
2008	550,759	257,768	292,991	444,641	38,953	67,165
2009	545,843	249,206	296,637	438,392	40,304	67,147
2010	510,115	233,248	276,867	407,379	33,564	69,172
2011	545,691	239,525	306,166	428,026	39,372	78,293
2012	570,598	245,586	325,012	446,587	42,670	81,341
2013	580,424	254,637	325,787	457,237	42,390	80,797
2014	599,980	265,270	334,710	477,367	42,914	79,699

Source: DANE, 2015

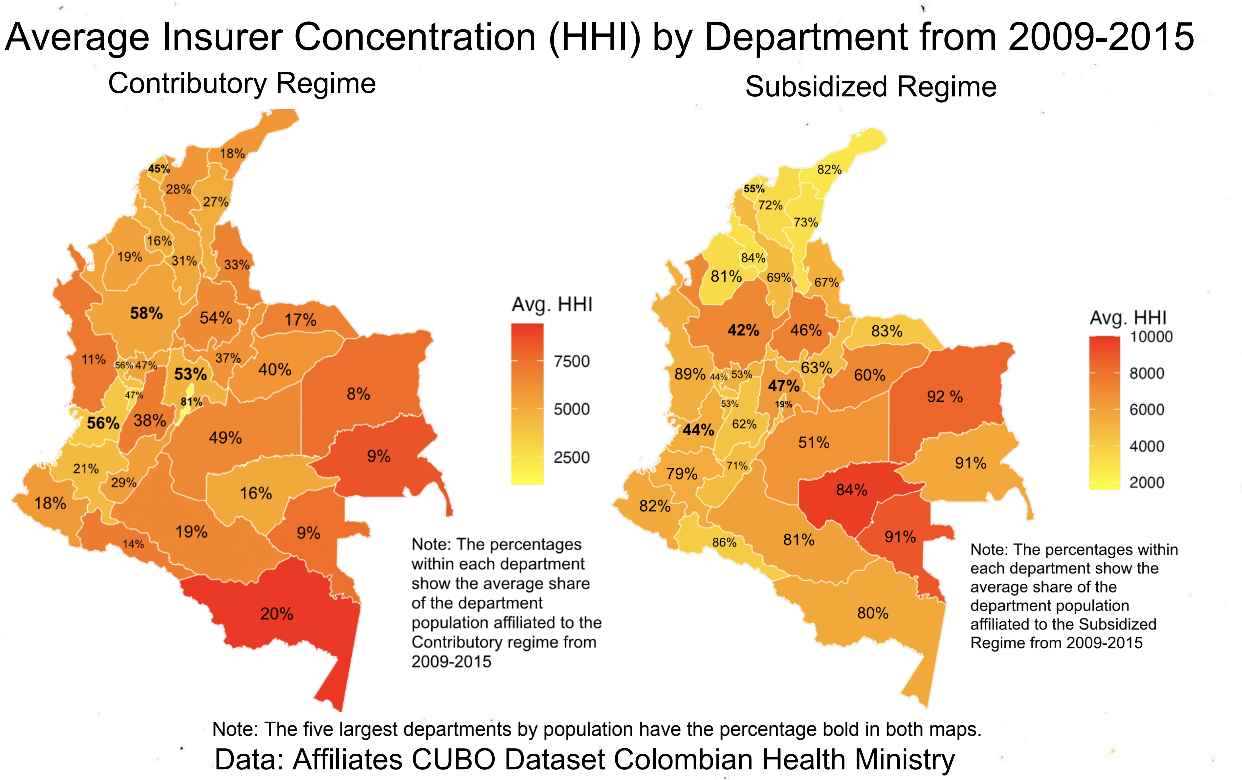
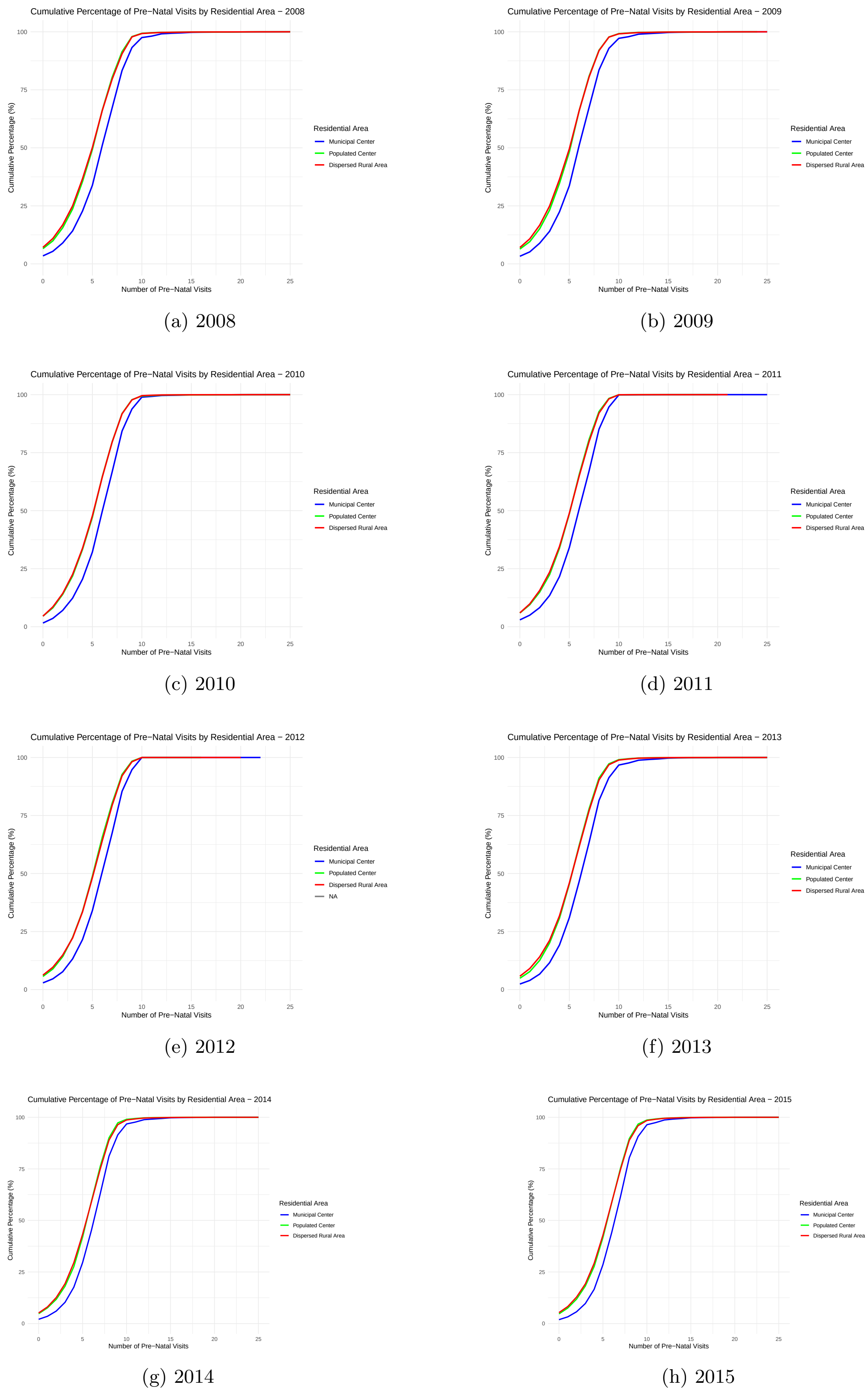


Figure 2: Maps of Mean Herfindahl-Hirschman Index (HHI) by Department from 2009-2015.



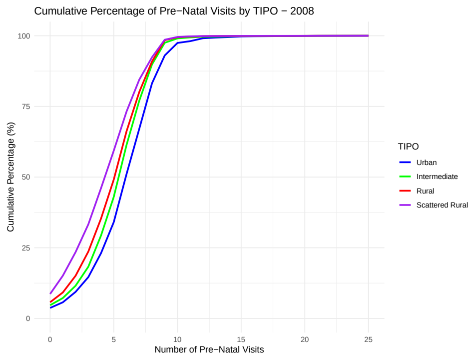
(a) 2008 (b) 2009

(c) 2010 (d) 2011

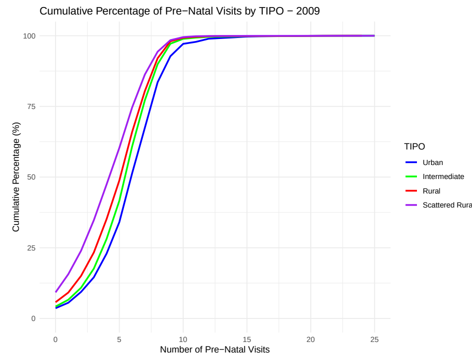
(e) 2012 (f) 2013

(g) 2014 (h) 2015

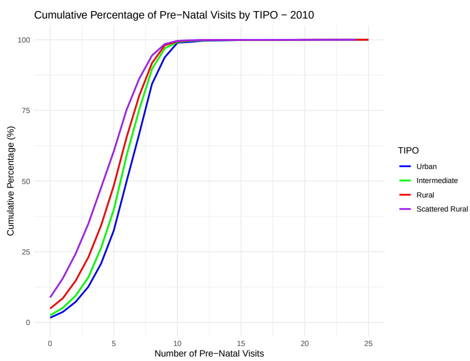
Figure 3: Cumulative Percentage of Prenatal Visits by Year (2008-2015)



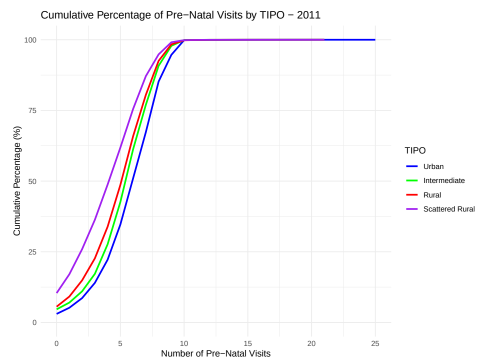
(a) 2008



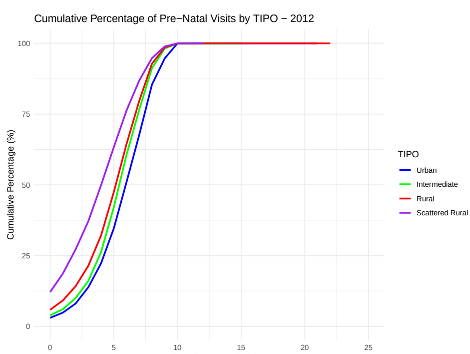
(b) 2009



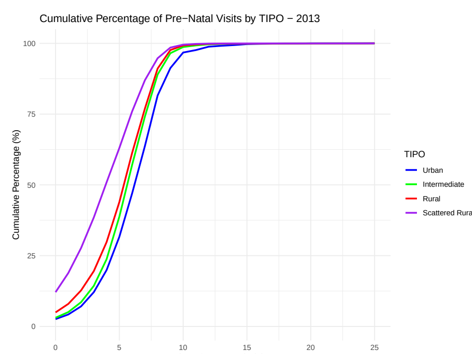
(c) 2010



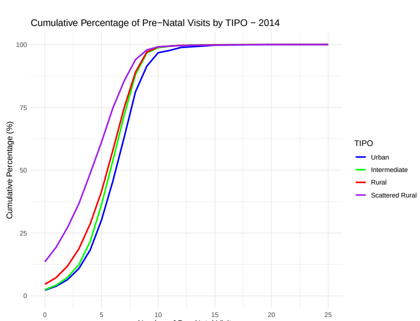
(d) 2011



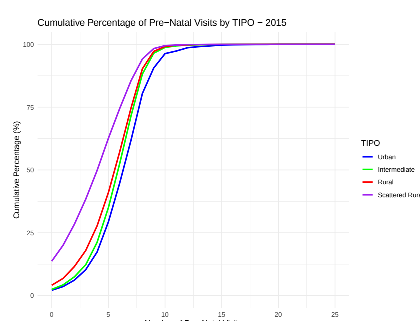
(e) 2012



(f) 2013



(g) 2014



(h) 2015

Figure 4: DNP Cumulative Percentage of Prenatal Visits by Year (2008-2015)

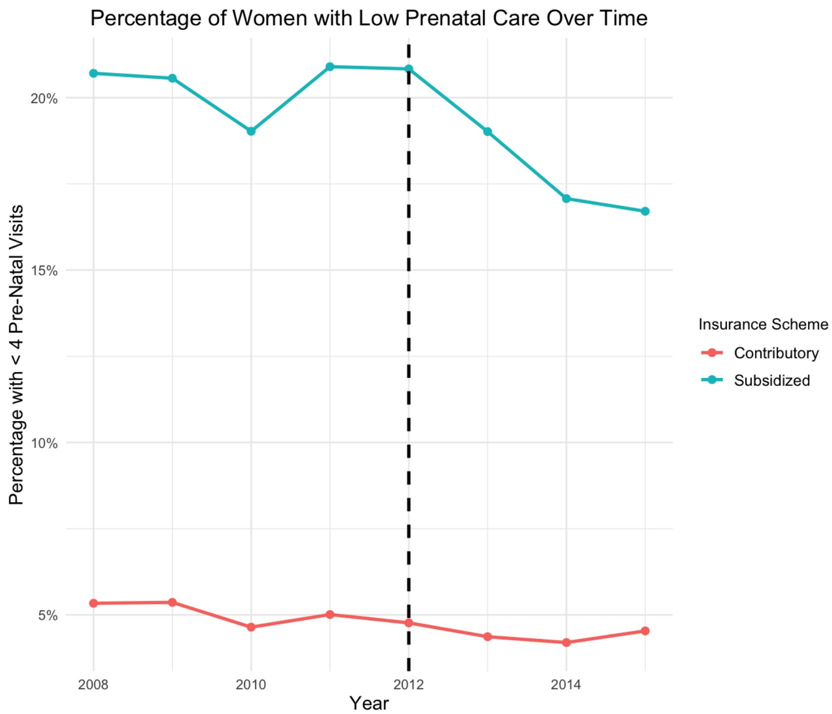


Figure 5: Percentage of Women with 4 or fewer Prenatal Visits over time across both Schemes

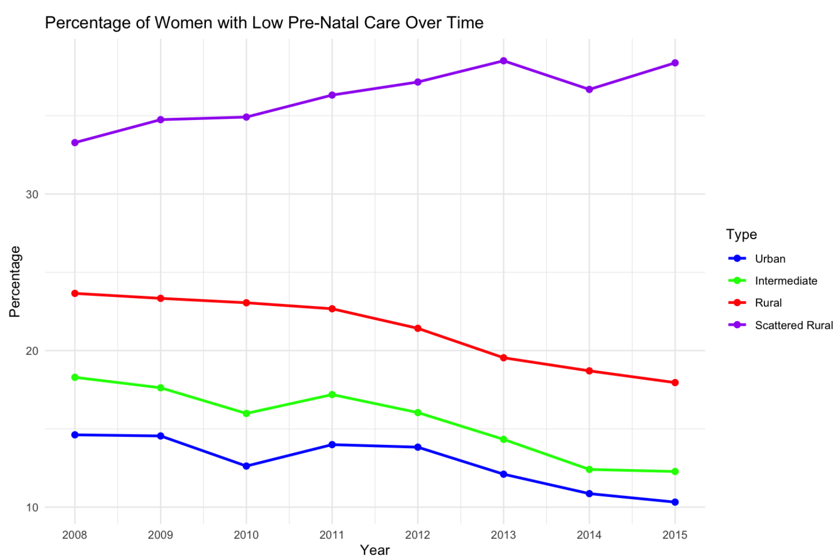


Figure 6: Percentage of Women with 4 or fewer Prenatal Visits per year for each rurality category

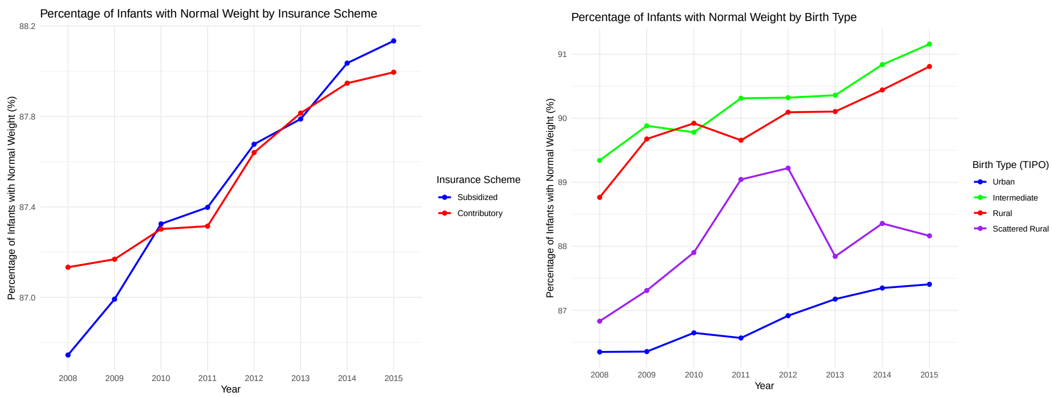


Figure 7: Annual Share of Newborns with Birth Weight Between 2.5 and 4 kg by Health Insurance Scheme (left) and by Rurality Category (right)

Source: DANE, 2014

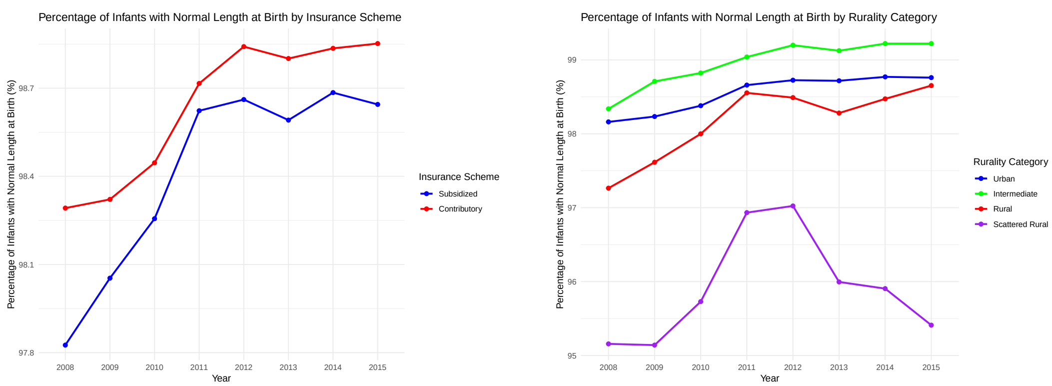


Figure 8: Annual Share of Newborns with Normal Length at Birth (40- 50 cm) by Health Insurance Scheme (left) and by Rurality Category (right)

Source: DANE, 2014

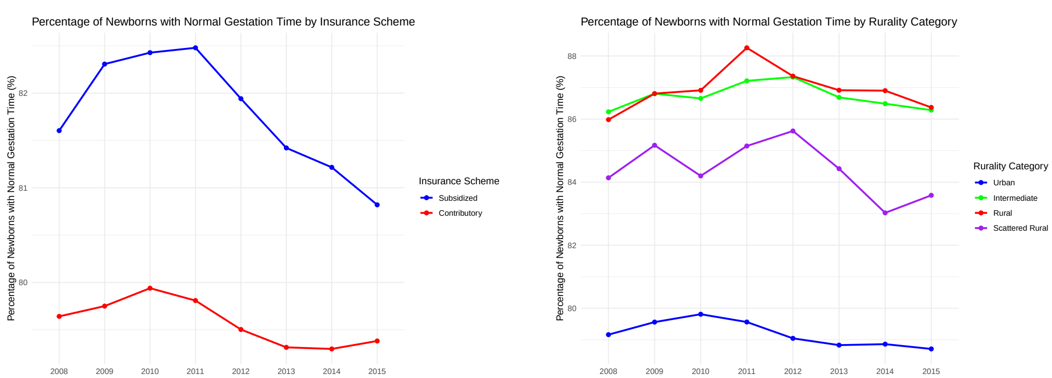


Figure 9: Annual Share of Newborns with Normal Gestation Time (38-41 weeks) by Health Insurance Scheme (left) and by Rurality Category (right)

Source: DANE, 2014

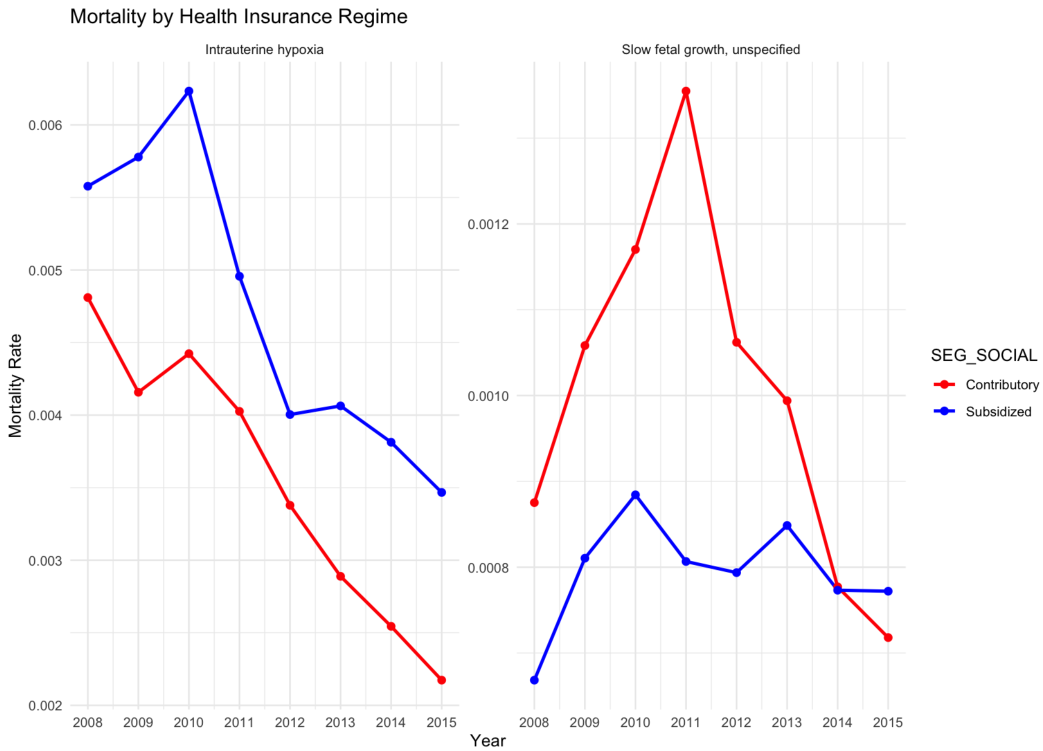


Figure 10: Mortality for Hypoxia and Slow Fetal Growth Across Health Schemes

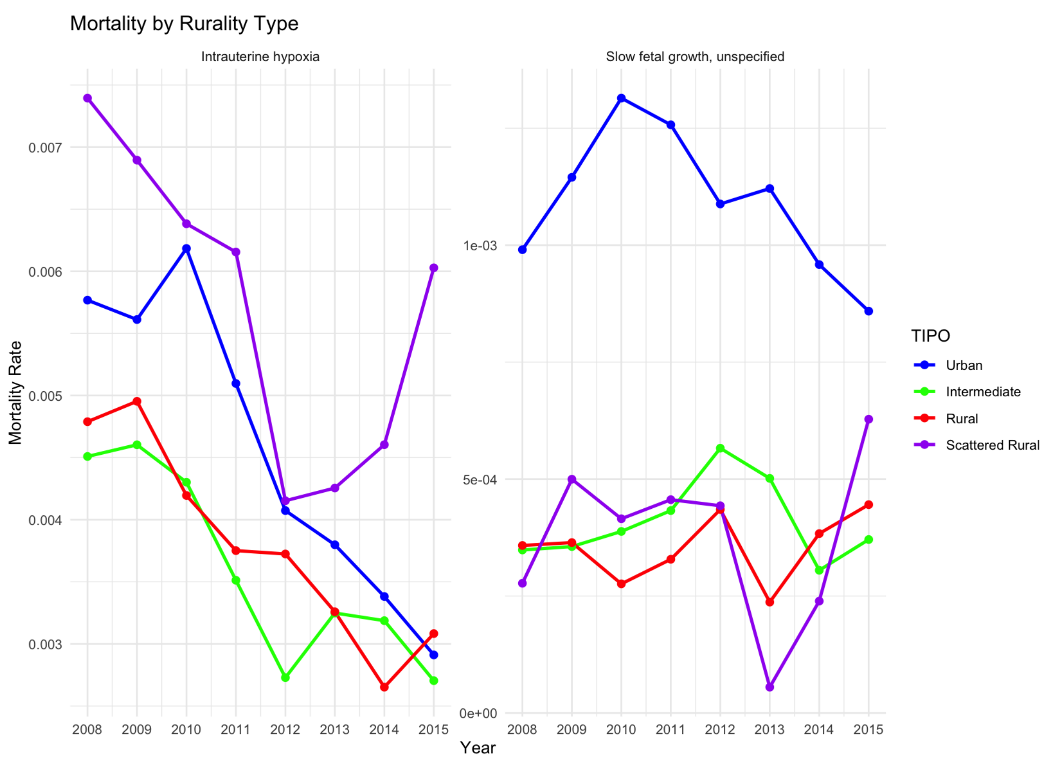


Figure 11: Mortality for Hypoxia and Slow Fetal Growth Across Rurality Categories

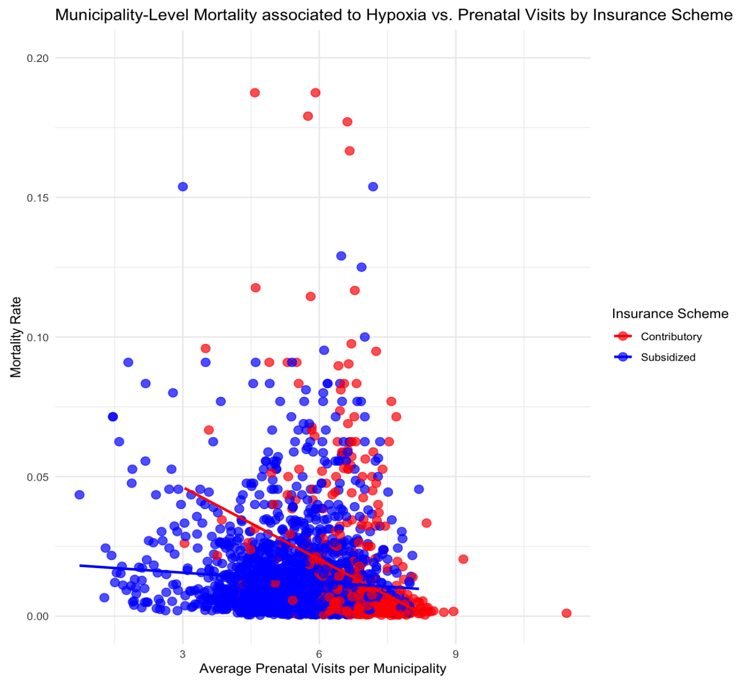


Figure 12: Hypoxia-Related Mortality vs. Average Prenatal Visits across Insurance Schemes in Municipalities

Notes: Municipalities with less than 10 yearly reported births were excluded from the graph

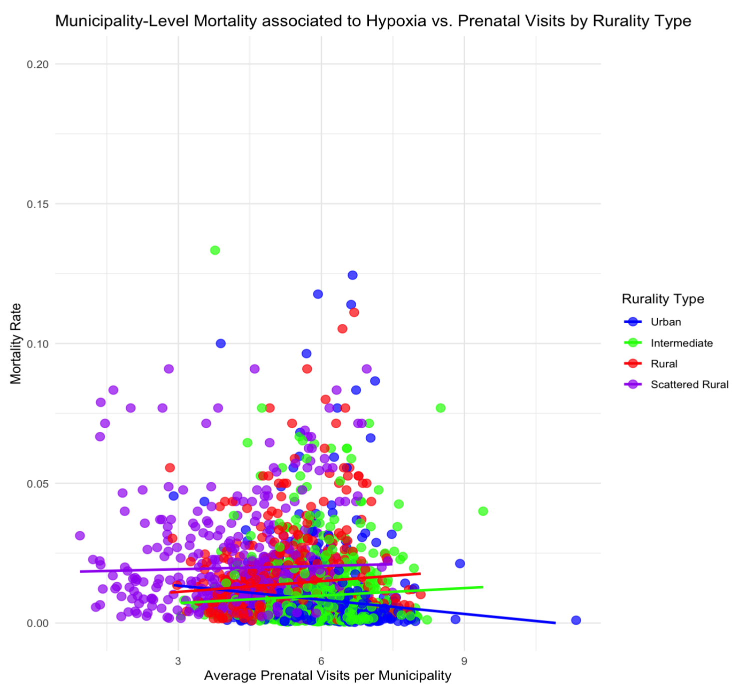


Figure 13: Hypoxia-Related Mortality vs. Average Prenatal Visits across Rurality Category in Municipalities

Notes: Municipalities with less than 10 yearly reported births were excluded from the graph

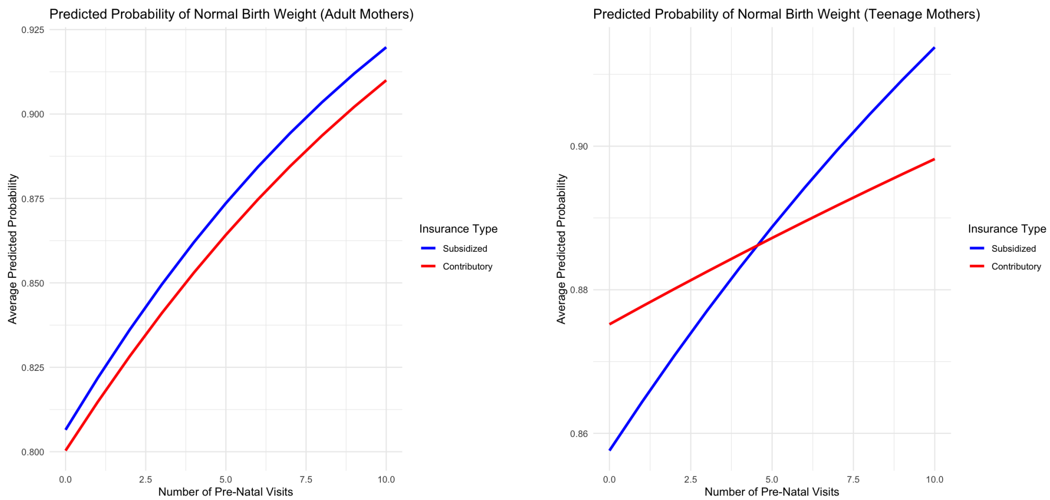


Figure 14: Predicted Share of Newborns with Birth Weight Between 2.5 and 4 kg by Health Insurance Scheme conditioned on the Number of Prenatal visits for Adult Mothers (left) and Teenage Mothers (right)

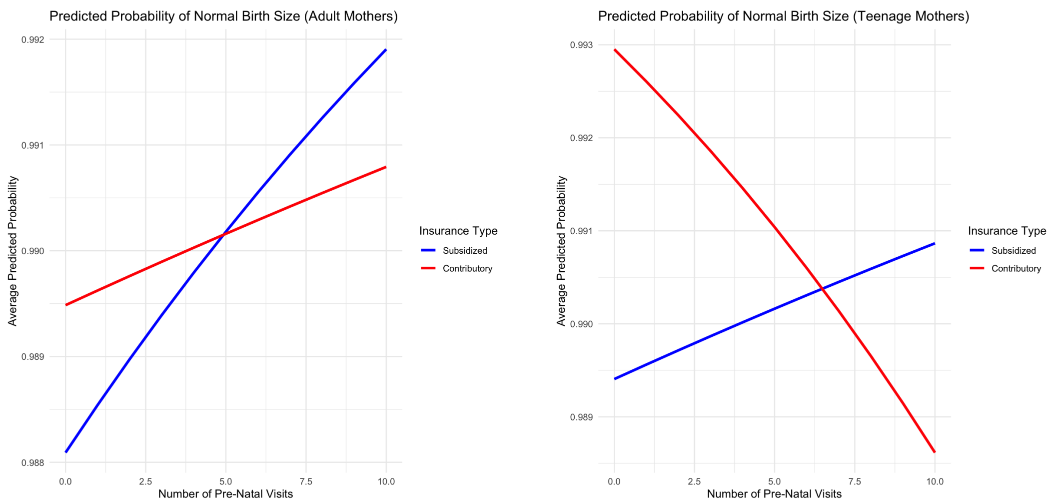


Figure 15: Predicted Share of Newborns with Normal Length at Birth (40- 50 cm) by Health Insurance Scheme conditioned on the Number of Prenatal visits for Adult Mothers (left) and Teenage Mothers (right)

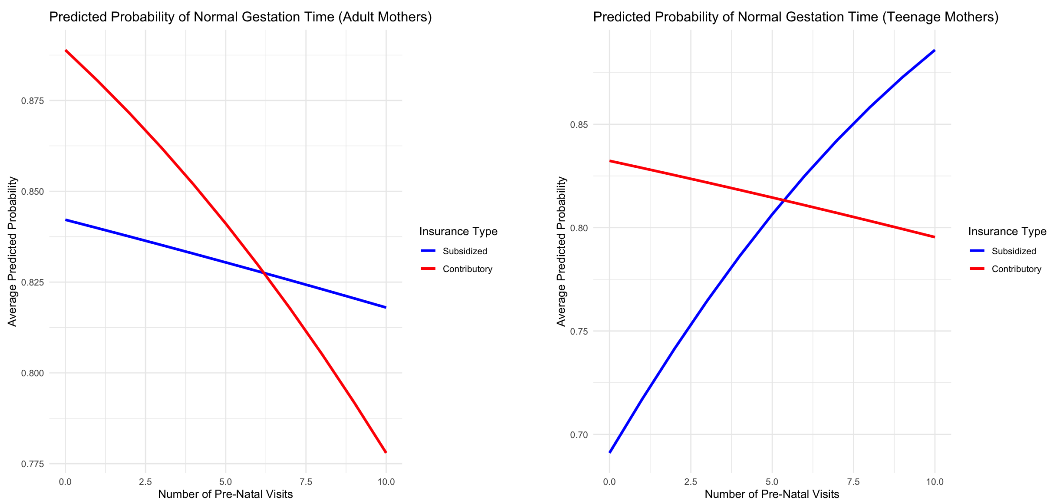


Figure 16: Predicted Share of Newborns with Normal Gestation Time (38-41 weeks) by Health Insurance Scheme conditioned on the Number of Prenatal visits for Adult Mothers (left) and Teenage Mothers (right)

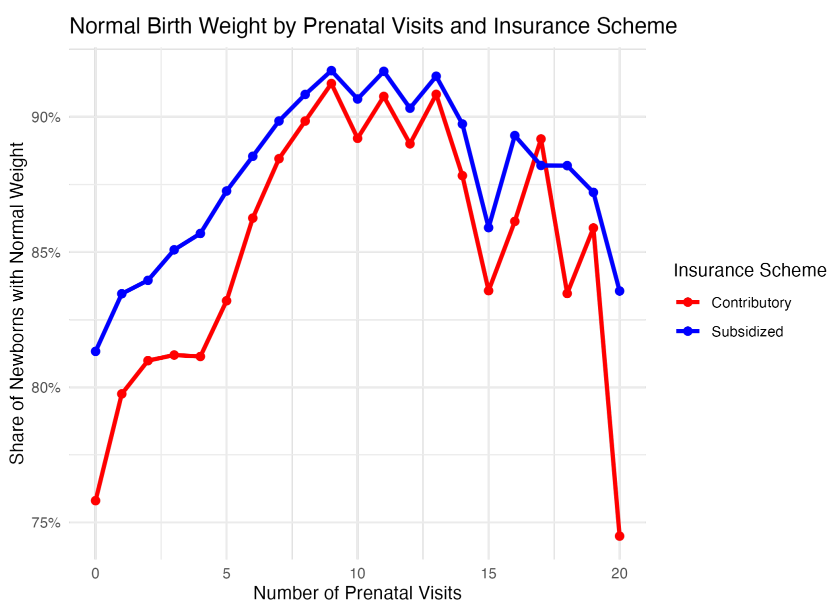


Figure 17: Share of Newborns with Normal Birth Weight by Number of Prenatal Visits and Insurance Type

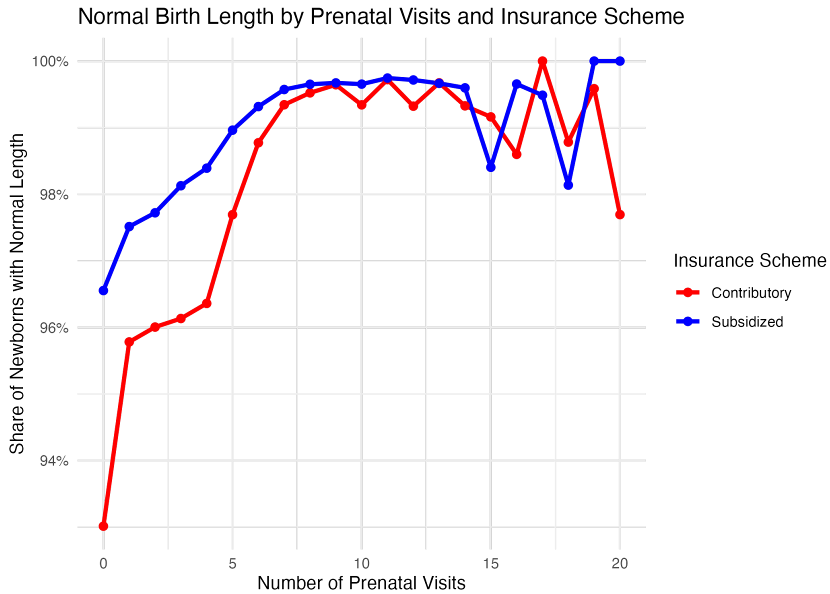


Figure 18: Share of Newborns with Normal Birth Length by Number of Prenatal Visits and Insurance Type

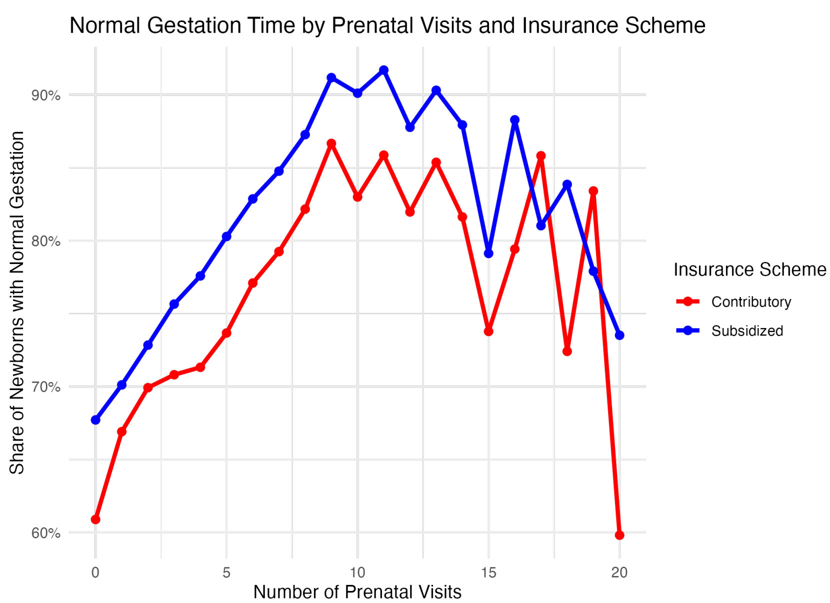


Figure 19: Share of Newborns with Normal Gestation Time by Number of Prenatal Visits and Insurance Type

Table 3: Difference-in-Differences Regression on Log Prenatal Visits for Insured Population for Law 1438 of 2011

Dependent Variable:	Logaritm of Prenatal Visits	
Model:	(1)	(2)
Variables		
Non-Urban	-0.0699***	
	(0.0209)	
Intermediate		0.0413**
		(0.0166)
Rural		0.0135
		(0.0208)
Scattered Rural		-0.1028***
		(0.0216)
Contributory	0.2795***	0.3021***
	(0.0329)	(0.0299)
Post × Non-Urban	-0.0039	
	(0.0108)	
Post × Contributory	-0.0160	-0.0170
	(0.0103)	(0.0114)
Non-Urban × Contributory	-0.0613**	
	(0.0270)	
Post × Intermediate		-0.0025
		(0.0165)
Post × Rural		0.0109
		(0.0120)
Post × Scattered Rural		-0.0753***
		(0.0232)
Contributory × Intermediate		-0.1407***
		(0.0336)
Contributory × Rural		-0.1082**
		(0.0432)
Contributory × Scattered Rural		-0.0720
		(0.0435)
Fixed-effects		
Year	Yes	Yes
Department	Yes	Yes
Fit statistics		
Observations	4,694,796	4,694,796
R^2	0.12496	0.12505
Within R^2	0.08109	0.08118

Clustered Department standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The first column uses the dataset's definition of Rurality, while the second uses the DNP categorization. Both regressions include all necessary interaction terms. However, non-significant triple interaction terms have been omitted from the table for clarity.

Table 4: Difference-in-Differences Regression on Log Prenatal Visits for Population aged 12-17 for the Unification of the Benefits Plans

Dependent Variable:	Logaritm of Prenatal Visits	
Model:	(1)	(2)
Variables		
Non-Urban	-0.0671***	
	(0.0187)	
Intermediate		0.0520***
		(0.0172)
Rural		0.0343
		(0.0204)
Scattered Rural		-0.0652***
		(0.0216)
Contributory	0.2301***	0.2520***
	(0.0370)	(0.0332)
Post × Contributory	-0.0297**	-0.0320**
	(0.0117)	(0.0120)
Post × Non-Urban	-0.0121	
	(0.0122)	
Contributory × Non-Urban	-0.0646**	
	(0.0294)	
Post × Intermediate		-0.0095
		(0.0202)
Post × Rural		-0.0085
		(0.0161)
Post × Scattered Rural		-0.0916***
		(0.0254)
Contributory × Intermediate		-0.1357***
		(0.0357)
Contributory × Rural		-0.1172**
		(0.0497)
Contributory × Scattered Rural		-0.0895**
		(0.0415)
Fixed-effects		
Year	Yes	Yes
Department	Yes	Yes
Fit statistics		
Observations	1,069,123	1,069,123
R^2	0.07577	0.07522
Within R^2	0.03674	0.03616

Clustered Department standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The first column uses the dataset's definition of Rurality, while the second uses the DNP categorization. Both regressions include all necessary interaction terms. However, non-significant triple interaction terms have been omitted from the table for clarity.

Table 5: Difference-in-Differences Regression on Log Prenatal Visits for Adults for the Unification of the Benefits Plans

Dependent Variable:	Logaritm of Prenatal Visits		
Model:	(1)	(2)	(3)
Variables			
Post	0.0272***	0.0282***	0.0489***
	(0.0055)	(0.0060)	(0.0118)
Contributory	0.2811***	0.3037***	0.4129***
	(0.0303)	(0.0274)	(0.0546)
Non-Urban	-0.0688***		-0.0507
	(0.0211)		(0.0359)
Intermediate		0.0369**	
		(0.0173)	
Rural		0.0111	
		(0.0211)	
Scattered Rural		-0.1179***	
		(0.0229)	
Post × Contributory	-0.0263***	-0.0276***	-0.0366**
	(0.0084)	(0.0088)	(0.0136)
Post × Non-Urban	-0.0073		-0.0358
	(0.0078)		(0.0230)
Post × Intermediate		-0.0007	
		(0.0136)	
Post × Rural		0.0112	
		(0.0115)	
Post × Scattered Rural		-0.0907***	
		(0.0236)	
Contributory × Non-Urban	-0.0559**		-0.0366
	(0.0251)		(0.0461)
Contributory × Intermediate		-0.1456***	
		(0.0325)	
Contributory × Rural		-0.0996**	
		(0.0430)	
Contributory × Scattered Rural		-0.0779*	
		(0.0458)	
HHI			1.78×10^{-5}***
			(5.14×10^{-6})
Post × HHI			-1.08×10^{-5}**
			(5.23×10^{-6})
Contributory × HHI			-5.42×10^{-5}***
			(1.46×10^{-5})
Non-Urban × HHI			-9.61×10^{-6}
			(8.03×10^{-6})
Post × Contributory × HHI			1.09×10^{-5}**
			(5.32×10^{-6})
Fixed-effects			
Year	Yes	Yes	Yes
Department	Yes	Yes	Yes
Fit statistics			
Observations	3,625,673	3,625,673	1,280,062
R^2	0.13353	0.13404	0.14026
Within R^2	0.08756	0.08810	0.09316

Clustered Department standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The first and third column use the dataset's definition of Rurality, while the second uses the DNP categorization. The third column controls for HHI. The three regressions include all necessary interaction terms. However, non-significant triple interaction terms have been omitted from the table for clarity.

Table 6: Logit Fitted Probability Estimates from Second-Stage DDIV Regression Using 2011 Law as Policy

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Prenatal Visits	0.0868	0.0441	0.0372
	(0.0641)	(0.1043)	(0.0771)
Contributory	-0.0216	0.2197	0.5481*
	(0.1638)	(0.3205)	(0.3147)
Prenatal Visits × Contributory	-0.0106	-0.0400	-0.0946*
	(0.0275)	(0.0520)	(0.0524)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	4,666,025	4,666,025	4,666,025
Squared Correlation	0.00132	0.00043	0.00527
Pseudo R^2	0.00176	0.00379	0.00550
BIC	3,460,856.3	558,416.4	4,562,975.5

Clustered Department standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The reported standard errors reflect 2SLS estimation and are incorrect for interpreting the second-stage logit; they do not account for the first-stage uncertainty.

Table 7: Reduced Form Logit Estimates of 2011 Law on Birth Outcomes for Adults

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Non-Urban	-0.0132	0.0458	-0.0041
	(0.0247)	(0.0474)	(0.0223)
Contributory	0.0523**	0.0019	-0.0757*
	(0.0227)	(0.0243)	(0.0460)
Non-Urban × Post	0.0035	-0.0150	0.0401**
	(0.0138)	(0.0469)	(0.0188)
Non-Urban × Contributory	-0.0854***	-0.0527	-0.0149
	(0.0307)	(0.0647)	(0.0480)
Post × Contributory	-0.0111	0.0224	0.0083
	(0.0145)	(0.0232)	(0.0190)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	4,666,025	4,666,025	4,666,025
Squared Correlation	0.00132	0.00043	0.00524
Pseudo R^2	0.00176	0.00382	0.00546
BIC	3,460,889.1	558,446.0	4,563,195.2

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Non-significant triple interaction terms have been omitted from the table for clarity.

Table 8: Logit Fitted Probability Estimates from Second-Stage DDIV Regression Using Unification of Benefits as Policy for Adults

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Prenatal Visits	0.1013*	0.0390	-0.0172
	(0.0563)	(0.1009)	(0.0718)
Contributory	-0.0390	0.1260	0.4068
	(0.1562)	(0.3280)	(0.3559)
Prenatal Visits × Contributory	-0.0087	-0.0256	-0.0657
	(0.0229)	(0.0510)	(0.0555)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	3,603,422	3,603,422	3,603,422
Squared Correlation	0.00115	0.00046	0.00548
Pseudo R^2	0.00152	0.00412	0.00575
BIC	2,695,502.8	433,679.4	3,505,284.6

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The reported standard errors reflect 2SLS estimation and are incorrect for interpreting the second-stage logit; they do not account for the first-stage uncertainty.

Table 9: Logit Fitted Probability Estimates from Second-Stage DDIV Regression Using Unification of Benefits as Policy for Minors

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Prenatal Visits	0.0566	0.0150	0.1252
	(0.0951)	(0.1433)	(0.0898)
Contributory	0.1523	0.4113	0.8022**
	(0.2274)	(0.4196)	(0.3632)
Prenatal Visits × Contributory	-0.0336	-0.0634	-0.1498**
	(0.0443)	(0.0700)	(0.0652)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,061,539	1,061,539	1,061,539
Squared Correlation	0.00256	0.00036	0.00586
Pseudo R^2	0.00344	0.00316	0.00592
BIC	764,251.0	125,176.7	1,055,415.7

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The reported standard errors reflect 2SLS estimation and are incorrect for interpreting the second-stage logit; they do not account for the first-stage uncertainty.

Table 10: Reduced Form Logit Estimates of Unification of Benefits Impact on Birth Outcomes for Adults

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Non-Urban	-0.0223	0.0219	0.0284
	(0.0220)	(0.0421)	(0.0199)
Post	0.0181	0.0238	-0.0049
	(0.0133)	(0.0340)	(0.0144)
Contributory	0.0709***	-0.0068	-0.1017**
	(0.0166)	(0.0237)	(0.0468)
Non-Urban × Post	0.0037	0.0273	0.0274
	(0.0123)	(0.0530)	(0.0184)
Non-Urban × Contributory	-0.0632**	-0.0764	-0.0271
	(0.0246)	(0.0487)	(0.0517)
Post × Contributory	-0.0185	0.0490**	0.0198
	(0.0150)	(0.0220)	(0.0223)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	3,603,422	3,603,422	3,603,422
Squared Correlation	0.00115	0.00047	0.00548
Pseudo R^2	0.00153	0.00416	0.00575
BIC	2,695,557.3	433,722.5	3,505,364.9

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Non-significant triple interaction terms have been omitted from the table for clarity.

Table 11: Reduced Form Logit Estimates of Unification of Benefits Impact on Birth Outcomes for Minors

Dependent Variables:	normal_weight	normal_length	normal_gestation
Model:	(1)	(2)	(3)
Variables			
Non-Urban	0.0118	0.0983	-0.0164
	(0.0366)	(0.0661)	(0.0285)
Contributory	-0.0005	0.0112	-0.0556
	(0.0327)	(0.0749)	(0.0471)
Non-Urban × Post	-0.0065	-0.0718	-0.0058
	(0.0244)	(0.0734)	(0.0258)
Non-Urban × Contributory	-0.1343**	0.1557	-0.0461
	(0.0590)	(0.2090)	(0.0484)
Post × Contributory	0.0140	0.0290	0.0251
	(0.0241)	(0.0689)	(0.0227)
Fixed-effects			
Department	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,061,539	1,061,539	1,061,539
Squared Correlation	0.00258	0.00037	0.00575
Pseudo R^2	0.00346	0.00327	0.00580
BIC	764,277.5	125,205.5	1,055,577.0

Clustered (Department) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Notes:*Non-significant triple interaction terms have been omitted from the table for clarity.

Table 12: Panel Fixed Effects at the Municipality Level Model Relating Mortality Rates associated to Illnesses to Average Prenatal Visits

Dependent Variable:	Mortality Rate			
Associated Illness:	Hypoxia	Placental Abnormalities	Slow Growth	Chorioamnionitis
Model:	(1)	(2)	(3)	(4)
Variables				
Avg. Prenatal Visits	-0.0063*	-0.0013*	0.0006	-0.0004
	(0.0033)	(0.0007)	(0.0006)	(0.0003)
Contributory	0.0281	0.0047	0.0033*	-0.0004
	(0.0288)	(0.0064)	(0.0018)	(0.0006)
Non-Urban	-0.0058	0.0025	0.0049	0.0043
	(0.0046)	(0.0030)	(0.0036)	(0.0034)
Avg. Prenatal Visits × Contributory	-0.0046	-0.0006	-0.0005*	6.84×10^{-5}
	(0.0048)	(0.0010)	(0.0003)	(8.84×10^{-5})
Avg. Prenatal Visits × Non-Urban	0.0008	-0.0006	-0.0009	-0.0007
	(0.0008)	(0.0005)	(0.0005)	(0.0005)
Contributory × Non-Urban	-0.0310	-0.0099	-0.0076*	-0.0010
	(0.0287)	(0.0162)	(0.0040)	(0.0038)
Fixed-effects				
Municipality	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,856	684	554	187
R^2	0.95745	0.95472	0.99899	0.99995
Within R^2	0.08658	0.02863	0.05541	0.16190

Clustered Municipality standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

*Notes:*Non-significant triple interaction terms have been omitted from the table for clarity.

Table 13: Group-Time Average Treatment Effects for Unification of Benefits Staggered DiD

Group	**Time**	**ATT (g,t)**	**Std. Error**	**[95% Simult. Conf. Band]**
1	1	0.0232	0.0018	[0.0187, 0.0277]
1	2	0.0284	0.0017	[0.0241, 0.0328]
2	1	0.0185	0.0012	[0.0154, 0.0215]
2	2	0.0145	0.0011	[0.0119, 0.0172]

Table 14: Dynamic Effects Summary for Unification of Benefits Staggered DiD

Event Time	**Estimate**	**Std. Error**	**[95% Simult. Conf. Band]**
-1	0.0185	0.0011	[0.0159, 0.0211]
0	0.0171	0.0008	[0.0152, 0.0191]
1	0.0284	0.0017	[0.0245, 0.0324]

Table 15: Aggregate ATT Summary for Unification of Benefits Staggered DiD

ATT	**Std. Error**	**[95% Conf. Interval]**
0.0228	0.001	[0.0208, 0.0248]