Do Price Regulations on Birth Control Pills Decrease Fertility?

Ana Melissa Perez*

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Abstract

In 2018, the Colombian government intervened in the pharmaceutical market by creating cap prices on high-cost birth control pills. Given the necessity of these drugs, the effects of price reductions are not always clear. Also, there is no evidence of whether the policy effectively increased access to contraception and reduced pregnancy rates. Therefore, this study aims to analyze fertility changes due to price caps on birth control pills. Using administrative claims from an insurer in the contributory regime, I found little evidence that price regulation affected fertility, even for young women. The results indicate that the policy did not achieve its goal of reducing fertility.

Keywords: Cap prices regulation, pharmaceutical market, fertility, contraceptive pills

JEL Codes: I18, J13, I11

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1 Introduction

In 2013, the Colombian government introduced pricing policies that regulated drug prices in the country. When a drug´s price in Colombia is higher than a threshold determined as the quartile of a reference list of 17 countries that sell it, the government can intervene by setting a cap price (Prada et al., 2018a). In 2018, the Ministry of Health regulated the price of certain birth control pills, based on the argument their high price affected access to contraception services; decreasing them might help avoid unsafe abortions (Ministry of Health 2018). For instance, after the regulation, the retail price of the contraceptive drug Yasminq fell by almost 60%, from COP 58,000 to COP 22,364 (Espectador, 2020). The initial price for a one month supply was 8% of the Colombian monthly minimum wage in 2017. Due to the magnitude of these changes, the cap price policy could significantly affect the demand for contraceptive drugs in Colombia.

Given the importance of understanding the consequences of price regulation, the goal of this paper is to estimate the effect on prices and on the fertility of Colombian women of this cap price regulation for oral contraceptives. To do this, I use three different sources of data. The first is the Drug Price Information System, which contains national information from producers and importers of the drugs sold in the country. This allows me to quantify the magnitude of changes in the prices of these drugs. The second source is the Health Benefits Information System, which has data on all births that occur in the contributory or sudsidized regime in Colombia, with data aggregated to the provider-diagnostic level. This system operates under Universal Health Coverage, which makes my results representative. In addition, I use data from an insurer in the contributory regime that covers around 2% of the enrollees in the system. Its population includes low-income workers; most of whom earn less than twice the minimum wage. The data cover the period 2017-2020, with information regarding enrollment and each service the women had with their health insurance. Also, although the paper targets all women, it also studies teenage pregnancy, which may be more affected because teenagers have less access to contraceptives and may have a more elastic demand that reacts to price changes.

I use difference-in-differences regressions and event studies to identify the effects of this policy on prices, quantities and three fertility outcomes (deliveries, prenatal care services, and pregnancy). The identification strategy is challenging because Colombia is a centralized country where all legislation and price regulations apply to the whole territory. For the price analysis, I compare drugs that were regulated with those that were not regulated. The drugs that I use as controls should not experience price changes because they could also be subject to government intervention. For the fertility analysis, given some differences in the drug concentration across regions, some municipalities are more affected than others (see Graph 1). Therefore, the first difference is before and after the intervention was implemented in January 2019. The second difference is a continuous variable that compares women in low and high-prescription areas (use of birth control pill services as the proportion of all contraception methods in 2017). To accomplish this, I use linear regressions with fixed effects. Since I calculate the treatment based on pre-treatment data from an insurer, which does not represent the whole universe of the Colombian system, I also use a second source of information from the Health Services Information System (RIPS for its acronym in Spanish), which provides aggregated data for all insurers in Colombia. This allows me to confirm that the treatment (the demand for birth control pills after the law was implemented) is not sensitive to the population from the insurer in a given municipality.

Even though I find a sharp decline in prices, I find little evidence that price controls on contraception drugs affect fertility rates. The difference-in-differences regressions show no significant impact on deliveries and pregnancies. These results are confirmed by event studies that indicate that the effect was not different from zero. Similarly, the event studies and difference-in-differences regressions for teenagers yield the same results, showing null effects for the three outcomes. Even if the impact on the demand were immediate, deliveries might take time to show results (nine months on average); that is why I use other variables, such as prenatal care services and pregnancies. Even though 2020 is a problematic year due to Covid-19, I retain it in the regressions because deliveries, pregnancies, and prenatal care services could have occurred due to women not taking a pill before the COVID era. One year after the program was implemented, the prenatal care outcome appears to react to the policy (see Models 2 and 3 in Table 6). However, these results are not confirmed under the RIPS data, where the coefficients are not significant. Overall, the evidence indicates that prices of contraceptives do not seem to be the primary driver of pregnancies in Colombia, at least for this period of analysis.

The results from the robustness checks using the treatment from the RIPS data do not show any effect of the policy; after the price decrease, enrollees in municipalities with high demand for birth control pills do not show changes in fertility rates (see Models 4 and 6 in Tables 5, 6, and 7). Although these difference-in-difference results may seem at odds with the policy goals, a possible explanation is that women have an inelastic demand for contraceptives, and even if the private market dominates the supply of the contraception pills, changes in prices do not affect fertility rates, at least in the short term. It is also likely that there could exist a substitution effect with condoms; however, to analyze that, additional information is needed.

A priori, the effect of regulating prices on fertility is not predictable. If the elasticity of demand is large, a price decrease may increase the demand. However, if it is inelastic, indicating that the price is not the primary determinant of purchasing the drug, and perhaps other factors such as religion, cultural beliefs, or lack of contraception knowledge have a lager effect the impact of changes in prices. In this case, given the results from the difference-in-differences and event studies, the purchase of contraceptives may be driven by these other factors. Therefore, future policies that target fertility should not rely on reducing prices to induce changes in birth rates.

The literature on the topic can be divided into two main areas: access to contraception and its effects on fertility, and price regulations and consequences. In the former case, several studies shows that birth control pills caused a decline in the fertility rate. For instance, in the United States, the introduction of the pill changed its trend during the 1950s and 1960s (Bailey, 2006, 2010; Guldi, 2008), which allowed women to postpone the age of marriage and increase their years of schooling (Goldin and Katz, 2002). Recent studies show that the Affordable Care Act, which increased insurance access, is associated with more contraception use (Mulligan, 2015; Becker et al., 2021), birth rate declines, and fewer abortions (Abramowitz, 2018; Heim et al., 2018; Mulligan, 2015). So, even in the current era, access to contraception could impact fertility even more in Colombia, where abortion became legal only in 2022. Regarding price regulations, the studies find that international reference pricing allows price reductions (Leopold et al., 2012; Håkonsen et al., 2009). These reductions could increase the demand for drugs, which could be a negative outcome in unnecessary induced demand, but a positive one with contraception pills.

The literature in Colombia has focused on analyzing price cap regulations introduced in 2010 and the later policy of international reference pricing in 2013. The first drugs with price regulations were those for treating cancer, diabetes, Parkinson's, and Alzheimer's disease (Bardey et al., 2018). Thus, most of the literature in Colombia has focused on analyzing changes in price and quantities at the supply level. Furthermore, given the lack of free access data, the studies have identified aggregate changes at the drug level for national series (Prada et al., 2018b; Bardey et al., 2018; Andía, 2018; Contreras, 2019; Andia et al., 2022). Except for Andia et al. (2022), those studies were published before birth control pill regulation. So, they evaluate the impact of the policies on other drugs. The only paper close to this study is Andia et al. (2022), which analyzes the changes in prices and quantities of birth control pills in Colombia. The authors found that the policy effectively reduced prices and increased demand, using aggregate data of the national level and pharmacy surveys in one city. However, the paper did not focus on health outcomes, lacks representativeness, and did not use individual-level data, which did not allow them to assess the policy's effectiveness.

This paper makes several contributions to the literature on the effects of price regulations in developing countries. First, it shows that contraceptive pills could have inelastic demand, so that lead to no changes in fertility at least for the analysis period. Second, given that the literature has focused on aggregate price and quantity effects (Prada et al., 2018b; Bardey et al., 2018; Andía, 2018; Contreras, 2019; Andia et al., 2022), this study builds on the previous literature by providing evidence on a health outcome (fertility). Third, this is the first study in this area that uses individual administrative claims data. Moreover, this study has the advantage of having data from 2% of the population, provided by an insurer from the contributory regime in a health care system with universal coverage. It also provides evidence on fertility outcomes, which surveys' self-reported information cannot precisely capture. This panel contains daily bills from providers to insurers and their diagnoses for each service from January 2017 to December 2020. Fourth, changes at the national distribution levels (aggregate level) do not necessarily translate to more intake of contraception pills. Due to the low prices, pharmacies could buy the pills, but this does not mean that women actually purchase more contraception pills. Indeed, this paper finds that the policy was ineffective in reducing pregnancy rates, which is a new finding for Colombia.

I organize the rest of this paper as follows. Section 2 describes price regulations in Colombia. Section 3 introduces the data sources. Subsequently, section 4 explains the identification strategy and empirical methods. Section 5 presents the results and robustness checks; the final section summarizes the conclusions.

2 Background

The Colombian healthcare system has two regimes: subsidized and contributory. The former covers the population without a formal job, which is defined as a job with health insurance and a retirement pension. The latter includes formal workers and their dependents. According to Ministry of Health statistics, in 2019, 52% of the enrollees were in the contributory regime, indicating that only this half of the population paid for health insurance. The people in the subsidized regime do not pay for insurance, yet people in both regimes have access to the same benefits package.

The benefits package includes birth control pills; however, the brands offered are limited, and access to the healthcare system is affected by different factors. For instance, sometimes a person needs to wait in a line for hours to get an outpatient appointment; in other cases, they need to stay on the phone for several minutes or even hours to get an appointment. In addition, there may be a stigma or shame for teenagers to get a prescription. Those reasons make enrollees prefer to buy birth control pills in the private market. According to Profamilia (2015), the private contraceptive market for pills accounts around 42.6% of all pills sold; in addition, only about 25% of young women ages 13-14 know that they can get contraception methods almost for free from their insurers in both regimes. So, the lack of information also makes women get contraception in the private market. Therefore, changes in birth control pill prices in the private market could have lasting effects on fertility decisions.

Price regulation for contraceptives began in 2018, when the Ministry of Health created caps for prices of birth control pills. These caps establish the maximum price for selling the drug at wholesale. Nevertheless, only around half of birth control pills were regulated (Andia et al., 2022). Although previous regulations on other medicines were intended to reduce government expenditure, which is funded mainly by taxes on the subsidized regime, in this case, the incentive was not to reduce the spending, but to improve access and prevent unsafe abortions (given that abortion was legalized only in 2022).

The regulation stipulated that when the contraceptive pill price was higher than a threshold (the 25th percentile of a reference list of 17 countries where it is sold), the government would intervene by setting a price cap equivalent to the 25th percentile of those reference countries (Argentina, Brazil, Peru, Chile, Ecuador, Panama, Mexico, Uruguay, United States, Canada, Germany, Spain, France, Norway, Portugal, United Kingdom, Australia). When this cap is imposed, importers and national producers cannot sell the drug at a higher price, as they could face fines from the Superintendency of Industry and Commerce (SIC). This regulation on the prices of contraceptive pills took effect in 2019.

3 Data

This paper uses four sources of data from Colombia. The first source is the Drug Price Information System, which provides data on prices and quantities at the drug level for the whole country. Although I cannot track prices at the regional, city, or specific location level, this dataset allows me to compare prices across drugs. The second source is the Health Benefits Information System, which has information at the provider-diagnostic level in each municipality for the whole country. This source has the advantage of providing information for both the contributory and subsidized regimes across the whole country. Given Colombia's universal health coverage, this means that, except for home deliveries, all births occurring in clinics or hospitals are captured in this dataset. This allows me to compare across health regime systems while maintaining national coverage. Lastly, the third and fourth sources contain individual-level observations, which allows me to contrast results across different levels of aggregation.

3.1 SISMED Data

The third source of information is the Drug Price Information System (SISMED is its acronym in Spanish). It provides data on all drugs imported or produced in Colombia. Each observation in the dataset represents a drug and includes information on the number of units sold, the average price, period, method of administration (i.e., oral, injection, external, among others), the Anatomical Therapeutic Chemical (ATC) code , and the unique drug identifier (CUM, by its acronym in Spanish). The information is freely accessible on the Ministry of Health website.

For this dataset, I include information on 17 ATCs that contain contraceptive pills. Each ATC can have different drugs—treated, untreated, or both. Table 1 provides more details on all the Anatomical Therapeutic Chemical codes in the sample. It shows that, in the private market, regulated brands account for about 83.15% of contraceptive pill sales. Although I have data until 2022, I focus on the first year the regulation took place. I do this because SISMED changed the way data are reported, aggregating laboratories and wholesalers into one category, which could impact the analysis for 2020, 2021, and 2022. Nevertheless, I show both results. Figure 2 shows that the number of commercial brands increased in 2019 after implementation, meaning that even though some brands were not commercialized every year, all were produced or imported in 2019. However, afterward, the number of drugs commercialized appears to decrease from 2020 to 2022.

3.2 RIPS Data

The fourth source of information is the Health Benefits Information System (RIPS), which provides data disaggregated at the provider-diagnostic level. All services in the private and public healthcare systems in Colombia are reported to RIPS. The data are audited and required by law, so all claims in the health system, except out-of-pocket purchases, appear here. RIPS contains information on services, diagnostic codes, place of service, period, and type of service (i.e., emergencies, outpatient, inpatient services). Access to this dataset was obtained by attending an online course provided by the Ministry of Health. Although the dataset has individual-level information, due to data privacy restrictions, the information is provided to researchers at the provider-diagnostic level. This dataset has the advantage of including all claims in both the public and the private systems. For example, all deliveries attended by a provider appear in RIPS. In addition, procedures such as female sterilization also appear in this dataset.

3.3 HMO Data

This dataset comes from an institutional agreement between Universidad Icesi and a Health Maintenance Organization (HMO). It contains information about the enrollees and all their services during 2018-2020. The enrollee information provides variables such as sex, date of birth, state, municipality of residence, the highest degree of education, and the type of enrollee (dependent or insured). The services dataset has all the claims for each person who had a healthcare service during the period of interest.

The service dataset includes inpatient care, outpatient care, urgent care, and in-home visits, all coded by diagnostic groups classified by the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD10); it also classifies each claim as procedures or drugs, provides the insurance cost and the copayment paid by the patient of treatment based on the share of services related to birth control pills out of the total contraception services by municipalities. This share is also from 2017.

Ideally, I should include a treatment that indicates the private demand for birth control pills, but the Demographic Health Survey data are not statistically representative at the municipality level. When I use the data at this level, the results show inconsistencies, which is the reason why I include two institutional sources for the treatment.

4 Empirical Strategy

I use different strategies based on the datasets I have available to test the hypotheses in this paper. First, I conduct a two-by-two difference-in-difference estimation and event studies to estimate the impact of price regulation on quantities and prices of contraceptives. This approach provides evidence on whether price regulation had an impact on quantities produced in Colombia or imported from abroad. Since this information is at the National level, it helps to understand the magnitude of the impact it could have on prices, as a motivation to analyze fertility outcomes. Equation (1) describes the process at this level.

$$y_{it} = \alpha_0 + \beta Treat_t * D_i + \delta_i + \delta_t + \epsilon_{it} \tag{1}$$

where y_{it} is the average annual price or the total quantity commercialized (nationally produced or imported) in the private market of the contraceptive pill i at year t. $Treat_t$ is a variable that takes the value of one after 2018. D_i is a dummy variable that takes the value of one for the contraceptive pills that were regulated. The coefficient of interest is β, which shows the effects of the law on prices or quantities. I also test the pretends by estimating event studies, as shown in Equation (2).

$$y_{it} = \sum_{k=-\tau}^{\tau} \beta_k \cdot Treat_t * D_i + \delta_i + \delta_t + \epsilon_{it} \tag{2}$$

To estimate the impact of price regulation in birth control pills on fertility, I also use difference-in-difference estimations and event studies. For this analysis, I have data aggregated up to to the municipality-regime health system, where I compare the results on fertility from the subsidized and the contributory regimes. Given the lack of control groups due to the legislation being implemented at the same time, I used as treated the subsidized regime and as control the contributory regime. The hypothesis that low-income people (subsidized regime) could benefit by having low prices and be induced to buy a cheaper contraceptive pill. Equation 3 describes this method.

$$y_{mtr} = \alpha_0 + \beta Treat_t * D_{mr} + \delta_m + \delta_t + \epsilon_{mtr} \tag{3}$$

where y_{mtr} is the fertility outcome in the municipality m at year t in the regime r. $Treat_t$ is a variable that takes the value of one after 2018. D_{mr} is a dummy variable that takes the value of one for the subsidized regime. The coefficient of interest is β, which shows the effects of the law on fertility. I defined the dependent variables based on the International Statistical Classification of Diseases and Related Health Problems 10th Revision. The first outcome is delivery, a rate at the municipality of women with diagnosis codes related to encounter for delivery O80-O84. The prenatal care service rate is the second variable of interest; it was identified using the ICD-10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369). The third dependent variable (being pregnant) is also a rate, calculated as the sum of women who have encountered supervision and antenatal screening of the mother (Z340-Z369) or pregnant state (Z33) or a positive pregnancy test (Z321). I also test the parallel pretrends assumption by estimating event studies that are shown in Equation (4).

$$y_{mtr} = \sum_{k=-\tau}^{\tau} \beta_k \cdot Treat_t * D_{mr} + \delta_m + \delta_t + \epsilon_{mtr} \tag{4}$$

The next part of this paper estimates the conventional difference-in-differences setup, but instead of having two groups (treated and untreated), I use a continuous variable: the share of contraception pill consumption before the treatment. For this, I use two different sources, one provided by the Health Maintenance Organization and the other by the RIPS data. This allows for different groups to have different exposure to the treatment.

This happens because, in some places, women could have diverse preferences for contraception methods, given their cultural backgrounds. The unit of analysis is the individual level, including women between 13-49 years old. Given that the Health Maintenance Organization has information for all the individuals across time, it is possible to include municipality fixed effects to control for unobserved time invariant factors at the municipality level that could bias the estimates. The specification for this estimation is:

$$y_{imt} = \alpha_0 + \beta Treat_t * D_m + \delta_m + \delta_t + \epsilon_{imt} \tag{5}$$

Where y_{imt} is any of the outcome measures for fertility (having or not having a delivery, a prenatal care service, or being pregnant) for individual i at time t, in municipality m. T_t is the time variable, which in this case is given by quarters, starting in January 2017 and ending in December 2020. D_m are groups that come from a share of contraception pills consumption at the municipality level. The share is built as the proportion of women who encounter contraceptive pill surveillance (ICD10 diagnosis code Z304) over the women who requested a contraception service in the municipality m. δ_m and δ_t are municipality and time fixed effects.

As a second part of the analysis, I also estimate the coefficients for a binary variable D_m where the treated group is defined by values above and below the median of the share of contraception pills consumption. This allows for interpreting the coefficient in a better way.

The difference-in-differences setup without staggered adoption may have the problem of providing estimates with bias due to heterogeneous treatment effects across groups and time. According to De Chaisemartin and D'Haultfœuille (2020), a possible solution is to use a DIM_M estimator, which is related to a Wald estimator and could provide unbiased estimates under heterogeneous treatment. The third part of the analysis presents the results obtained with DIM_M. This methodology requires several assumptions. First, it is ideal to have a balanced panel of groups; Second, it should have a sharp design (but it may also be adapted to work for fuzzy ones); Third, groups should be independent; Fourth, strong exogeneity in the sense that the treatment could not be a response to a negative shock in any of the groups; Fifth, there are common trends; Sixth, it needs to have stable groups (De Chaisemartin and D'Haultfœuille, 2020). For the last part of the analysis, I estimated event studies to identify if the parallel trends assumption holds. The following equation describes the results.

$$y_{imt} = \sum_{k=-\tau}^{\tau} \beta_k \cdot Treat_t * D_m + \delta_m + \delta_t + \epsilon_{imt} \tag{6}$$

where β_k is the coefficient that changes across time. In this case, $-\tau$ is the number of placebos (quarters) before the treatment implementation. All the specifications use linear probability models with standard errors clustered at the municipality level.

5 Results

Table 2 presents the results for the difference-in-differences model for quantities and prices at the drug level in the commercial market. The results show that the effect on prices and quantities is not significant for the period 2015-2022. However, since the SISMED dataset underwent a change in how data is reported at the end of 2019, I limited the sample to only the first year after the regulation took place. Columns 3 and 4 show that prices decreased by approximately \$10,938 Colombian pesos, equivalent to a 31% decrease. Changes in quantities are not statistically significant. The event studies show that the parallel trends assumption holds and confirm previous results; they also show that quantities decline during the first year and then rise in 2022. However, the effect is not statistically significant.

Figure 5 presents the results for the difference-in-differences model for the delivery rate at the municipality level. As expected given the SISMED results, the first two years show no effect (in this intention-to-treat analysis) on the delivery rate between the subsidized and contributory regimes. However, in 2021 and 2022, the results show a significant positive effect, indicating that low-income women in Colombia had a higher probability of having a delivery after 2020. This effect, however, cannot be attributed to the legislation, given that the COVID-19 pandemic lockdowns could have directly impacted fertility in 2021-2022. Figure 6 and 7 also confirm previous findings, with prenatal services and pregnancy diagnosis with an increase during the post-Pandemic period. However, although it is not statistical significant, after 6 months of being implemented the legislation, the pregnancy diagnosis decline in the subsidized regime compared to the contributory regime. The effect appears to remain for around a year.

Table 5 presents the results for the difference-in-difference model for the probability of having a delivery. The coefficients, when treatment uses the HMO dataset (columns 1-3), are not significant for any of the specifications, either using the share of birth control pill contraception or by the binary category above the median. When the results are estimated by the DID_M estimator, which is robust under heterogeneous effects across groups, the coefficient, although negative, is still not statistically significant, confirming the previous findings. It is worth noting that the DID_M estimator drops many observations, perhaps because it requires a balanced panel.

To evaluate the accuracy of those regressions, I also show the event studies for the specifications. The graphs do not exhibit a tendency before the treatment with coefficients close to zero. After the treatment, the results do not show any change in the probability of having a delivery in any of the periods

Table 6 shows the results of having a prenatal care service. When the treatment is the continuous share of pills, the coefficient is not significant; however, it becomes significant when it is a binary variable. In both cases, under the conventional Difference-in-Difference and the DID_M estimator, the results have a negative effect, meaning that the price decrease could have decreased prenatal care services in those areas where women use more birth control pills compared to those where the share is below the median. Given that this variable could show a sooner effect than deliveries, it may indicate the efficacy of the policy. The event studies for having prenatal care services do not show a tendency only a year before the treatment, which could suggest that the effect is valid.

Table 7 presents the estimates for the probability of being pregnant. The coefficients are negative under the different specifications when the treatment is defined by the HMO (models 1-3), but they are not statistically significant. It means there are no changes in the decision of having a baby after changing the price of birth control pills for women ages 13-49. The event studies for those models also seem to hold, which supports the theory that there were no changes in the probability of pregnancy.

Regarding women ages 13-19, all the estimates for deliveries, having a prenatal care service, or being pregnant in the HMO treatment, have negative coefficients in all three specifications (models 1-3). However, they are not statistically significant. The event studies also show that all the estimates are small, with confidence intervals crossing the zero value. Although this population may be more sensitive to price changes and, therefore, have more elastic demand, the results do not allow us to confirm this hypothesis.

6 Robustness Checks

For the quantity and price analysis, I split the sample into three categories based on prices in 2018. So, they are split into low, medium, and high prices. The findings are presented in Table 3. It shows that after regulation, drugs with high prices decreased their price by $ 18,904 COL, approximately 55% compared to drugs with low prices. Even though medium price has a negative coefficient, it is not statistically significant. Overall, the results confirm previous findings.

For the second part of analysis in fertility, I run robustness checks given by RIPS data, where I create a different share of national administrative data. Results are not significant in most cases. For instance, although negative, the DID_M estimator for a delivery (Model 6 in Table 5) is not significant. In the case of prenatal care, where an impact is expected, the three specifications are not statistically significant (models 4-6). Similarly, the pregnancy probability is not different from zero under the different scenarios. Except for having a prenatal care service for women 13-49, all the robustness checks confirm the results found when the treatment comes from the HMO. For women with ages 13-19 years, the impact on deliveries, having a prenatal care service, or being pregnant is not statistically significant in all the specifications, validating previous findings.

7 Conclusions

This paper analyzes the effectiveness of price cap regulation on birth control pills in influencing fertility in Colombia, a developing country where abortion was not legal until 2022. To the best of my knowledge, this is the first paper that uses individual data to identify the effect on fertility in this sector in Colombia. Additionally, it uses institutional health claims that do not suffer from the bias of self-reported information in surveys.

The results indicate little to no effect from the price cap law. Deliveries or pregnancies show no changes under different treatment specifications. Even though prenatal care seems to decrease due to the law, these results do not hold under the robustness checks. The results for young women, although they in most cases have the expected negative sign, lack statistical significance. This leads to the conclusion that the policy, at least in the short term, has not been able to change fertility decisions for this population.

There are three possible hypotheses why I could not find a meaningful effect. First, women could have an inelastic demand. Even though Andia et al. (2022) found an aggregate demand increase, on the contrary, I do not find a significant increase in quantities in the first years. Second, the analysis period is not long enough to identify changes in fertility. It could take more years to react. Third, the price reduction could increase the birth control pills demand via a substitution effect. Women could buy more pills by reducing sterilization surgeries or condom consumption. However, the rate of sterilization per 1000 women increased until 2019 rather than declining, which may indicate that this is not the case, and women were not substituting this procedure for more contraceptive pills.

Further analysis may focus on understanding the possible shortage effect in the long run, as well as the incentives to create or import new drugs due to price regulation in the market. It is also important to identify changes in market power in the long run, to identify if the policy made the market more concentrated. In addition, given that there are no visible effects on fertility due to the policy, it would be interesting to identify the welfare effects on women, since they could save some money due to the policy.

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Table 1: Selected ATC Codes in SISMED, 2018 (before treatment)

	Control Group				Treated Group			
ATC Code	**N brands**	**Average Price**	**Sales Share**	**Q share**	**N brands**	**Average Price**	**Sales Share**	**Q share**
G03AA07					10	5725	5.93	21.81
G03AA09	4	45767	0.15	0.07				
G03AA10					4	51813	0.04	0.02
G03AA12					13	49096	11.83	5.07
G03AA14					6	53939	2.98	1.17
G03AA15	3	62898	2.61	0.87				
G03AB05	1	39660	0.00	0.00				
G03AB06	4	45993	1.53	0.70				
G03AB07	3	46104	1.78	0.81				
G03AB08					3	69249	0.39	0.12
G03AC09	4	34361	1.96	1.20				
G03CA03					2	62590	6.00	2.02
G03CA53	9	53253	2.74	1.08	1	44363	0.22	0.10
G03FA01	2	15255	1.69	2.33				
G03FA11					20	10374	23.93	48.58
G03FA15	3	69499	1.82	0.55	13	54705	19.50	7.51
G03FA17	12	49825	2.55	1.08	9	53089	12.33	4.89

Table 2: Regression Results SISMED

VARIABLES	(1) Quantity until 2022	(2) Price until 2022	(3) Quantity until 2019	(4) Price until 2019
After*Regulated	-10,391	-6,045	-27,414	-10,201**
	(50,833)	(3,680)	(36,486)	(4,034)
Constant	85,742***	34,553***	81,245***	35,509***
	(12,719)	(1,681)	(11,265)	(1,180)
Observations	886	886	649	649
R-squared	0.638	0.729	0.698	0.756
CUM fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES
Mean outcome	96,467	30,882	89,595	32,814

cluster standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Heterogeneous Effects by Price Category, SISMED

VARIABLES	(1) Quantity until 2022	(2) Price until 2022	(3) Quantity until 2019	(4) Price until 2019
Regulated	46,921	-2,070	51,605	-1,234
	(164,412)	(5,988)	(147,399)	(6,442)
After*Regulated	-67,526	-2,591	-54,330	-4,856
	(80,475)	(3,968)	(62,811)	(4,789)
Price Category 2 (Medium)	47,508	14,238**	29,628	16,841**
	(78,773)	(6,494)	(67,163)	(6,954)
Price Category 3 (High)	145,518	11,369	96,396	17,228*
	(136,508)	(11,398)	(107,089)	(9,364)
After*Price Category 2	10,106	-9,687*	1,198	-8,678
	(19,818)	(5,042)	(10,544)	(6,152)
After*Price Category 3	18,722	-9,285	3,902	-2,459
	(19,970)	(7,635)	(9,877)	(8,400)
Regulated*Price Category 2	27,867	281.7	-4,278	1,276
	(141,591)	(6,949)	(150,582)	(7,741)
Regulated*Price Category 3	-77,317	6,873	-63,050	3,502
	(160,231)	(10,585)	(146,989)	(8,511)
Triple interactions:				
After*Regulated*Price Cat. 2	8,402	-5,833	5,452	-8,225
	(48,441)	(5,750)	(31,102)	(7,068)
After*Regulated*Price Cat. 3	140,755	-13,177	77,375	-18,904*
	(88,678)	(9,023)	(64,016)	(9,653)
Constant	25,592	28,318***	43,514	26,368***
	(49,254)	(5,193)	(37,383)	(5,260)
Observations	778	778	583	583
R-squared	0.754	0.773	0.863	0.792
CUM fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES
Mean outcome	106,203	31,670	99,286	34,390

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Treatment Effects on Health Outcomes, rates per 1000 enrollees, RIPS

	Until 2022			Until 2020			Until 2019		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Delivery	Prenatal	Pregnancy	Delivery	Prenatal	Pregnancy	Delivery	Prenatal	Pregnancy
Treated	-0.116	-3.758*	-4.080*	-0.132	-3.764*	-4.077*	-0.138	-3.818*	-4.119*
	(0.118)	(2.028)	(2.189)	(0.118)	(2.035)	(2.197)	(0.118)	(2.034)	(2.196)
Treated*After	0.323	2.066	2.056	0.121	-1.195	-1.419	0.245	1.343	1.106
	(0.202)	(2.237)	(2.406)	(0.408)	(4.706)	(4.965)	(0.510)	(4.139)	(4.473)
Constant	1.768***	16.94***	18.44***	1.884***	18.71***	20.33***	1.790***	17.59***	19.24***
	(0.110)	(1.618)	(1.697)	(0.149)	(2.100)	(2.204)	(0.133)	(1.633)	(1.738)
Observations	160,300	160,300	160,300	106,530	106,530	106,530	79,753	79,753	79,753
R-squared	0.126	0.221	0.220	0.203	0.296	0.294	0.189	0.271	0.269
Municipality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean outcome	1.819	15.75	17.09	1.848	16.53	17.94	1.762	15.91	17.37

Robust standard errors clustered at municipality level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Difference-in-difference of having a delivery, 2017-2020, ages 13-49

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Delivery	Delivery	Delivery	Delivery	Delivery	Delivery
After*Treatment (Share)	0.000155			-0.000299		
	(0.000773)			(0.000954)		
After*Treatment (Median)		0.000173			-0.000997***	
		(0.000354)			(0.000347)	
After*Treatment			-0.00047			-0.000452
(Estimated by $\widehat{DID}$)			(0.00054)			(0.000474)
Observations	4,587,218	4,587,218	291,396	4,587,213	4,587,213	291,396
R-squared	0.001	0.001		0.001	0.001	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.00304	0.00304		0.00304	0.00304	

Robust standard errors clustered at municipality level in parentheses

*** p<0.01, ** p<0.05, * p<0.1.

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Table 6: Difference-in-difference of having any prenatal care service, 2017-2020, ages 13-49

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care
After*Treatment (Share)	-0.00145			-0.00266		
	(0.00410)			(0.00596)		
After*Treatment (Median)		-0.00403**			0.00212	
		(0.00176)			(0.00182)	
After*Treatment			-0.002995			0.001806
(Estimated by $\widehat{DID}$)			(0.002620)			(0.001906)
Observations	4,587,218	4,587,218	291,396	4,587,213	4,587,213	291,396
R-squared	0.002	0.002		0.002	0.002	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.0181	0.0181		0.0181	0.0181	

Robust standard errors clustered at municipality level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (any prenatal care service) was identified using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369). Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Table 7: Difference-in-difference of pregnancy 2017-2020, ages 13-49

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant
After*Treatment (Share)	-0.000500			0.000371		
	(0.00330)			(0.00414)		
After*Treatment (Median)		-0.00300*			0.00139	
		(0.00154)			(0.00150)	
After*Treatment			-0.002943			0.001539
(Estimated by $\widehat{DID}$)			(0.002194)			(0.001839)
Observations	4,587,218	4,587,218	291,396	4,587,213	4,587,213	291,396
R-squared	0.002	0.002		0.002	0.002	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.0193	0.0193		0.0193	0.0193	

Robust standard errors clustered at municipality level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (being pregnant) was identified by using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Table 8: Difference-in-difference of having a delivery, 2017-2020, ages 13-19

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Delivery	Delivery	Delivery	Delivery	Delivery	Delivery
After*Treatment (Share)	-0.000122			0.000617		
	(0.000835)			(0.00142)		
After*Treatment (Median)		0.000158			-0.000637	
		(0.000398)			(0.000535)	
After*Treatment			-0.000028			0.000113
(Estimated by $\widehat{DID}$)			(0.000635)			(0.000837)
Observations	794,702	794,702	50,071	794,702	794,702	50,071
R-squared	0.001	0.001		0.001	0.001	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.00233	0.00233		0.00233	0.00233	

Robust standard errors clustered at municipality level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Table 9: Difference-in-difference of having any prenatal care service, 2017-2020, ages 13-19

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care	Prenatal Care
After*Treatment (Share)	-0.00190			-0.00304		
	(0.00414)			(0.00598)		
After*Treatment (Median)		-0.00356**			0.00127	
		(0.00166)			(0.00156)	
After*Treatment			-0.002648			0.000822
(Estimated by $\widehat{DID}$)			(0.002089)			(0.002733)
Observations	794,702	794,702	50,071	794,702	794,702	50,071
R-squared	0.003	0.003		0.003	0.003	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.0142	0.0142		0.0142	0.0142	

Robust standard errors clustered at municipality level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (any prenatal care service) was identified using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369). Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

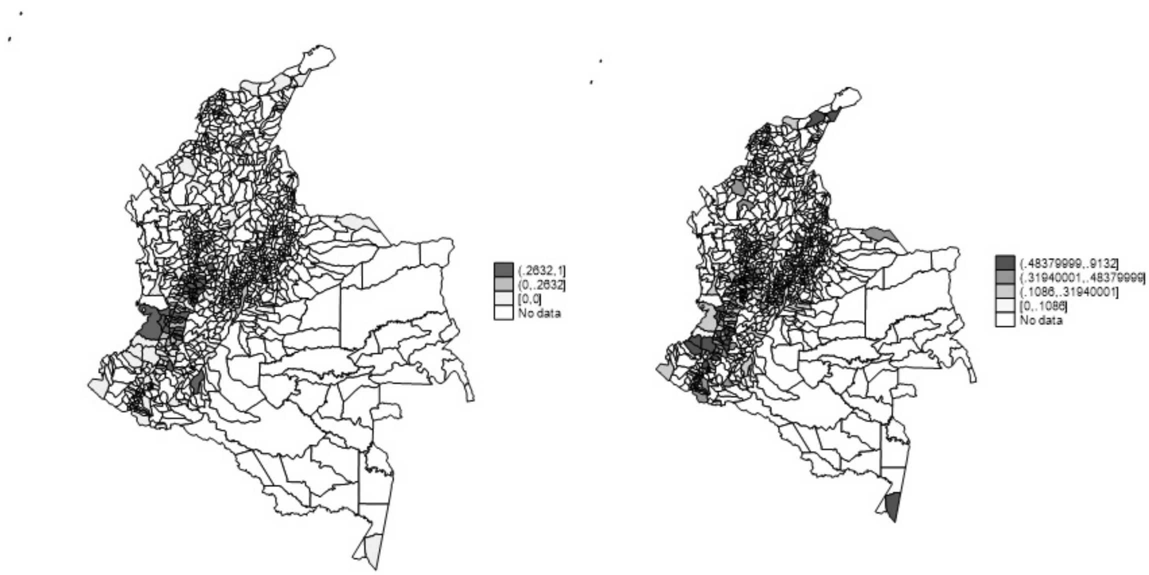
Table 10: Difference-in-difference of being pregnant, 2017-2020, ages 13-19

	Treatment defined by the insurer			Treatment defined by RIPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment \ Dependent variable	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant	Being Pregnant
After*Treatment (Share)	-0.00149			-0.00135		
	(0.00338)			(0.00498)		
After*Treatment (Median)		-0.00289*			0.000452	
		(0.00158)			(0.00144)	
After*Treatment			-0.002706			-0.000302
(Estimated by $\widehat{DID}$)			(0.002308)			(0.002283)
Observations	794,702	794,702	50,071	794,702	794,702	50,071
R-squared	0.003	0.003		0.003	0.003	
Municipality fixed effects	YES	YES	YES	YES	YES	YES
Quarter fixed effects	YES	YES	YES	YES	YES	YES
Treatment: Share Pills 2017	YES			YES		
Treatment: above median 2017		YES	YES		YES	YES
Cluster SE	YES	YES	YES	YES	YES	YES
Mean outcome	0.0151	0.0151		0.0151	0.0151	

Robust standard errors clustered at municipality level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications use a linear probability model without covariates and with municipality and quarter-fixed effects. The dependent variable (being pregnant) was identified by using the ICD-10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). Models (1)-(6) use treatment at the municipality level based on the proportion of women ages 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) out of those who asked a birth control service during 2017. While the treatment from models (1)-(3) comes from an insurer dataset, from models (4)-(6) comes from RIPS. Models (1) and (4) use as continuous variables. Models (2), (3), (5), and (6) use a binary variable, which takes the value of one for values above the median. Models (3) and (6) use the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

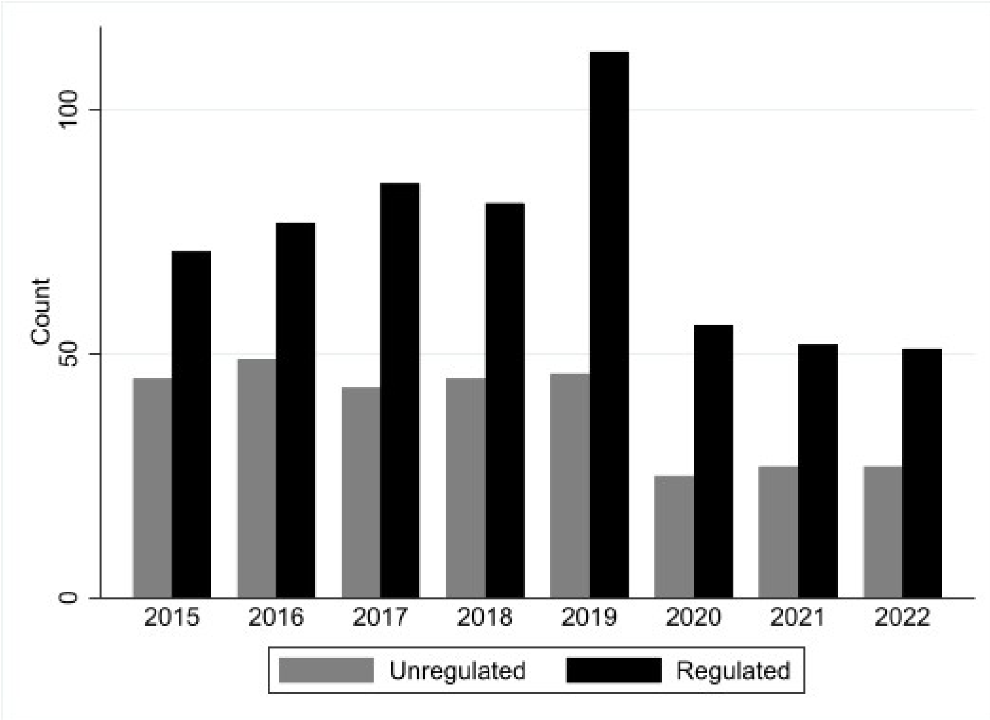
Figure 1: Demand for birth control pills



A: A insurer in the contributory regime, 2017 B: Health Services Information System, 2017

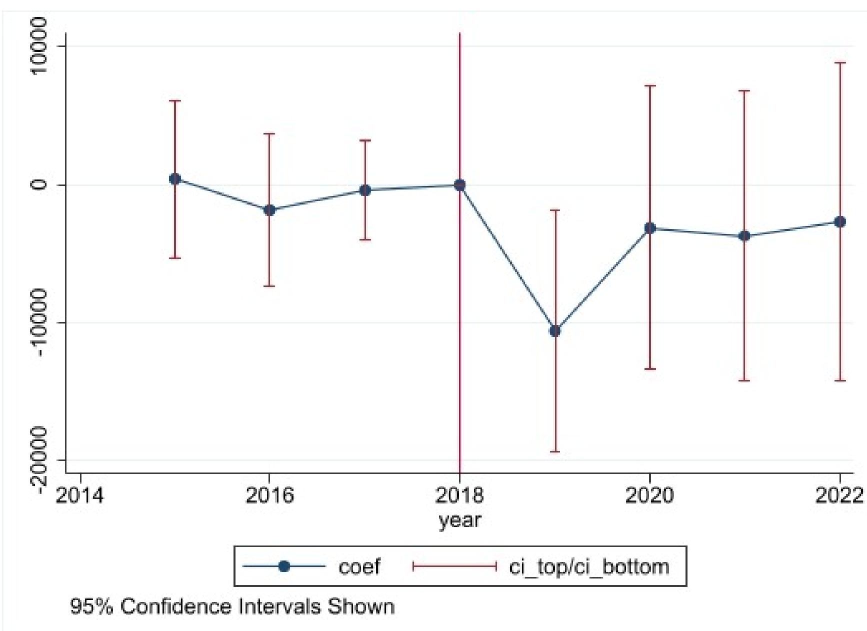
Note: Notes: Graph A shows the proportion of women aged 13-49 who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in a health insurer during 2017. Graph B reports the proportion of services from women between ages 13 and 49 who requested any health services related to birth control from any insurers in Colombia. The data from Graph B comes from RIPS. Most of the municipalities from the eastern and southern parts belong to the Amazon, where there is a small or no population at all.

Figure 2: Number of drugs under the 17 ATC codes, SISMED



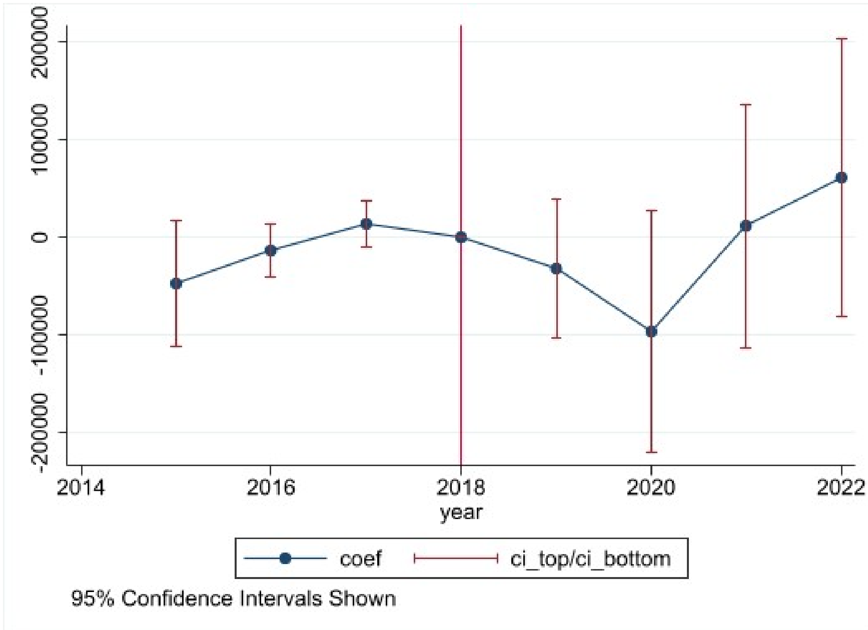
Note: Number of drugs measured by the Unique Drug Identifier available by year in the commercial channel.

Figure 3: SISMED, Average Price Effect, COL $



Note: The dependent variable (average price per drug) is in Colombian pesos. The graphs have years beginning in 2015. The vertical line indicates the period when the law was enacted.

Figure 4: SISMED, Quantity Effect



Note: The dependent variable (sum of quantities). The graphs have years beginning in 2015. The vertical line indicates the period when the law was enacted.

Figure 5: RIPS 2017-2022, Deliveries Effect

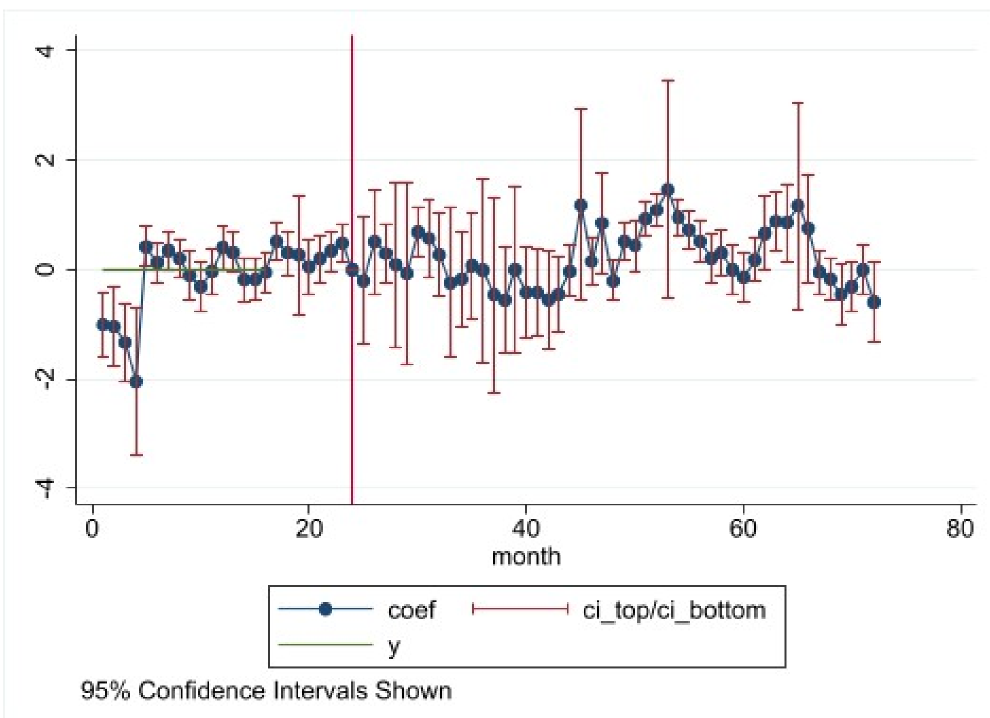


Figure 6: RIPS 2017-2022, Prenatal Effect

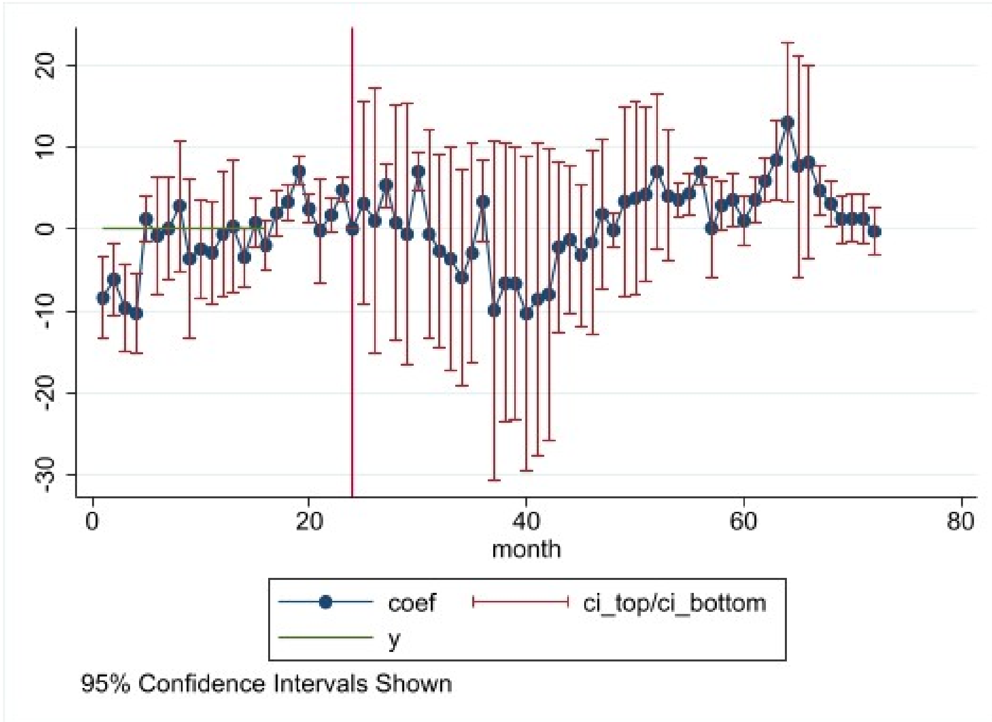


Figure 7: RIPS 2017-2022, Pregnancy Effect

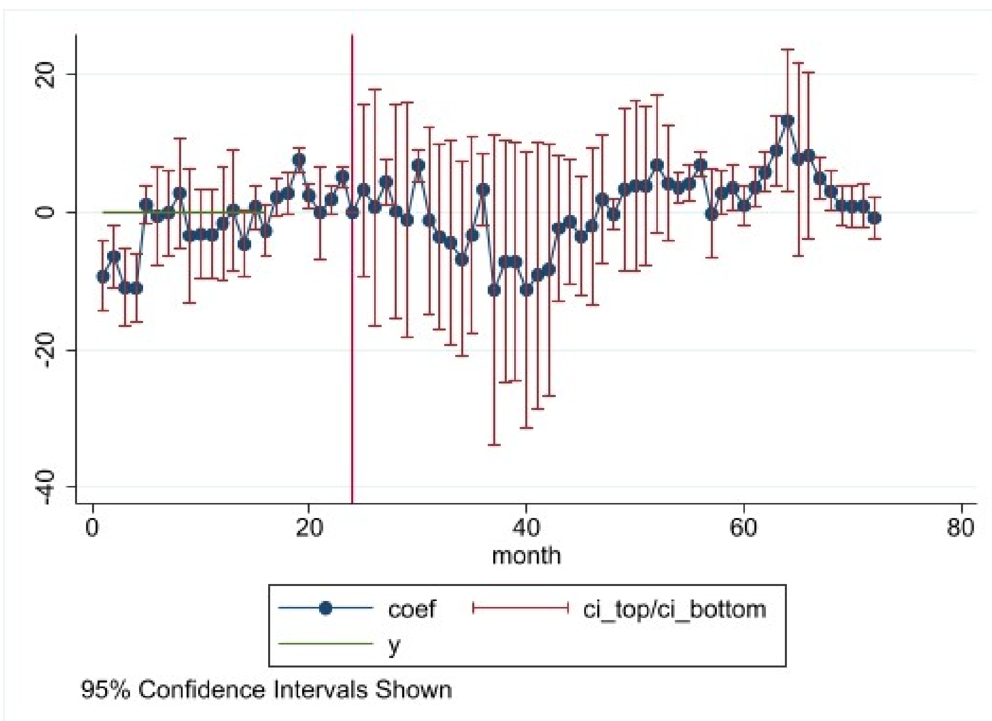
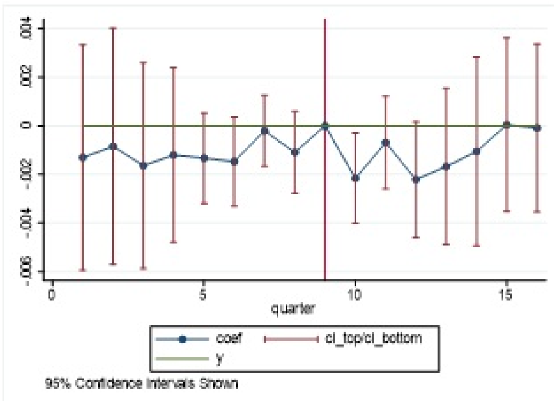
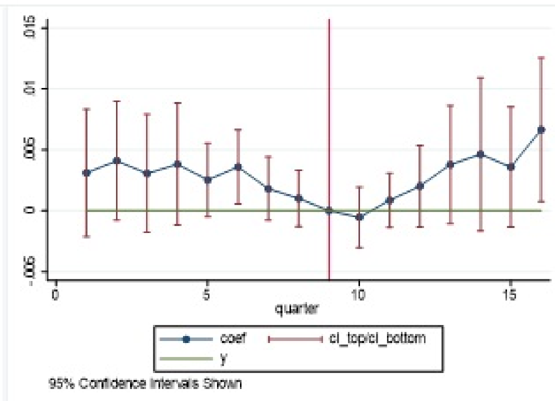


Figure 8: Linear probability model of having a delivery, women ages 13-49

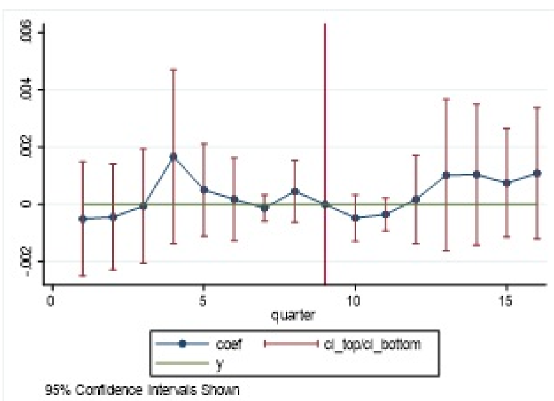
Treated groups defined by insurer (**left**) Treated groups defined by RIPS (**right**)



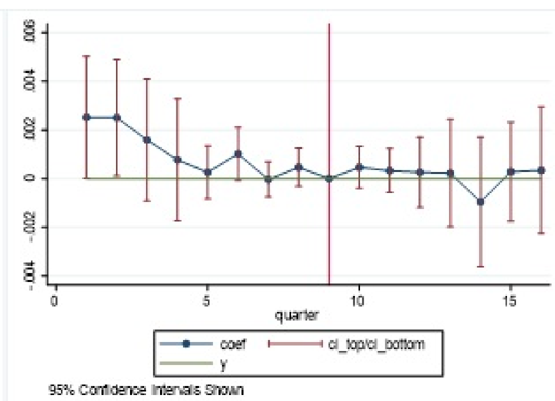
A1: Continuous share



A2: Continuous share



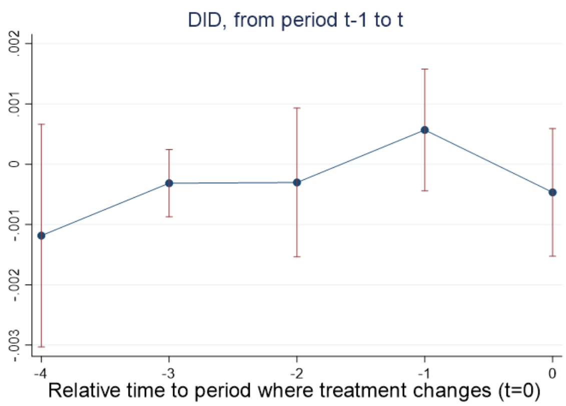
B1: Binary variable above the median



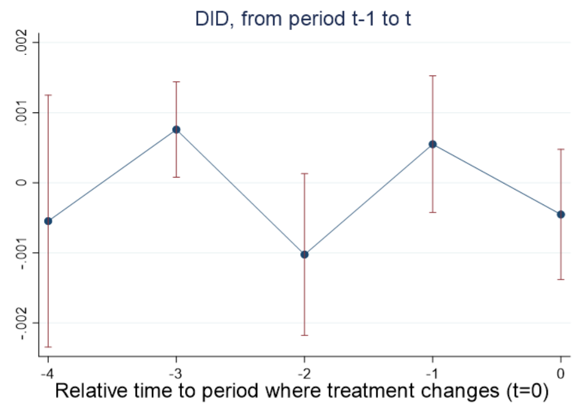
B2: Binary variable above the median

Note: Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 9: Linear probability model of having a delivery, women ages 13-49. Binary variable with a corrected DID_M



(a) Treated groups defined by Insurer

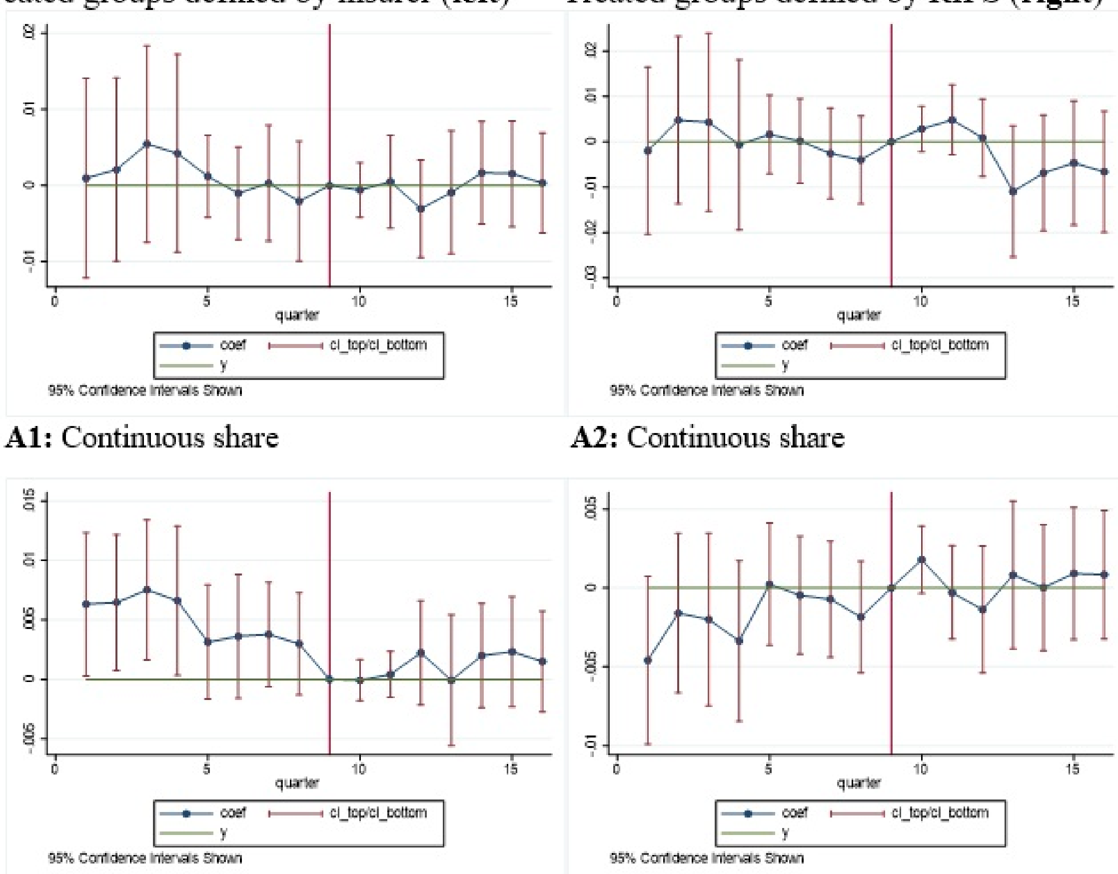


(b) Treated groups defined by RIPS

Note: The dependent variable (being pregnant) was identified by using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). It takes the value of one if the woman has one or more of those diagnosis codes and zero otherwise. Data starts in 2018. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Figure 10: Linear probability model of having any prenatal care service, women ages 13-49

Treated groups defined by insurer (**left**) Treated groups defined by RIPS (**right**)

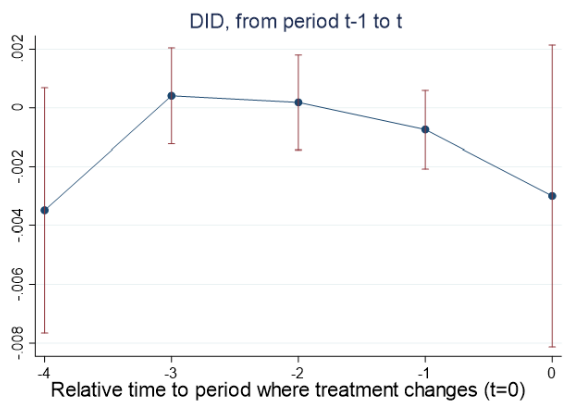


A1: Continuous share **A2:** Continuous share

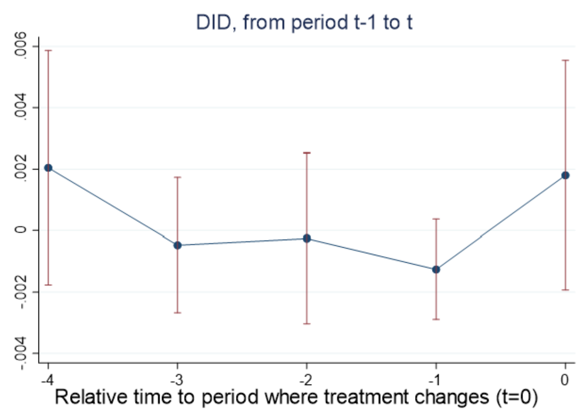
B1: Binary variable above the median **B2:** Binary variable above the median

Note: Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (any prenatal care service) was identified using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369). It takes the value of one if the woman has one or more prenatal care services and zero otherwise. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 11: Linear probability model of having any prenatal care service, women ages 13-49. Binary variable with a corrected DID_M



(a) Treated groups defined by Insurer

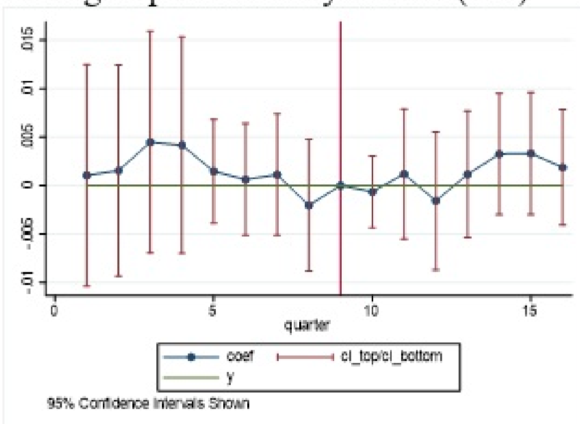


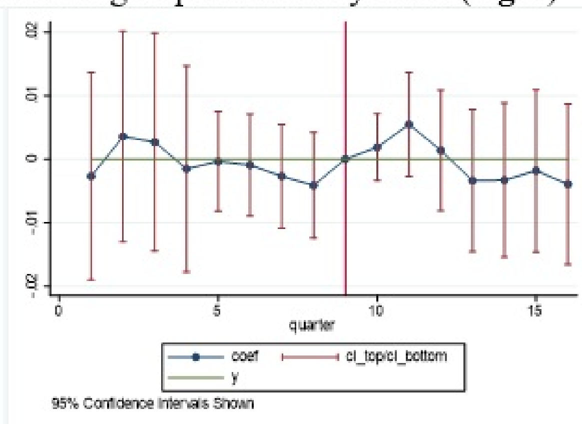
(b) Treated groups defined by RIPS

Note: The dependent variable (being pregnant) was identified by using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). It takes the value of one if the woman has one or more of those diagnosis codes and zero otherwise. Data starts in 2018. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Figure 12: Linear probability model of pregnancy, women ages 13-49

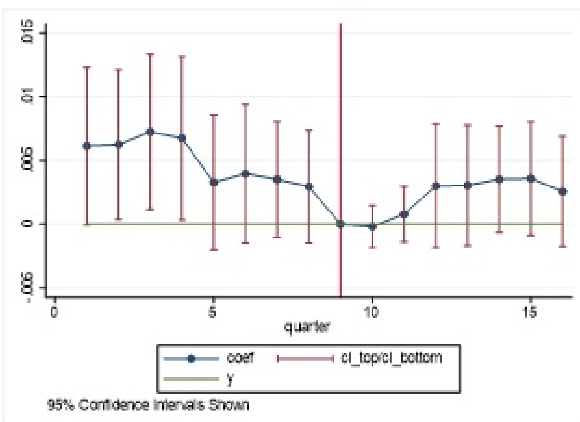
Treated groups defined by insurer (**left**) Treated groups defined by RIPS (**right**)

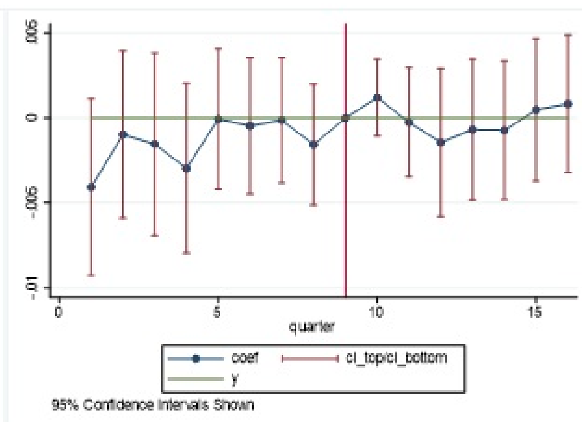




A1: Continuous share

A2: Continuous share



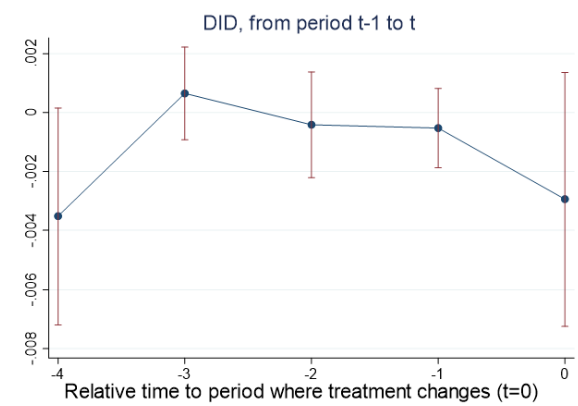


B1: Binary variable above the median

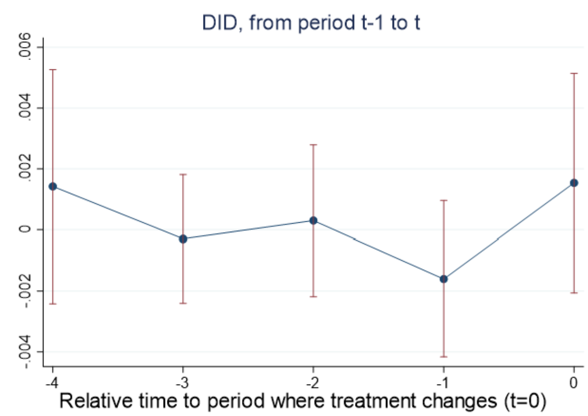
B2: Binary variable above the median

Note: Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (being pregnant) was identified by using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). It takes the value of one if the woman has one or more of those diagnosis codes and zero otherwise. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 13: Linear probability model of pregnancy, women ages 13-49. Binary variable with a corrected DID_M



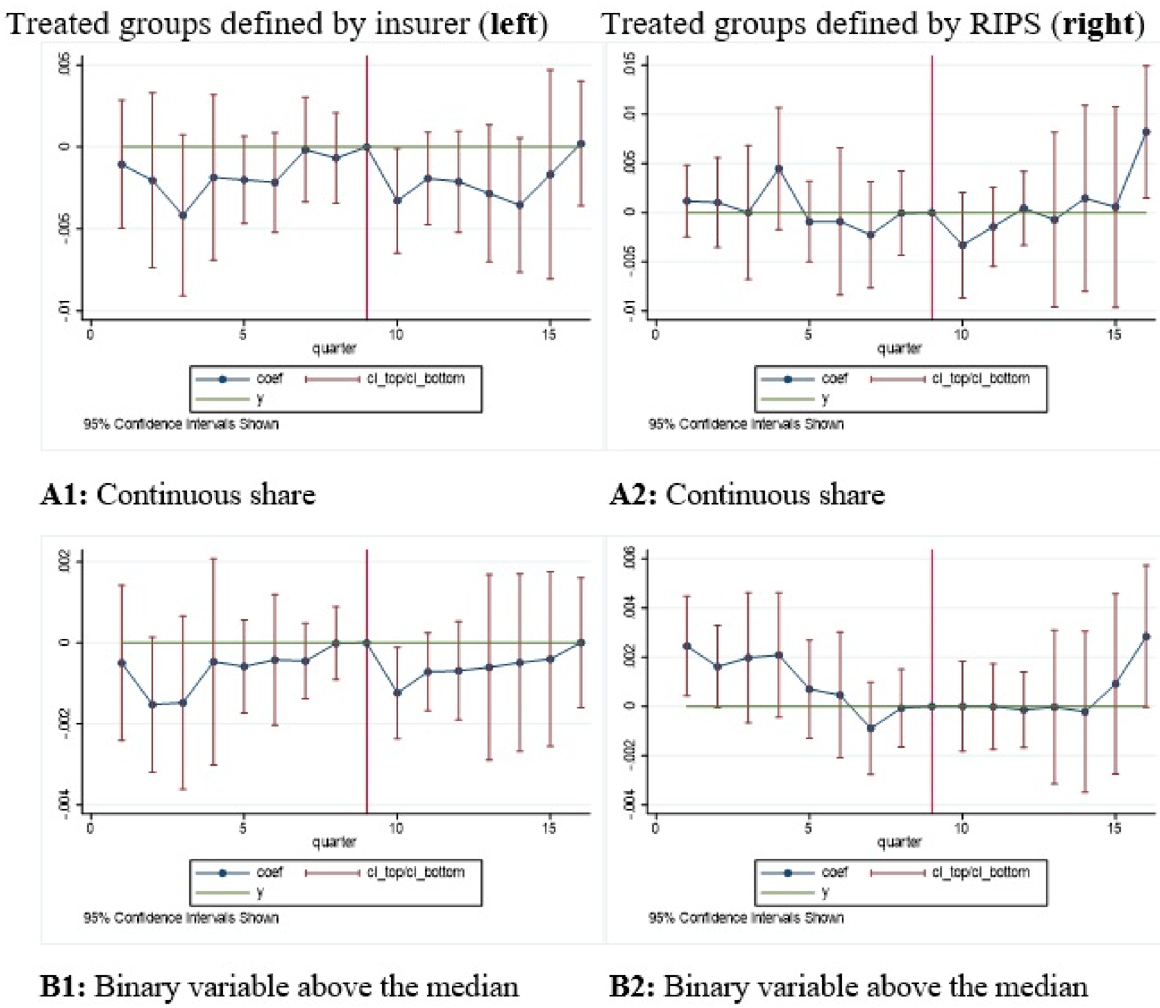
(a) Treated groups defined by Insurer



(b) Treated groups defined by RIPS

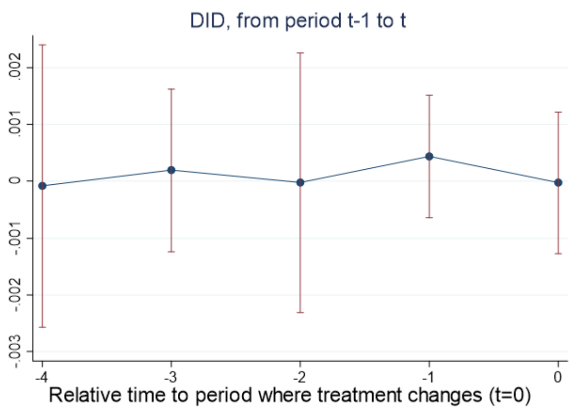
Note: Panels a and b use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (being pregnant) was identified by using the ICD10 diagnosis codes related to encounters for supervision and antenatal screening of the mother (Z340-Z369), pregnant state (Z33), and a positive pregnancy test (Z321). It takes the value of one if the woman has one or more of those diagnosis codes and zero otherwise. Data starts in 2018. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Figure 14: Linear probability model of having a delivery, woman ages 13-19

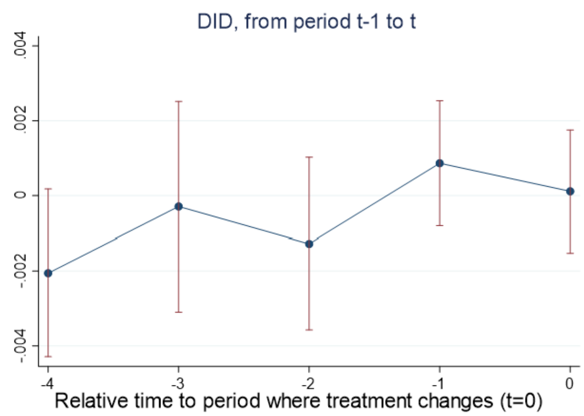


Note: : Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 15: Linear probability model of having a delivery, woman ages 13-19. Binary variable with a corrected DID_M



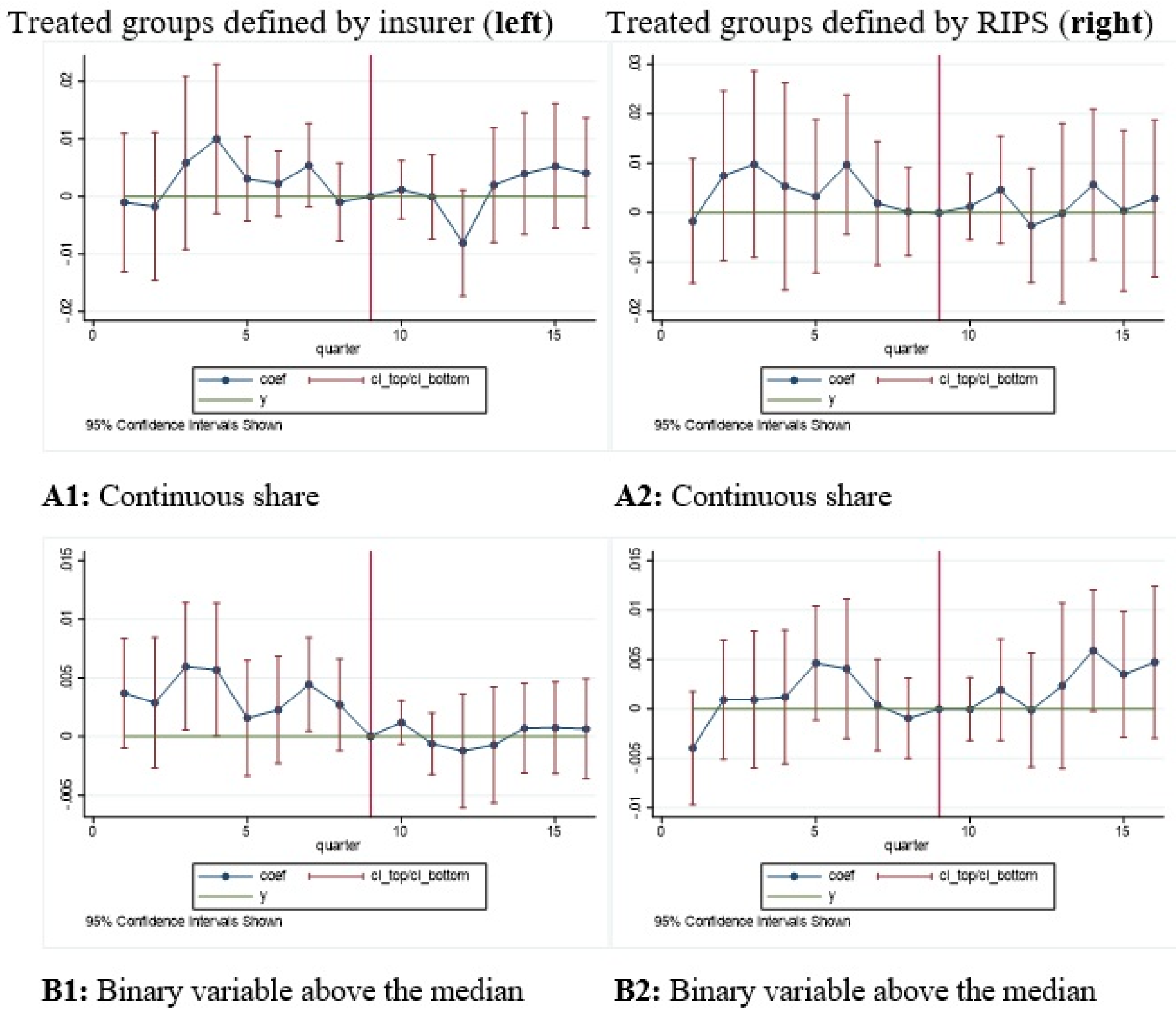
(a) Treated groups defined by Insurer



(b) Treated groups defined by RIPS

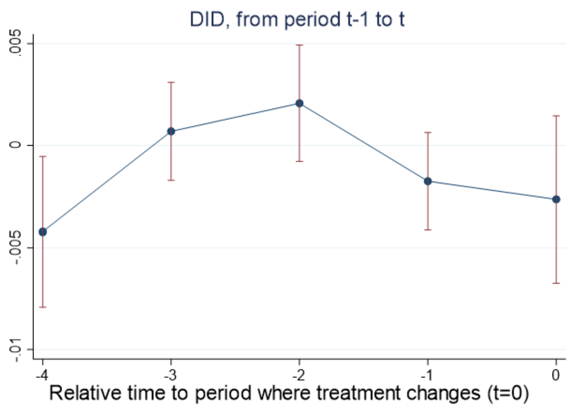
Note: Panels a and b use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. Data starts in 2018. The diffThece between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Figure 16: Linear probability model of having any prenatal care service, women ages 13-19

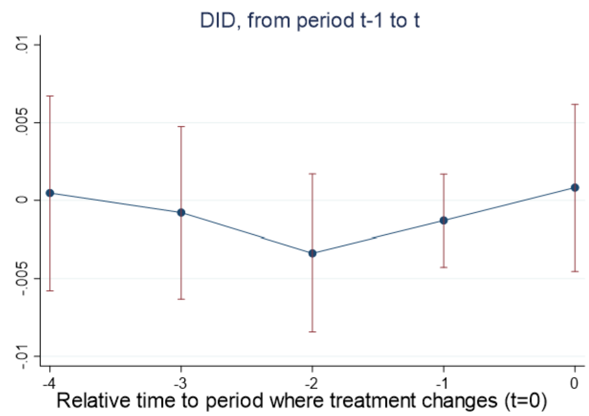


Note: : Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 17: Linear probability model of having any prenatal care service, women ages 13-19. Binary variable with a corrected DID_M



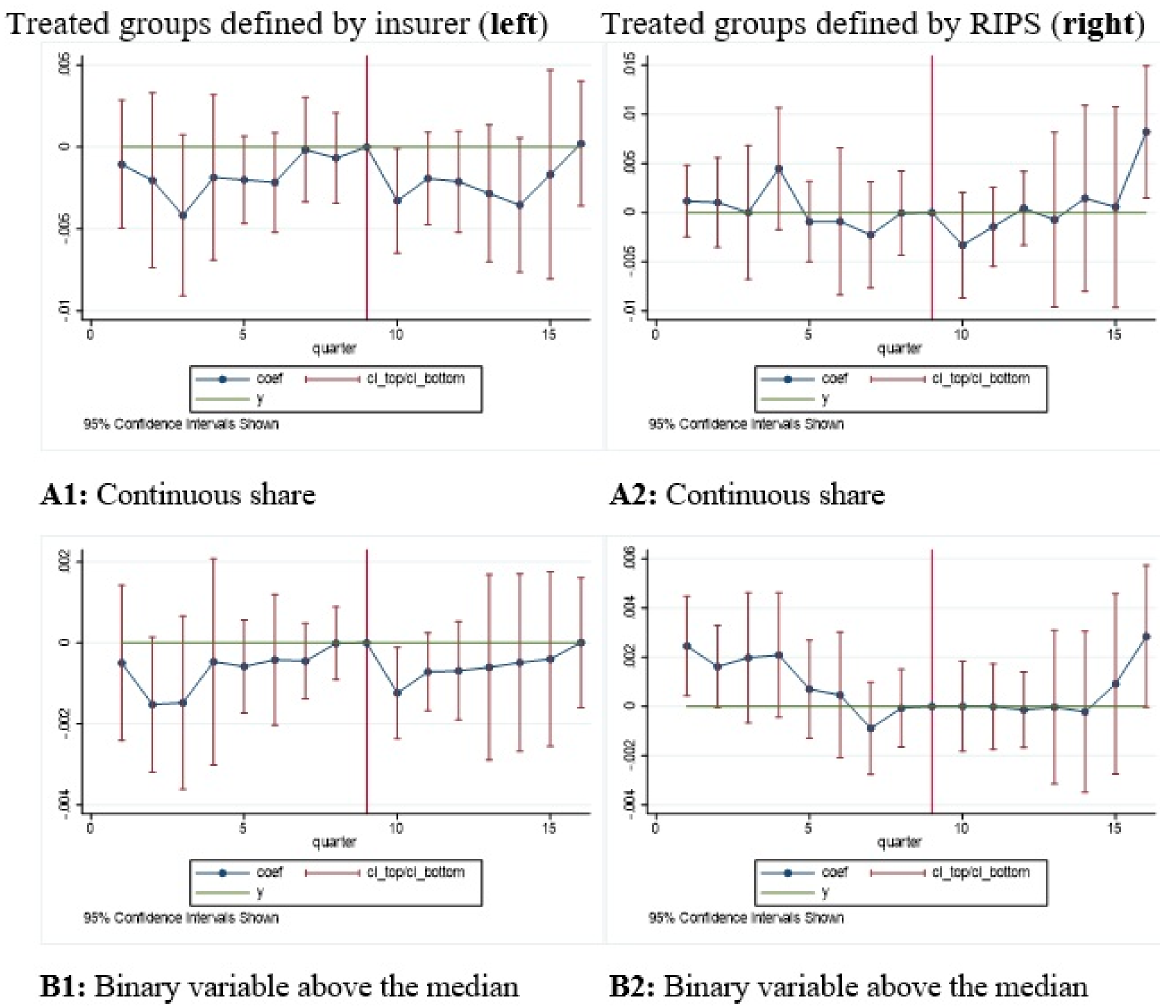
(a) Treated groups defined by Insurer



(b) Treated groups defined by RIPS

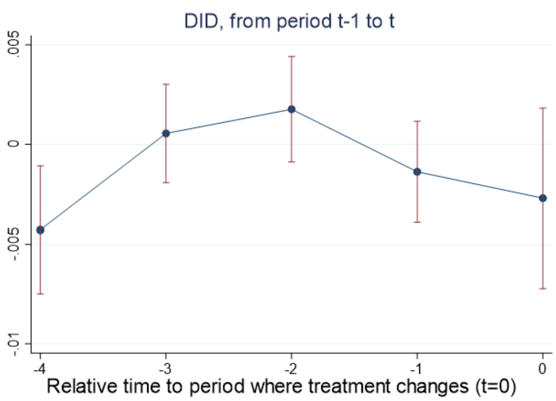
Note: Panels a and b use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. Data starts in 2018. The diffThece between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).

Figure 18: Linear probability model of being pregnant, women ages 13-19

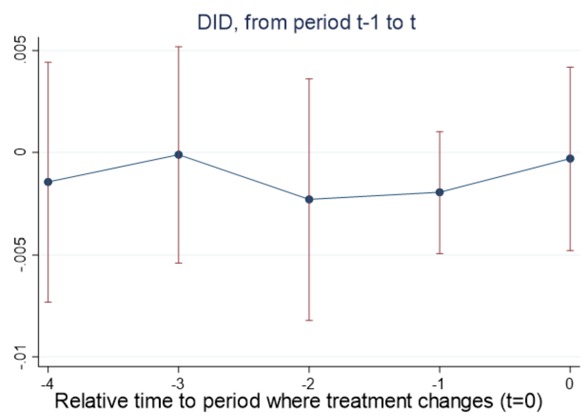


Note: : Panels A and B use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. The graphs have quarters beginning in 2017. The vertical line indicates the first quarter of 2019 when the law began to be implemented. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel A defines the treatment as a continuous variable based on the proportion of services from women who requested any health services related to birth control pills (ICD10 diagnosis code Z304: Encounter for surveillance of contraceptive pills) in 2017. Panel B discretizes the treated group for values above the median.

Figure 19: Linear probability model of being pregnant, women ages 13-19. Binary variable with a corrected DID_M



(a) Treated groups defined by Insurer



(b) Treated groups defined by RIPS

Note: Panels a and b use a linear probability model with municipality and quarter-fixed effects and no covariates. The dependent variable (delivery) was identified using the ICD10 diagnosis codes related to encounters for delivery O80-O84. Data starts in 2018. The difference between the graphs from left and right is that on the left, the insurer's dataset defines the treatment, and on the right, the RIPS. Panel C uses the corrected estimator by De Chaisemartin and D'Haultfœuille (2020).