Unintended Consequences of Policy Interventions: Evidence from a Mandated Health Insurance Coverage*

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Abstract

We investigate unintended consequences of a policy intervention that mandated health insurance coverage for expensive in Vitro Fertilization (IVF) treatment that vary widely in coverage generosity across states in the US. Despite the speculation, using administrative data, we find that more generous coverage causes an increase in the incidence of risky and costly multiple births. The increase is driven by the change in the patients' composition, where more older women with lower fertility pursue aggressive treatments. This is mirrored by a greater decline in child adoption to older women in states with more generous coverage. Ignoring compositional effects could mean that increased access without regulation might impose additional burdens on the healthcare system.

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Keywords: healthcare costs; healthcare utilization; health insurance; mandated benefits; in vitro fertilization; child adoption.

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1 Introduction

Healthcare spending in the US has risen rapidly, from 5 percent of GDP in 1960 to 17.9 percent in 2017 (CMMS, 2017). Lifestyle changes and an aging population have contributed to increases in chronic illnesses such as cancer, musculoskeletal conditions, diabetes, and heart disease. These conditions have expensive treatment options, raising concerns about access to treatment and its overall costs. Policy interventions that mandate health insurance coverage for expensive medical treatments intend to increase the treatment's accessibility by decreasing patients' out-of-pocket costs. Mandated coverages could have a collection of different effects on patients' choice: increasing access to the treatment, and shifting choices within the treatment depending on the generosity of the coverage. A more generous coverage can affect existing patients' utilization behavior since such coverage makes seeking additional expensive treatments less costly. However, more generous coverage could also expand the access to new patients who might have used a cheaper alternative, further contributing to increases in healthcare costs, particularly if more generous coverage leads to changes in the composition of the patients seeking treatment such that patients with lower probabilities of success initiate treatment. This could have ambiguous effects on patients' choices and the outcomes and might further contribute to the rise in healthcare spending. Patients' behavioral responses to the increased accessibility of expensive treatments is critical to understanding the ramifications of health policy interventions.

Mandated health insurance coverage for in Vitro Fertilization (IVF) treatment in the US provides an appealing case study for several reasons. First, the generosity of mandated coverage varies widely across states and over time. States range from no coverage to coverage of infertility treatments excluding IVF, to covering an unlimited number of cycles, and mandates vary across several other dimensions of generosity as well.[1] This variation across states and time allows the identification of the effects of the coverage's generosity on patient's utilization and the outcomes. Second, patients choose

[1] The other dimensions include age restrictions, coverage of unmarried women, coverage of cycles with frozen or donor eggs, minimum years of infertility to qualify for coverage, and whether mandates apply to Health Maintenance Organizations (HMOs). For more information see Table 1.

the intensity of their treatment –through the number of transferred embryos– based on their preferences and the expected costs and benefits, and this choice directly affects both success rates and the likelihood of risky and costly multiple births. Finally, IVF resembles other medical treatments like those for heart disease or cancer, which are expensive and have uncertain outcomes (Shapiro and Recht, 2001).

In this paper, we empirically investigate how the generosity of mandated coverage for IVF treatment affects patients' utilization behavior and the composition of those utilizing the treatment. In the absence of data on the utilization of IVF treatment for all years, we examine multiple births as a proxy for the intensity of IVF treatment.[2] More generous coverage could have two competing effects on the likelihood of multiple births. First, holding the patients' pool constant, patients face less pressure to conceive in each cycle so that they might choose to transfer fewer embryos (Jain et al., 2002; Reynolds et al., 2003). This intensive margin effect would decrease the incidence of multiple births.[3] Second, generous mandates expand access to new patients who might not have pursued treatment in the absence of insurance coverage. This extensive margin effect could lead to an overall increase in the incidence of multiple births, but might not change the number of embryos being transferred per patient or per cycle. However, these extensive margin effects could also change the composition of patients seeking treatment, such that patients with a lower probability of success initiate treatment, requiring an increase in the number of embryos transferred per woman or per cycle.[4] The overall effect of more generous coverage for IVF treatment on the incidence of multiple births is therefore ambiguous.[5]

[2]See Section 3 for a discussion of the weaknesses of this measure and see section 4.2 for suggestive evidence that the increase in multiple births is driven by IVF treatment.

[3]Note that we are thinking of the intensive margin here in terms of intensity of the cycle. Alternatively, one could consider the intensity of treatments within a given patient over time, which could show an increase in multiple births if a patient with a failed first attempt then re-enters the pool.

[4]However, if more generous coverage leads some patients to skip cheaper alternatives to IVF (for example, ovulation-boosting drugs), then the extensive margin effects could lead to a reduction in the incidence of multiple births.

[5]Buckles (2013) estimates the effects of mandated IVF coverage on the incidence of multiple births using a Difference-in-Differences (DD) model comparing mandated states with never-mandated states between 1980 and 2002. However, they do not explore the generosity levels within the set of states with mandated coverage. We explore the generosity levels of the mandated coverage using more recent data (1975–2014), which allows us to include two states with more recent mandates: Connecticut (mandate year: 2005) and New Jersey (2001). They find a small and statistically insignificant impact on the

We use a Generalized Synthetic Control (GSC) model (Xu, 2017) to estimate the causal effects from the generosity of IVF coverage on the incidence of multiple births, using administrative birth certificate data from the Detail Natality File on all births in the US between 1975 and 2014; exploiting variation in generosity levels across states and over time. Then, to shed light on intensive versus extensive margin effects, we use fertility clinic data from the Society for Assisted Reproductive Technologies (SART) to examine the association between more generous IVF coverage and the composition of patients, the number of initiated IVF cycles, and the number of embryos transferred per cycle. Finally, using data from the National Data Archive on Child Abuse and Neglect (NDACAN), we investigate the association between the generosity of IVF coverage and adoptions of children aged 0-6, as such adoptions could be considered in some circumstances a substitute for conceiving through IVF. In all of our estimates, we control for state-level characteristics from the March supplement of Current Population Survey (CPS) including the percentage of women of childbearing age, the percentage of college-educated women, female labor force participation rate, the percentage of employees working in big firms, the percentage with private health insurance, and real per capita income.

Our empirical analysis has three main findings. First, after controlling for state-level characteristics, more generous coverage for IVF treatment causes an increase in the incidence of multiple births, and the increase is driven mostly by older women. In Massachusetts –which has unlimited coverage– the estimated effect on multiple births per hundred live births for women of 35 years and older is twice as large as the estimate for women under 35 years (44.09% or 6.35% increase in extra infants per thousand live births versus 20.59% or 2.18% increase in extra infants). Meanwhile, in Arkansas and Hawaii –which cover only one cycle– the estimated effect on multiple births per hundred live births for women 35 and older is -17.27% (22.25% decrease in infants per thousand live births), which is statistically insignificant, and for women under 35 years is 7.52% (8.16% increase in extra infants per thousand live births). Second, we find evidence of

incidence of multiple births, while our estimates are quite large and significant. Bundorf et al. (2007), and Hamilton et al. (2018) discuss intensive versus extensive margin effects of IVF coverage, but not in the context of differing generosity levels within the set of states which mandate coverage.

intensive margin effects of generosity for all women, where states with the more generous coverage have fewer embryos transferred per cycle. Finally, we find that the states with the more generous coverage also see significant increases in the share of cycles performed on older women with lower fertility, as new patients are drawn into treatment. This is mirrored to a greater decline in child adoption to older women in states with more generous IVF coverage. Our finding suggests that these compositional extensive margin effects dominate the intensive margin effects –decrease in embryos transferred per cycle– leading to overall increases in the incidence of multiple births.

Our paper is related to the literature investigating the effects of mandated coverage for infertility treatments on a variety of outcomes including utilization of treatment, infant and child health outcomes, fertility, age at first birth, time of marriage, women's choice to pursue professional careers, and labor supply over the life cycle (Schmidt, 2005; Bitler and Schmidt, 2006; Bundorf et al., 2007; Schmidt, 2007; Bitler, 2008; Bitler and Schmidt, 2012; Abramowitz, 2014, 2017; Kroeger and La Mattina, 2017; Lundborg et al., 2017; Gershoni and Low, 2020a,b). Most of these studies use either state-year or state-year-age variation in mandated IVF coverage in Difference-in-Differences (DD) and Difference-in-Difference-in-Differences (DDD) frameworks, respectively.[6]

Studies that relate most closely to our work examine the effects of the IVF mandates on the incidence of multiple births. Most of these studies find that mandates increase multiple births and are associated with worse health outcomes in terms of birth weight and gestation (Kulkarni et al., 2013; Bitler, 2008; Bundorf et al., 2007). Buckles (2013) finds that mandated coverage for IVF treatment have a small but statistically insignificant impact on the incidence of multiple births. This study does not include states with more recent mandated coverage; this might be a reason for their finding. Also, this study does not explore the generosity levels within the set of states with mandated coverage. Studies that use fertility clinic-level data find that treated patients with health insurance plans covering IVF treatment transfer fewer embryos compared to those with no insurance

[6]There are two exceptions: Machado and Sanz-de Galdeano (2015) uses a synthetic control model to estimate the effects of mandated IVF coverage in the US on the timing of first births and women's total fertility rates. Lundborg et al. (2017) uses IVF treatment as an instrumental variable to women's fertility decisions, and examine the effects of having children on Danish women's careers.

coverage (Jain et al., 2002; Reynolds et al., 2003; Henne and Bundorf, 2008; Hamilton and McManus, 2012). Much of this previous studies ignores the differences in generosity within the set of states that mandate coverage for IVF.

Our contribution to this literature is that we study how patient utilization responds to the *generosity* of mandated IVF coverage. This is important for understanding the cost implications since more generous coverage could affect utilization on both the intensive and extensive margins, and therefore could alter the composition of those seeking treatment. We also update previous studies using more recent data, which allows us to explore the mandates' effects in states with more recent mandates. The DD approach used in many previous studies relies on the assumption that trends in the treatment (mandate to cover) and control (never mandate) states would have evolved in the same way in the absence of the mandates. While previous studies all address this parallel trends assumption when comparing all mandated states to never mandated states, it might be less plausible in the context of differences in generosity within the set of states that choose to mandate coverage of IVF (see Figure 1). We use a GSC model to generate causal estimates.[7]

Our findings suggest that change in patients' composition is important to understand the policy implications of increased health insurance generosity, consistent with previous studies on the role of incentives in healthcare utilization. Chernew et al. (2000) suggest that in an optimal insurance plan, patients should pay higher out-of-pocket costs for more expensive treatment. Einav et al. (2016) (in the case of breast cancer treatments) and Hamilton et al. (2018) (in the case of infertility treatments) both suggest that top-up pricing for more aggressive treatments could be optimal. Also, Bhalotra et al. (2020) shows that a Swedish single embryo transfer policy reduced the incidence of multiple births and improved maternal and infant health.

[7]We also estimate DD (exploiting variation across states and time) and DDD (exploiting variation across states, time and women's age) models as robustness tests, and for easier comparability to the previous literature.

2 Background

2.1 IVF treatment

Infertility, defined as the inability to conceive or carry a pregnancy to full term, is recognized as a disease by both the American Society for Reproductive Medicine and the World Health Organization. Treatment for infertility usually begins with medical tests and physician advice and is often followed by the woman's use of one of several drugs to stimulate egg production. If these less expensive treatment methods are not successful, then assisted reproductive technologies such as IVF treatment are often recommended. Success rates of a single IVF cycle are as low as 20 percent (CDC, 2015), and many patients require more than one cycle of treatment to achieve a live birth. The costs of one cycle of IVF treatment can be as high as 46 percent of the average US family's annual disposable income (Kissin et al., 2016).

In IVF treatment, eggs are extracted, a sperm sample is obtained, and eggs and sperm are then manually combined. The fertilized eggs, called embryos, are then transferred into the woman's uterus.[8] The practice committee of the American Society of Reproductive Medicine provides guidelines on the maximum number of embryos to transfer per cycle (Klitzman, 2016).[9] However, given the high costs and low success rates of IVF, patients often wish to exceed these guidelines to improve their odds of success, and in doing so, increase the likelihood of multiple births. Most monetary costs of IVF treatment are covered by insurance, and many patients with fertility problems view multiple births as a desirable outcome (Gleicher and Barad, 2009), buy multiple births are costly and risky for both mothers and infants (Merritt et al., 2014; Caserta et al., 2014).[10]

[8] The first infant conceived using an IVF treatment was born in 1978 in the UK.

[9] Currently, recommendations are for 1-2 embryos per cycle for women under the age of 35 and increase with age. See Table D.1 in Appendix D.

[10] The average cost of a singleton birth was $27,000 in 2012, while twin and triplet births cost $115,000 and $435,000, respectively (Lemos et al., 2013). The risks of multiple births to mothers include high blood pressure, gestational diabetes and a higher rate of cesarean sections. The risks to infants include low birth weight, prematurity and sometimes long-term disabilities like autism and cerebral palsy (Hoffman and Reindollar, 2002; Fritz, 2002; Martin and Park, 1999; Reynolds et al., 2003).

2.2 Mandated IVF coverage in health insurance plans

Due in part to concerns about the high cost of IVF treatment, between 1978 and 2005, 15 states in the US passed legislation pertaining to coverage of infertility treatment in employer-provided private health insurance plans.[11] In these *mandate to cover* states, private health insurance companies are required to cover infertility treatment in all of their policies.[12]

The level of coverage in the mandate to cover states is quite heterogeneous. During our study period, Montana (mandate year: 1987), New York (1990), Ohio (1991), and West Virginia (1995) mandate coverage for some types of infertility treatment, but do not require coverage of IVF. Arkansas (1987) and Hawaii (1989) mandate coverage for only one cycle of IVF; Connecticut (2005) mandates up to two cycles; Rhode Island (1989) and Maryland (1985) mandate up to three cycles; Illinois (1991) and New Jersey (2001) mandate up to four cycles; and Massachusetts (1987) has no limit. Mandates also vary along with a number of other dimensions, including (but not limited to) age restrictions, coverage of unmarried women, minimum years of infertility to qualify for coverage, coverage for cycles with frozen or donor eggs, and whether mandates apply to health maintenance organizations (HMOs). However, as shown in Table 1, these dimensions of generosity are highly correlated with the mandated number of cycles, so we treat the number of cycles as a proxy for the overall generosity level of mandated coverage. There are 35 states which never legislated policies to mandate coverage for infertility treatments.[13] These *never mandate states* serve as a control group in our analysis.

[11] Under the 1974 Employer Retirement Income Security Act (ERISA), self-insured firms are exempt from these mandates.

[12] In *mandate to offer* states, health insurance companies are required to offer plans that would cover infertility treatment but are not required to include this coverage in all policies. We exclude these states (California, Texas, and Louisiana) from our empirical analysis.

[13] Since the end of our study period in 2014, 4 additional states have mandated IVF coverage: Colorado (2020), New Hampshire (2020), New York (2020) and Delaware (2018). We do not include these mandates in our analysis but include these states in our control group.

3 Data

We use several data sources for our empirical analysis. First, we use administrative birth certificate data from the National Center for Health Statistics Detail Natality Files. The data comprise records of live births in the US from 1975 to 2014, and include parental information such as mother's age, education, and race, father's race, parental marital status, and state of residence; and infant information such as sex, birth order, and the plurality (single or multiple births). Our study sample includes the 12 mandate to cover states (treatment group), and the 35 never mandate states (control group). We aggregate the data into state-year cells for our empirical analysis.[14]

Our primary outcome variable is the multiple birth rate defined as the number of multiple births (i.e., not singletons) per hundred live births.[15] Multiple births are a useful proxy for the aggressiveness of treatment. More than one-third of twins and more than three-quarters of triplets and higher-order multiples in the US in 2011 resulted from conception assisted by infertility treatments (Kulkarni et al., 2013). However, one caveat of this approach is that in the birth certificate data, we have no way of knowing whether the multiple births are naturally occurring, or due to IVF treatment, or due to other infertility treatments besides IVF.[16] Our multiple birth indicator also cannot differentiate between a twin birth and a quadruplet birth, even though these have very different cost implications, so we also examine the effects of generosity on the number of infants per thousand births.

Second, we use the March Annual Social and Economic Supplement of the Current Population Survey (CPS) to create control variables at the state-year level, including the

[14]The public-use birth certificate data provided by the National Bureau of Economic Research (NBER) include the mother's state of residence only through 2004, so we use restricted access data files from 2005 to 2014. A few states do not report some parental information in some years. We impute these missing values in the state-year aggregated data by setting them to the average of the corresponding variable in the years before and after.

[15]There is one record for each infant in the data file (e.g., there are three records for a triplet birth). The number of infants, therefore, over-represents the incidence of multiple births. To deal with this issue, we follow Buckles (2013) and construct a weight by dividing one by the plurality of each infant (i.e., the weight of each infant in a triplet birth is set as 1/3). We use these weights to convert the unit of analysis from infant to birth.

[16]The birth certificate data includes a variable indicating births with assisted reproductive technology starting from 2011. However, the variable has lots of missing values and not much informative.

population percentage of women of childbearing age, the female labor force participation rate and real per capita income.[17] To account for the share of women who will be affected by the mandates, we control for the percentage of working-age individuals with private health insurance, as well as the percentage of working-age individuals in large firms (defined as +500 employees) as a proxy for the share of workers in self-insured firms and therefore not subject to the mandates under the Employer Retirement Income Security (ERISA) act.[18]

Third, we use fertility clinic-level data collected from 1996 to 2010 by the Society for Assisted Reproductive Technology (SART) to study patients' utilization of IVF treatment.[19] The data include information on the number of cycles initiated in each clinic, the share of cycles performed on women 35 and older, and the average number of embryos transferred by mothers' age. We exclude frozen and donor cycles, since only fresh and non-donor cycles are covered by mandates in many states.

Finally, we use data on child adoptions from the National Data Archive on Child Abuse and Neglect (NDACAN) from 2000 to 2014.[20] The data includes the records of all the public adoptions in the US and has information on adoptive parents' age and race and the adopted children's age, sex and race, and the year and the state the adoption is finalized. We focus on these ages since younger children might be closer substitutes for newborn infants. We aggregate the data into state-year cells and create a variable representing the number of young adopted children (ages 0-6) per one thousand live births in that state and year.[21]

[17]We convert all dollar values to 2007 dollars using the Consumer Price Index.

[18]Large firms are more likely to self-insure (Gabel et al., 2003; Park, 2000).

[19]SART has a voluntary reporting system and about 10% of the clinics do not report data. SART does not regulate clinic practices.

[20]The data is collected under a federally mandated system for all children in foster care and on children adopted under the auspices of the state public child welfare agency.

[21]Our data does not include private adoptions (either domestic or international). However, our analyses of the insurance mandates' effects will be biased if the generosity of mandated IVF coverage differentially affects private adoptions versus those through the state welfare system.

4 Empirical analysis

4.1 Descriptive evidence

Table 2 presents summary statistics from the birth certificate data from 1975 to 2014, presented in ten-year intervals, and broken out by IVF mandate status. Mothers in more recent years are, on average older, more educated, and less likely to be married. Multiple births per hundred live births and the number of infants per thousand live births are also higher in more recent years. The incidence of multiple births in states with mandated coverage is higher than that in the never mandate states, and this gap is widening over time.

The age of 35 is considered to be a turning point in women's fertility: one-third of women older than 35 experience fertility problems (CDC, 2015). Therefore, we present all of our empirical analyses first for all women, then separately by women 35 and older and women younger than 35 years. Figure 1 plots trends in multiple births per hundred live births by generosity level of mandated IVF coverage, first for all women, then separately for older and younger women. Three main patterns emerge. First, the incidence of multiple births is increasing across all states over our study period. Second, more generous coverage is associated with more rapid growth in the incidence of multiple births. Third, the association between coverage generosity and the incidence of multiple births is stronger for older women than for younger women.[22]

4.2 Is the increase in multiple births driven by IVF treatment?

Figure 2 plots the multiple births per hundred live births by women's age; it increases by women's age, and this pattern is stronger in recent decades. Older women are more likely to have multiple births even in the absence of infertility treatment, but the increase in the incidence of multiple births in recent decades reflects an increase in infertility treatments due to mandated IVF coverage. To provide suggestive evidence, we compare the multiple birth rates of women eligible for the mandated IVF coverage with the rates for women

[22] The patterns for the number of infants per thousand live births are similar.

who are not eligible.

Women over 40 years old in Connecticut and Rhode Island and women over 46 years old in New Jersey are not eligible for the mandated coverage (see Table 1). Figure 3 plots the trends in the multiple births per hundred live births in these states around the eligibility age thresholds. The figure shows a sharp jump down in multiple birth rates at the threshold.

We explore the sharp discontinuity in the eligibility ages for the mandated coverage in these three states using a Regression Discontinuity Design (RDD) model, using women's age as the running variable. We compare the incidence of multiple births to women right above the age eligibility threshold –those who are not eligible for the mandated coverage– to those right below the threshold. We estimate a regression of the form:

$$y_{ia} = \delta + f(a) + \rho D_a + \beta X_i + \epsilon_i \tag{1}$$

where y_{ia} denotes the plurality of the birth to woman i with age a; it is defined as a dummy variable switching on for multiple births. D_a is the treatment dummy that switches on for women above the eligibility age threshold. X_i is a set of individual characteristics, including women's race, education, and marital status. $f(a)$ denotes a polynomial age trend to control for age variation in the incidence of multiple births that would have occurred in the absence of the mandated IVF coverage, and ϵ_i is the error term. The coefficient of interest is ρ, which captures the intent-to-treat effect of the mandated coverage on the multiple birth rate. The identification assumption is that the other unobservable variables affecting the incidence of multiple births change smoothly in the neighborhood of the age eligibility threshold (Hahn et al., 2001).

We follow Schmidt (2007) and allow mandated coverage to affect multiple births with a two-year delay. This effective mandated coverage year accounts for two factors: first, infertility treatments may not lead immediately to conception, and second, a successful conception will not translate into a birth until nine months later. Therefore, we use the birth certificate data from two years after the mandated coverage in each state up to 2014. The bandwidth and the degree of the fitted polynomial are selected using the method of

Calonico et al. (2020), and the standard errors are clustered at the age level. Table 6 shows that after controlling for individual characteristics, the incidence of multiple births for women not eligible for the mandated coverage decreases by 7.29%, 5.94%, and 5.55% respectively in Connecticut, Rhode Island, and New Jersey.

To check our findings' robustness, we estimate the effects on the incidence of multiple births in New Jersey from a placebo eligibility age threshold at 40 years. The last panel of Figure 3 shows the trends in multiple birth rates around the placebo threshold, and the last panel of Table 6 shows the estimated effects. Findings show that there is no sharp change in multiple birth rate, and the estimated effect is negligible and insignificant.

The findings from our RDD analysis provide suggestive evidence that mandated coverage for IVF treatment is a driving factor in the increase in the incidence of multiple births in the states with mandated coverage.

4.3 Identification strategy

States mandated insurance coverage for IVF treatment at different times. We could follow the previous literature and use this state- and time-level variation to estimate the effects of the generosity of mandated coverage on the incidence of multiple births using a DD framework. However, interpretation of the estimated effects as causal requires that in the absence of treatment, the incidence of multiple births in the treated and control states would have followed parallel paths over time. Figure 1 suggests that the parallel trend assumption might be violated in some states.

To estimate causal effects when the parallel trends assumption is likely to be violated, we use a GSC framework developed by Xu (2017).[23] This model is a generalization of the conventional fixed effect models using a linear interactive fixed effect framework, in the spirit of the weighting scheme of the original synthetic control method developed by (Abadie et al., 2010).[24] A GSC model uses the control group and the treatment group

[23]A DDD framework can be used to estimate causal effects when the parallel trends assumption is likely to be violated, since it adds a third dimension (in our case, mother's age in addition to state and year). We estimate DDD models as a robustness check. See Appendix C.

[24]There are two main approaches to estimate causal effects when the common trend assumption is likely to be violated. The first approach uses a matching method to condition on pre-treatment observable characteristics (Abadie, 2005; Abadie et al., 2010, 2015). This approach helps to balance the effects of

–in pre-treatment periods– to impute treated counterfactuals. We estimate a model of the form:

$$y_{it} = \delta_{it} D_{it} + \beta X_{it}' + \lambda_i' f_t + \epsilon_{it}, \tag{2}$$

where i and t respectively denote state and time and y_{it} denotes the outcome variable. Our main outcome variables are the multiple births per hundred live births and the number of infants per thousand live births. D_{it} is a dummy variable that is coded as one for treated state i in years following the mandated coverage. We follow Schmidt (2007) and allow the mandated coverage to affect multiple births with a two-year delay. The vector X_{it} is a set of time-varying state-level characteristics, which includes mothers' age, marital status, and education, mothers' and fathers' race. We also include the state-level socioeconomic characteristics from the CPS data discussed earlier.

$\lambda_i' f_t$ denotes the interactive fixed effects where λ_i and f_t are r-vectors of respectively state-specific intercepts and time-varying coefficients, capturing unobserved common factors that can be decomposed into a state-year multiplicative form. This interactive component covers a wide range of unobserved heterogeneity, but it does not capture unobserved confounders that are independent across states. ϵ_{it} is the error term and captures any remaining unobserved components that affect the outcome variable. r is estimated thorough a data-driven procedure where a larger value covers a broader range of unobserved heterogeneity. Intuitively, a GSC framework allows the data to tell which model fits better.[25] Details of the estimation procedure of a GSC framework are provided in Appendix A.

The coefficients of interest are δ_{it} which capture the treatment effect on treated state i at time t. The average treatment effect on the treated (ATT) at time t is the average of the estimates for all the treated states at time t. We use data from a 15-year window around the effective mandated coverage year (15 pre- and 15 post-treatment periods) for

time-varying confounders between the treatment and control groups. The second approach is to explicitly model the unobserved time-varying confounders using an interactive fixed effect model, which includes state-specific intercepts interacted with time-varying coefficients (Bai, 2009). GSC links the matching and interactive fixed effect methods and brings together synthetic control and interactive fixed effect models where the DD model is a special case.

[25]For instance, for $r = 2$ if we set $\lambda_i' = (1, \alpha_i)$ and $f_t' = (\tau_t, 1)$ then $\lambda_i' f_t = \alpha_i + \tau_t$. In this case, the GSC model is reduced to a conventional fixed effect model with state and time fixed effects.

our estimations.[26] We aggregate the data into state-year cells and estimate the model separately for each generosity level indicated in Table 1. Standard errors are estimated with a parametric bootstrapping procedure using 2,000 re-sampling draws of the residuals (Xu, 2017).

The GSC framework has several advantages relative to the original synthetic control method by Abadie et al. (2010). First, it allows for more than one treated state with variable treatment periods. Second, it provides estimates of standard errors and confidence intervals, making inference more reliable. Third, it provides a data-driven procedure to select the number of factors in an interacted fixed effect model (r) to minimize the perdition error and reduce the risk of over-fitting. This approach furthermore enables us to take advantage of the long pre-treatment panel to decrease the bias of the estimated effects.[27]

To compare together the mandates enacted at different times, we make two implicit assumptions. First, we assume that patients in all states respond the same to the generously level of the mandated coverage, and therefore we can compare the incidence of multiple births across the states. Second, we assume that the responsiveness to the mandated coverage at the relative time to the mandated coverage is similar across the mandated states, such that our analysis picks up the differences in generosity levels of the mandated coverage. These assumptions are plausible since we control for flexible state and time effects and time-varying state-level characteristics, which might affect the utilization and outcome of IVF treatment.

4.4 Results

Table 7 presents the estimated effects of the generosity level of mandated coverage on the multiple births per hundred live births from GSC model.[28] The first set of columns

[26] Exceptions are Connecticut (mandate enacted in 2005) with an 8-year post-treatment period and Hawaii (1987) and Arkansas (1987) with 10-year pre-treatment periods because the 15-year window for these states falls outside our data availability period of 1975–2014.

[27] See Abadie (2019) for a review of recent synthetic control methods.

[28] Plots presenting the estimated counterfactual and estimated effects on the treated states for each level of coverage are presented in Appendix B. The plots suggest that the GSC estimator works quite well in imputing counterfactuals for the treated states to match the control group in the pre-treatment periods.

presents the estimated effects for all women. Panel A presents the estimates using one indicator that pools all mandate to cover states, regardless of generosity level. The first column shows that any mandated coverage increases the multiple birth rate by 0.10 percentage points relative to the never mandated states, approximately an 8.84% increase from a mean value of 1.13. The second column adds covariates to the model, which reduces the magnitude of the estimated effect to a 0.05 percentage point increase in the multiple birth rate (or a 4.42% increase).

Panels B through G show the estimated effects broken out by the level of generosity. Panel B shows that coverage for less invasive infertility treatment only (level 0) does not affect the multiple birth rate relative to states that never enact mandates. This finding is relatively consistent across our results. Panel C through G show that, in general, states with more generous coverage exhibit larger increases in multiple birth rates. Estimated effects with covariates range from a 0.08 percentage point increase (8.33%) in states with level 1 coverage to a 0.28 percentage point increase (26.92%) in states with level 5 coverage.

The remaining columns of Table 7 present the estimates for women 35 and older versus younger than 35. After controlling for covariates, the estimated effects for women 35 and older tend to be larger than those of younger women, especially at higher levels of coverage. For older women, the estimated effects after controlling for covariates vary from -0.24 percentage points (-17.26%) in states with level 1 coverage to 0.56 percentage points (44.09%) in states with level 5 coverage. The estimated effects for younger women are much smaller and range from 0.07 percentage points (7.52%) in level 1 states to 0.21 percentage points (20.59%) in level 5 states.[29]

While the multiple births per hundred live births tell whether the birth included more than one infant, our alternative outcome measure, the number of infants per thousand births, allows, for example, triplets to count more than twins. Table 8 presents the effects of the generosity level of mandated coverage on the number of infants per thousand live births. The overall findings are quite consistent with those from the multiple birth per

[29]We also estimated the effects separately for each state with mandated coverage. These effects (available upon request) are quite similar to those aggregated by the coverage level.

hundred live births specification. The estimated effect of any mandated coverage (Panel A) after controlling for covariates is 0.64 infant (5.51% increase in extra infants per thousand live births). The estimated effects by the generosity level of coverage after including covariates range from 0.91 infants (9.37%) in states with level 1 coverage to 2.92 infants (27.68%) in states with level 5 coverage, and again, the effects are larger for older women. The estimated increases in the number of infants per thousand live births, in general, are larger than the estimates for the multiple births per hundred live births; suggesting that the majority of the multiple births in states with more generous coverage are higher order births.

Overall, our estimates from the GSC framework show that mandated coverage causes an increase in the incidence of multiple births, that states with more generous coverage experience larger estimated effects, and that effects are larger for women over 35 years.[30]

4.5 Robustness analysis

We estimate the effects of the generosity level of mandated coverage on the incidence of multiple births using a DD framework by exploring variations across states and over time. In addition to robustness check of our findings from GSC framework and facilitating comparison with the previous literature, this analysis updates findings of Buckles (2013) –which uses data from 1980 to 2002– using more recent data from 1975 to 2014, allowing us to include two states with more recent mandated coverage; Connecticut and New Jersey, which mandated coverage in 2005 (2 cycles) and 2001 (3 cycles), respectively.

To further investigate the robustness of our findings from the GSC framework, we estimate the effects of the mandated coverage on the incidence of multiple births using a DDD framework. Table 7 and Table 8 show that the estimated effects of mandated

[30] There are other dimensions besides age that are strongly associated with infertility and IVF utilization, including education, marital status, and race (Bitler and Schmidt, 2006). College-educated women face incentives to postpone childbearing and invest in their professional careers and are more likely to work in jobs that offer private health insurance. Married women struggling with fertility seek infertility treatment and especially IVF, more often than unmarried women, and some mandated coverage explicitly excludes unmarried women. Although white women are less likely to experience infertility than black women, they are more likely to seek infertility treatment. We estimated the effects of the generosity of mandated coverage on the incidence of multiple births along these dimensions, and results are mostly consistent with the patterns found in the previous literature. Results are available from authors on request.

coverage on the incidence of multiple births are higher for women 35 and older. In our DDD analysis, we further refine the treatment group by mothers' age. We use variations in mandated coverage over the state, year, and women's ages (below and above 35 years old). This analysis allows us to control for two kinds of potentially confounding trends. First, we control for any time trends in the incidence of multiple births for women of a particular age that are constant across states. Second, we control for differences across states in the incidence of multiple births that affect all mothers, possibly due to other state policies or state-level economic conditions that might affect women's fertility decisions.

We aggregate the birth data into state-year and state-year-age cells for estimating the DD and DDD models, respectively. Specifications of the models and the estimated effects on multiple births per hundred live births and the number of infants per thousand live births are presented in Appendix C. Our estimates from the DD model are statistically significant and more substantial than the estimates of Buckles (2013). This finding could be driven by the states with most recent mandated coverage, which were not included in (Buckles, 2013). The overall story is the same as our findings from the GSC framework; more generous coverage is associated with an increase in the incidence of multiple births, and this association is stronger for older women.

5 Patients' behaviour

Our estimates from the GSC models show that more generous coverage causes an increase in the incidence of multiple births. This is in spite of speculation that more generous coverage might reduce the incidence of multiple births by reducing patients' incentives for transferring more embryos per cycle. If mandated coverage has only intensive margin effects on patients' utilization behavior, then we would expect more generous coverage to reduce the incidence of multiple births. However, more generous IVF coverage could also have extensive margin effects, as new patients with lower probabilities of success seek treatment.

To shed light on patients' behavior from the generosity of mandated coverage, we use two additional data sources. First, we investigate patients' utilization behavior using fertility clinic-level data. Second, we investigate child adoption as the main alternative to live birth. However, since data collection for both of these datasets started after several of the mandates are passed, these analyses should be thought of as descriptive and not as providing causal estimates.

5.1 Evidence from IVF clinics

We use SART's clinic-level data from 1996 to 2010 to directly investigate how the generosity of mandated coverage affects patients' utilization behavior. Table 3 presents summary statistics, and Figure 4 plots the trends in our outcome variables by generosity level of the mandated coverage. The average number of transferred embryos is decreasing over our study period in both mandated and never mandated states, likely due in part to changes in SART's recommendations.[31] More embryos are transferred per cycle for women 35 and older than for younger women. The share of cycles performed on women 35 and older is 10 percentage points higher in recent years in the mandated states relative to the never mandated states.

We cannot use GSC or DD models to examine how generosity of coverage affect patients' utilization behaviour because the mandated coverage date for 6 out of 8 states falls before the availability of SART data. Including clinic or state fixed effects would absorb all the variation. The main issue here is that the independence condition for causal inference in a linear model – which states observations are independent of each other– is violated due to a hierarchical structure of the data since clinics are nested within the states with a particular level of coverage. We utilize this hierarchical structure using a Linear Mixed Effect (ME) model to investigate the relationship between the coverage generosity and patients' utilization behaviour.[32] We exploit random variation between

[31]A major change to SART's guidelines occurred in 2004. We estimate an event study model and find that this change is associated with a reduction in the number of embryos transferred for both younger and older patients. However, the estimated effects do not vary by coverage generosity. For more details, see Appendix D.

[32]ME models are extensively used in education research where the independence assumption for causal inference in a linear model is violated; for instance, in studies where students and teachers are nested in classrooms, schools and districts (Goldstein, 1999).

clinics within states in addition to the variation across the states. An example of random variation between the clinics is doctors subjective opinion about the quality of a woman's eggs to suggest the appropriate number of embryos to transfer, which would affect the incidence of multiple births from an IVF cycle. We estimate a model specified as:

$$y_{ist} = \alpha + \rho Level_{st} + \beta X'_{st} + \lambda_t + \nu\gamma_i + \omega\gamma_s + \epsilon_{ist}, \tag{3}$$

where i, s and t denote clinic, state, and yea, respectively, and y_{ist} denotes the outcome variable. Our outcome variables are the total number of cycles, the share of cycles performed on women 35 and older, and the average number of transferred embryos per cycle. $Level_{st}$ is an indicator for the generosity level of mandated coverage in state s at year t, with never mandated states as the control group. The vector X_{st} includes the time-varying state characteristics from the CPS data we used in our GSC analysis. λ_t denotes year fixed effects, which pick up any factors changing over time that are common across the states and clinics (e.g., advances in IVF technology at the national level). γ_i and γ_s denote clinic and state random effects, respectively. ϵ_{ist} captures any remaining unobserved factors affecting the outcome variable. The coefficient of interest is ρ, which captures the relationship between the generosity level of mandated coverage and the outcome variable. ME models assume that first, clinic and state-level residuals are uncorrelated; second, the errors –as measured by the residuals– at the state level are uncorrelated.

Table 9 presents the estimated effects for all women as well as results broken out by age. These results suggest the following: First, more generous coverage is associated with a significant increase in the average number of cycles in a clinic and the share of cycles initiated by older women, which is suggestive of extensive margin effects on the composition of the patients seeking treatment. Given that older women transfer more embryos per cycle, this would imply an increase in the incidence of multiple births. Second, the relationship between the generosity of mandate coverage and the average number of transferred embryos per cycle reflects intensive margin effects: more generous coverage is associated with fewer transferred embryos for both older and younger women, with stronger effects for younger women. This would imply a decrease in the incidence of multiple births. The fact that our GSC results using birth data show an overall causal increase in the incidence of multiple births suggests that the compositional or extensive margin effect must dominate.

5.2 Evidence from child adoption

Women who cannot naturally conceive an infant have two alternative pathways to motherhood: using IVF treatment or adopting a child. There is a significant overlap between these two options. More than half of the individuals who received infertility treatment had also considered adoption (Chandra et al., 2005). Gumus and Lee (2012) show that one-third of individuals who consider adoption have also sought IVF treatment. Both of these options have pros and cons. Despite technological advances, IVF treatment is expensive and has a low probability of success. Adopting a child is also expensive, uncertain, and can take a long time. Furthermore, some individuals might prefer to have their own biological child. If more generous mandated coverage for IVF induces more older women to initiate IVF, we would expect that effect to be accompanied by a decrease in child adoptions.

Previous studies have examined the relationship between IVF treatment and child adoption. Gumus and Lee (2012) find that higher adoption rates at the state-year level are associated with a lower number of IVF cycles performed. Cohen and Chen (2010) find that mandated IVF coverage did not affect child adoption in mandated states relative to never mandated states. However, the effects of mandated coverage on adoption could be quite heterogeneous, depending on the generosity of coverage and the mother's age.

We use NDACAN's child adoption data for children aged 0-6 years from 1995 to 2014 to investigate the relationship between the generosity level of mandated IVF coverage and child adoption. Table 4 presents descriptive statistics. In the early years of our study period, the adoption rate is higher in the mandated states than in the never mandated states. However, by the later half of our time period, this pattern had reversed itself, so that the never-mandated states saw two more adopted children per ten thousand live births than did the mandated states. Figure 5 plots the number of adopted children per ten thousand newborn infants by the age of the adoptive mother. This figure provides two main insights. First, more generous coverage is associated with lower rates of child adoption. Second, adoption rates are higher for older women than younger women.

To examine the effects of the generosity of IVF coverage on child adoption, we estimate an ME model similar to Equation (3), including time fixed effects and state random effects.[33] Table 10 presents the estimated effects, first for all women, and then broken out by the age of adoptive women. Our results suggest a negative association between the generosity level of mandated coverage and the number of adopted children per ten thousand newborn infants that is much stronger for older women than for their younger counterparts.

Our analyses of these three different data sources, birth certificate, fertility clinics, and child adoption, have three main takeaways. First, more generous IVF coverage increases the incidence of multiple births. Second, the intensive margin effects of more generous coverage (i.e., the decrease in the number of transferred embryos) are found for all women but are stronger for younger patients than older patients. Third, the extensive margin effects of more generous coverage show a compositional change, where the share of cycles performed on women over 35 increases with coverage generosity. This is mirrored by a decrease in child adoption to older women in states with more generous coverage. These findings suggest that the extensive margin effects of more generous coverage are stronger than the intensive margin effects on the number of embryos transferred per cycle, resulting in the overall increase in risky and costly multiple births.

6 Conclusion and policy implications

How do increases in the accessibility of expensive medical treatments affect patients' utilization behavior, and what are the resulting implications for healthcare costs? We explore the generosity of state-level mandated coverage for IVF treatment in the US

[33] Similar to our analysis of SART data, we are unable to use GSC or DD models because the mandated coverage date for 6 out of 8 mandated states falls before the availability of the adoption data. Further, including state and time fixed effects would absorb most of the variation.

and find that more generous coverage significantly increases the incidence of risky and expensive multiple births. This is true despite the fact that more generous coverage has been proposed as a way to decrease the incidence of multiple births by affecting patients' utilization behavior along the intensive margin, i.e., by encouraging less intensive treatment through the transfer of fewer embryos per cycle. We find that while more generous coverage has these predicted intensive margin effects for all women (and stronger effects for younger women), it also has sizeable extensive margin effects, increasing the share of cycles performed on older women. Our analysis highlights the importance of unintended consequences of the increased accessibility of an expensive medical treatment through the change in the composition of the patients seeking treatment.

Our results are consistent with work by Bitler and Carpenter (2016), who show that mandated insurance coverage for mammography significantly increased mammography screenings and subsequently increased the detection of pre-cancers. However, they also find that a large share of the increased screenings resulted from utilizations that were not consistent with recent recommendations of the American Cancer Society. Our findings are also related to suggestions by Hamilton et al. (2018) –in the context of IVF– and Einav et al. (2016) –in the context of breast cancer treatment– for either regulating/limiting the aggressiveness of treatments; or for imposing a top-up price for more aggressive treatments; or some combination of the two. In the IVF context, Hamilton et al. (2018) argue that a value-based policy in which insurance plans cover single embryo cycles but patients must pay a top-up cost for transferring additional embryos could maximize welfare. This is consistent with findings of Bhalotra et al. (2020) from a Swedish single embryo transfer policy which reduced the incidence of multiple births and improved maternal and infant health. Ignoring compositional effects could mean that increased access without regulation might impose additional burdens on the healthcare system.

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Tables

Table 1: Mandated infertility coverage in private health insurance plans

Generosity level	**State**	**Mandate year**	**IVF coverage**	**Notes**
0	Montana	1987	None	Applies to HMOs only; other insurers are specifically exempt from having to provide coverage.
0	New York	1990	None	Exempts coverage for IVF in the individual and small group markets, and coverage for GIFT or ZIFT. Must be 21-44 years old; must have the insurance policy at least 1 year before use; minimum 1 year of infertility if age $\leq$35 and min 6 month if age $>$ 35.
0	Ohio	1991	None	Does not define infertility. Requires HMOs to cover infertility services under basic health care services.
0	West Virginia	1995	None	Requires HMOs to cover infertility services under basic health care services.
1	Arkansas	1987	1 cycle	Lifetime $15,000 cap; minimum 2 years of infertility.
1	Hawaii	1989	1 cycle	Provides a one-time only benefit covering all outpatient expenses arising from IVF; minimum 5 years of infertility.
2	Connecticut	2005	2 cycles	Must be $<$40 years; mininimum 1 year of infertility; no more than 2 embryos implemented per cycle.
3	Maryland	1985	3 cycles	3 cycles per live birth, with a lifetime $100,000 cap. Businesses with $\leq$50 employees are exempt from mandated coverage.
3	Rhode Island	1989	3 cycles	Must be 24–40 years old; minimum 2 years infertility; $100,000 lifetime cap; insurer may impose up to a 20% co-payment.
4	Illinois	1991	4 cycles	Up to 4 egg retrievals; if a live birth occurs 2 additional egg retrievals covered for a lifetime maximum of 6 retrievals; minimum 1 year of infertility; Businesses with $\leq$25 employees are exempt.
4	New Jersey	2001	4 cycles	Min 2 years of infertility if age$\leq$35 and min 1 year of infertility if age$>$35; Must be $<$ 46 year.
5	Massachusetts	1987	No limit	No limit on the number of cycles or dollar lifetime cap; 1 year of infertility if age$\leq$35 and 6 month if age$>$35.

Notes: Source: RESOLVE: The National Infertility Association `http://www.resolve.org/family-building-options/insurance_coverage/state-coverage.html` [Accessed on June 15, 2017].

Table 2: Summary statistics for Detail Natality Data, 1975-2014

	Never mandated states (control group)				*Mandate to cover states (treatment group)*			
	1975-1984	1985-1994	1995-2004	2005-2014	1975-1984	1985-1994	1995-2004	2005-2014
Multiple births per hundred live births	0.98	1.16	1.50	1.68	1.02	1.24	1.81	2.03
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of infants per thousand live births	1,009.92	1,011.89	1,015.55	1,017.24	1,010.38	1,012.74	1,018.96	1,012.90
Mean mothers' age	24.80	26.05	26.82	27.35	25.51	27.02	28.18	28.63
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mothers over 35 years (%)	4.39	7.79	11.74	12.86	5.55	10.16	16.49	18.16
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Married mothers (%)	82.16	73.24	66.52	60.08	78.80	72.31	67.98	61.69
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Mothers with college degree (%)	36.13	41.23	56.34	70.56	38.37	46.19	62.95	89.82
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
White mothers (%)	81.85	79.88	79.65	77.24	77.94	75.71	74.56	71.86
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
First time mothers (%)	36.54	32.94	33.21	32.44	36.38	33.61	32.18	31.33
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Number of births	17,578,332	19,207,128	19,849,815	20,966,038	5,009,715	5,701,859	5,477,201	5,217,796

Notes: Source: National Center for Health Statistics Detail Natality files. Weights constructed as described in Section 3 are used to calculate statistics in this table. Standard deviations appear in parentheses.

Table 3: Summary statistics for Society for Assisted Reproductive Technology (SART) infertility clinics data, 1996-2010

	Never mandated states (control group)		*Mandate to cover states (treatment group)*	
	1996-2004	2005-2010	1996-2004	2005-2010
Total number of cycles	231,699	201,147	199,085	176,306
Average number of embryos transferred	3.25	2.45	3.18	2.47
for all women	(0.01)	(0.01)	(0.03)	(0.02)
Multiple births per hundred live births	34.87	30.95	33.48	28.92
for all women	(0.36)	(0.42)	(0.45)	(0.50)
Cycles for women 35 and older (%)	48.10	50.13	56.17	59.40
Average number of embryos transferred	3.39	2.64	3.30	2.66
for women 35 and older	(0.02)	(0.01)	(0.02)	(0.02)
Average number of embryos transferred	3.12	2.23	3.03	2.22
for women under 35 years	(0.02)	(0.01)	(0.03)	(0.02)
Total number of IVF clinics	326	255	118	94

Notes: Standard deviations appear in parentheses.

Table 4: Summary statistics for National Data Archive on Child Abuse and Neglect (NDACAN) adoption data, 1994-2015

	Never mandated states (control group)		*Mandate to cover states (treatment group)*	
	1994-2004	2005-2015	1994-2004	2005-2015
Number of adopted children per ten thousand newborn infants	5.23	8.78	6.37	6.86
Number of adopted children	103,327	188,072	37,926	36,811
Number of newborn infants	19,736,577	21,411,844	5,955,365	5,362,502
Adopting women 35 and older (%)	79.31	79.99	85.21	82.95
	(0.13)	(0.09)	(0.18)	(0.19)
Mean age of adopting mothers	40.99	41.41	42.70	42.04
	(0.02)	(0.02)	(0.04)	(0.04)
Mean age of adopting fathers	43.04	43.55	45.27	44.52
	(0.02)	(0.01)	(0.03)	(0.03)
White adopting mothers (%)	62.20	69.47	38.90	53.76
	(0.15)	(0.10)	(0.25)	(0.25)
White adopting fathers (%)	55.05	59.71	32.26	44.53
	(0.15)	(0.11)	(0.24)	(0.25)
Mean age of adopted children	3.31	3.02	3.61	3.07
	(0.01)	(0.00)	(0.01)	(0.01)
White adopted children (%)	48.93	51.76	28.47	39.31
	(0.15)	(0.11)	(0.23)	(0.25)
Adopted boys (%)	50.89	51.52	50.79	51.49
	(0.15)	(0.11)	(0.26)	(0.25)

Note: Data include children age 0-6 adopted in the US. Standard deviations appear in parentheses.

Table 5: Summary statistics of Current Population Survey (CPS)

	Never mandated states (control group)				*Mandate to cover states (treatment group)*			
	1975-1984	1985-1994	1995-2004	2005-2014	1975-1984	1985-1994	1995-2004	2005-2014
Women of child bearing age (18-49 years) (%)	38.66	39.38	38.12	34.78	38.34	39.53	38.20	35.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female labor force participation rate (%)	61.45	69.31	73.03	71.21	62.54	70.45	74.16	72.08
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Employee in firms of +500 employee (%)	16.19	16.29	15.86	13.88	17.61	17.72	17.07	14.91
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Private health insurance (%)	78.23	76.24	74.80	69.55	81.72	79.94	76.89	73.74
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Real average per capita income (2007 USD)	25,076	29,958	35,033	36,093	26,400	31,624	37,576	39,161
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: The sample includes working age individuals (18 to 64 years). Standard deviations appear in parentheses.

Table 6: Effects of mandated IVF coverage on multiple births per hundred live births, RDD model

	Connecticut		Rhode Island		New Jersey		Placebo effects in New Jersey	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimated effect	-0.58***	-0.53***	-0.43***	-0.34***	-1.58***	-1.28***	0.0009	0.04
	(0.001)	(0.004)	(0.006)	(0.008)	(0.003)	(0.002)	(0.06)	(0.06)
Mean	7.95	7.95	5.72	5.72	23.06	23.06	7.71	7.71
	(27.05)	(27.05)	(23.23)	(23.23)	(42.13)	(42.13)	(26.68)	(26.68)
Cut off age	40	40	40	40	46	46	40	40
Bandwidth	1.94	1.95	1.97	2.01	2.43	2.24	3.26	3.63
Degree of polynomial	1	1	1	1	1	1	1	1
Covars	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	49,904	49,904	30,732	30,732	19,790	19,790	199,959	199,959

Note: This table presents the estimated effects of mandated IVF coverages on multiple births per hundred live births from the RDD model. The data includes all the births to 35 to 45 years old women in Connecticut between 2007 (two years after mandated IVF coverage in 2005) and 2014, and in Rhode Island between 1991 (two years after mandated IVF coverage in 1989) and 2014 form the birth certificate data. The running variable is women's age with the cut-off at 40 years old. The placebo estimates in New Jersey uses data on all the births to 35 to 45 years old women between 2003 (two years after mandated IVF coverage) and 2014. The included covariates are indicators for married, white, and college educates women. The bandwidth and degree of the fitted polynomial are selected using Calonico et al. (2020). Standard errors are clustered at age level and are presented in parentheses.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: Effects of IVF coverage generosity level on multiple births per hundred live births, GSC model

	All women		Women 35 and older		Women under 35		Number of state-year cells
	(1)	(2)	(3)	(4)	(5)	(6)	
A. All levels	0.10***	0.05***	0.18***	0.12**	0.05***	0.05	1,923
	(0.01)	(0.01)	(0.06)	(0.06)	(0.01)	(0.02)	
Pre-mandate mean	1.13	1.13	1.55	1.55	1,09	1.09	
	(0.30)	(0.30)	(0.57)	(0.57)	(0.23)	(0.23)	
B. Level 0	0.02	0.03	-0.22	0.01	0.05	0.02	1,404
	(0.05)	(0.04)	(0.17)	(0.13)	(0.07)	(0.03)	
Pre-mandate mean	1.05	1.05	1.43	1.43	1.02	1.02	
	(0.11)	(0.11)	(0.37)	(0.37)	(0.11)	(0.11)	
C. Level 1	-0.11*	0.08	-0.32*	-0.24	-0.10*	0.07*	1,110
	(0.06)	(0.04)	(0.15)	(0.16)	(0.05)	(0.04)	
Pre-mandate mean	0.96	0.96	1.39	1.39	0.93	0.93	
	(0.11)	(0.11)	(0.37)	(0.37)	(0.10)	(0.10)	
D. Level 2	0.16	0.16	0.23	0.15	0.02	0.24	936
	(0.11)	(0.13)	(0.27)	(0.27)	(0.06)	(0.11)	
Pre-mandate mean	1.46	1.46	2.09	2.09	1.33	1.33	
	(0.47)	(0.47)	(0.87)	(0.87)	(0.34)	(0.34)	
E. Level 3	0.17***	0.09*	0.52***	0.52***	0.12***	0.00	1,036
	(0.01)	(0.03)	(0.13)	(0.13)	(0.01)	(0.03)	
Pre-mandate mean	1.01	1.01	1.34	1.34	0.99	0.99	
	(0.08)	(0.08)	(0.37)	(0.37)	(0.07)	(0.07)	
F. Level 4	0.14***	0.17***	0.40**	0.31**	0.07**	0.12***	1,480
	(0.03)	(0.03)	(0.17)	(0.16)	(0.03)	(0.03)	
Pre-mandate mean	1.26	1.26	1.67	1.67	1.20	1.20	
	(0.33)	(0.33)	(0.62)	(0.62)	(0.25)	(0.25)	
G. Level 5	0.55**	0.28*	0.90**	0.56**	0.23**	0.21***	1,080
	(0.19)	(0.17)	(0.35)	(0.34)	(0.13)	(0.08)	
Pre-mandate mean	1.04	1.04	1.27	1.27	1.02	1.02	
	(0.08)	(0.08)	(0.14)	(0.14)	(0.08)	(0.08)	
Covars	No	Yes	No	Yes	No	Yes	

Notes: This table presents the estimated average treatment effect on the treated (ATT) from the GSC model specified in Equation (2). Data aggregated to the state-year cell level. Included covariates in the model are mothers' age, marital status, education, and race; fathers' race; infant's sex; percentage of women of childbearing age; percentage of college-educated women; female labor force participation rate; the percentage of employees working in big firms (employee $>$ 500); percentage with private health insurance; and real per capita income. Parametric bootstrapped standard errors estimated by 2,000 draws appear in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 8: Effects of IVF coverage generosity level on the number of infants per thousand live births, GSC model

	All women		Women 35 and older		Women under 35		Number of state-year cells
	(1)	(2)	(3)	(4)	(5)	(6)	
A. All levels	1.06***	0.64***	1.64***	0.82**	0.52***	0.57***	1,923
	(0.08)	(0.07)	(0.30)	(0.42)	(0.07)	(0.12)	
Pre-mandate mean	1,011.61	1,011.61	1,015.95	1,015.95	1,011.12	1,011.12	
	(3.25)	(3.25)	(6.22)	(6.22)	(2.51)	(2.51)	
B. Level 0	0.18	0.27	-2.78	0.12	0.52	0.23	1,404
	(0.61)	(0.46)	(1.9)	(1.60)	(0.76)	(0.42)	
Pre-mandate mean	1,010.64	1,010.64	1,014.56	1,014.56	1,010.40	1,010.40	
	(1.22)	(1.22)	(3.85)	(3.85)	(1.15)	(1.15)	
C. Level 1	-1.25*	0.91***	-3.68***	-3.25*	-1.11*	0.77*	1,110
	(0.76)	(0.42)	(1.00)	(1.26)	(0.64)	(0.43)	
Pre-mandate mean	1,009.70	1,009.70	1,014.20	1,014.20	1,009.44	1,009.44	
	(1.12)	(1.12)	(3.71)	(3.71)	(1.07)	(1.07)	
D. Level 2	2.89	2.09*	4.30	2.09	1.53	2.39	936
	(1.50)	(1.29)	(2.57)	(2.62)	(0.99)	(1.18)	
Pre-mandate mean	1,015.13	1,015.13	1,021.88	1,021.88	1,013.74	1,013.74	
	(5.07)	(5.07)	(9.41)	(9.41)	(3.70)	(3.70)	
E. Level 3	1.94***	0.68***	3.73**	3.82***	1.34***	0.42	1,036
	(0.12)	(0.16)	(1.50)	(0.65)	(1.10)	(0.20)	
Pre-mandate mean	1,010.21	1,010.21	1,013.69	1,013.69	1,010.00	1,010.00	
	(0.78)	(0.78)	(3.85)	(3.85)	(0.76)	(0.76)	
F. Level 4	1.93***	1.66***	4.76***	3.43***	1.24***	1.31***	1,480
	(0.26)	(0.20)	(0.71)	(0.65)	(0.20)	(0.27)	
Pre-mandate mean	1,013.07	1,013.07	1,017.40	1,017.40	1,012.40	1,012.40	
	(3.71)	(3.71)	(6.95)	(6.95)	(2.80)	(2.80)	
G. Level 5	6.50**	2.92*	10.04**	6.35**	2.31**	2.18**	1,080
	(2.32)	(2.12)	(3.50)	(3.84)	(1.65)	(0.87)	
Pre-mandate mean	1,010.55	1,010.55	1,012.90	1,012.90	1,010.37	1,010.37	
	(0.84)	(0.84)	(1.48)	(1.48)	(0.79)	(0.79)	
Covars	No	Yes	No	Yes	No	Yes	

Note: See notes for Table 7.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 9: Effects of IVF coverage generosity level on patients' IVF utilization behavior, ME model

	All women				Women 35 and older				Women under 35	
	Total number of cycles		Average number of transferred embryos		Share of cycles		Average number of transferred embryos		Average number of transferred embryos	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
All levels	34.88***		-0.02		0.03***		-0.05		0.02	
	(13.11)		(0.05)		(0.01)		(0.06)		(0.04)	
Level 0		80.40**		0.07		-0.00		0.06		0.15
		(33.78)		(0.10)		(0.03)		(0.08)		(0.10)
Level 1		-34.79		0.01		0.06		-0.03		0.06
		(26.84)		(0.39)		(0.10)		(0.41)		(0.24)
Level 2		13.74		0.09***		0.03***		0.11***		0.06**
		(11.38)		(0.02)		(0.00)		(0.03)		(0.03)
Level 3		192.66***		0.00		0.09***		0.03		-0.07
		(37.71)		(0.06)		(0.01)		(0.05)		(0.08)
Level 4		42.06***		-0.05*		0.03***		-0.10***		0.02
		(13.27)		(0.03)		(0.00)		(0.04)		(0.04)
Level 5		650.22***		-0.50***		0.14***		-0.45***		-0.65***
		(14.27)		(0.04)		(0.01)		(0.04)		(0.04)
Constant	-372.10	-381.85*	4.32***	4.29***	0.44***	0.44***	4.42***	4.37***	4.35***	4.32***
	(230.14)	(204.30)	(0.52)	(0.52)	(0.10)	(0.10)	(0.51)	(0.50)	(0.59)	(0.59)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State and clinic random effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covars	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	4576	4,576	3,821	3,821	4,574	4,574	3,822	3,822	4,562	4,562

Notes: Source: SART's data of all women receiving IVF in a clinic in the US from 1996 to 2010. All estimates include year fixed effects and clinic random effects. Included state-level covariates from the CPS are listed in Notes to Table 7. We also control for the number of IVF clinics in each state. Standard errors are clustered at the state level and appear in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 10: Effects of IVF coverage generosity level on adopted children per ten thousand live births, ME model

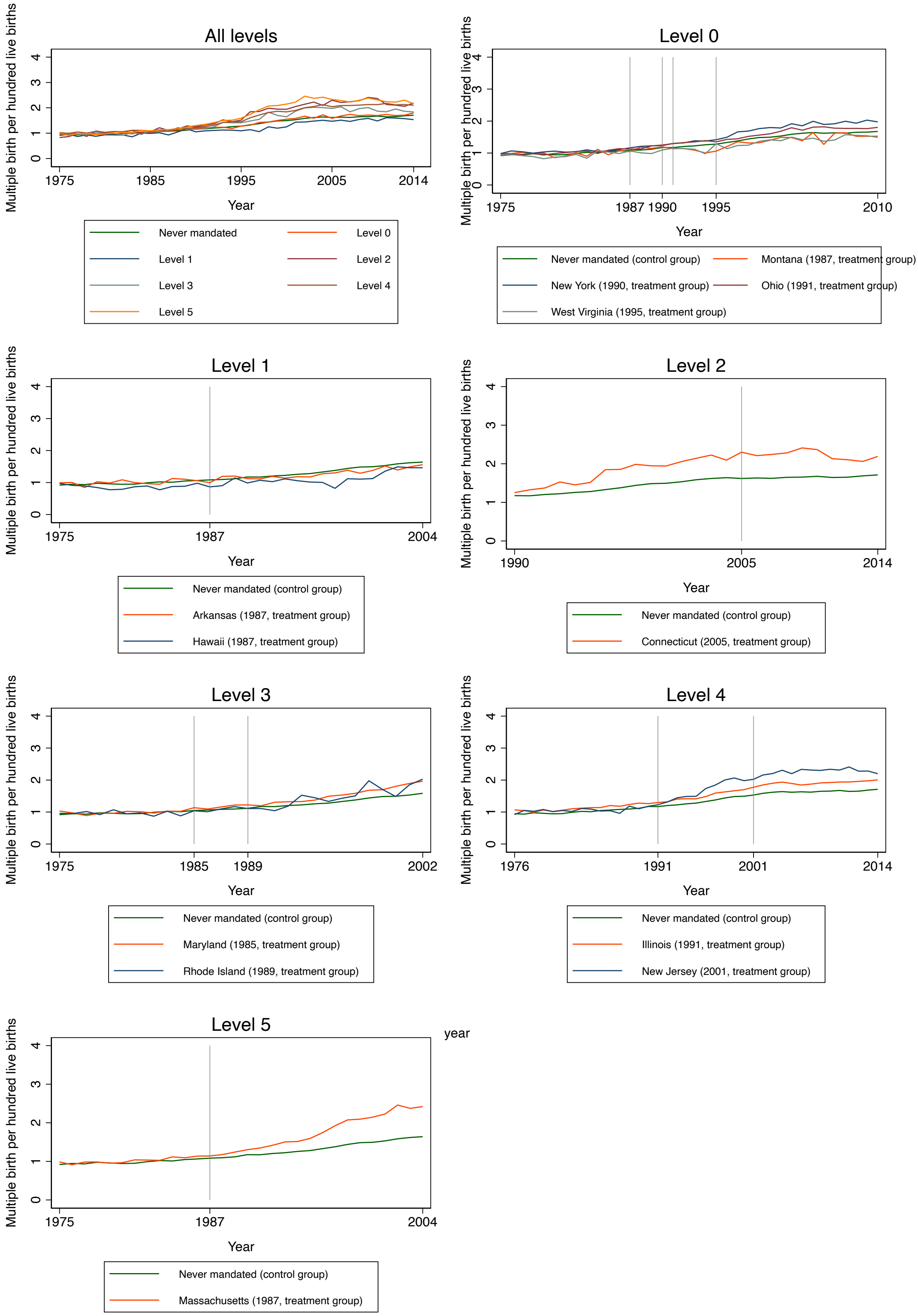
	All women		Women 35 and older		Women under 35	
	(1)	(2)	(3)	(4)	(5)	(6)
All levels	3.11		-11.83		-0.04	
	(6.79)		(52.77)		(1.23)	
Level 0		9.72		170.11		0.17
		(14.25)		(136.52)		(3.11)
Level 1		-29.76		-143.18		-5.36
		(19.23)		(208.76)		(5.66)
Level 2		16.57***		76.91**		1.33
		(6.26)		(39.23)		(1.65)
Level 3		5.88		-146.50		-1.15
		(24.27)		(153.16)		(3.12)
Level 4		-2.85		-65.27		0.92
		(7.73)		(55.73)		(1.24)
Level 5		-2.73		-233.43***		-2.11
		(7.59)		(62.94)		(1.75)
Constant	151.85	159.97	-53.39	-99.45	32.34	33.50
	(134.27)	(139.29)	(1340.20)	(1369.47)	(39.12)	(40.04)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State random effects	Yes	Yes	Yes	Yes	Yes	Yes
Covars	Yes	Yes	Yes	Yes	Yes	Yes
Observations	906	906	906	906	883	883

Note: Data include children ages 0-6 adopted between 1994 to 2014, aggregated into state-year cells. All estimated effects include year fixed effects and state random effects. Included state-level covariates from the CPS are listed in notes to Table 7. We also control for the number of IVF clinics in each state. Robust standard errors appear in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

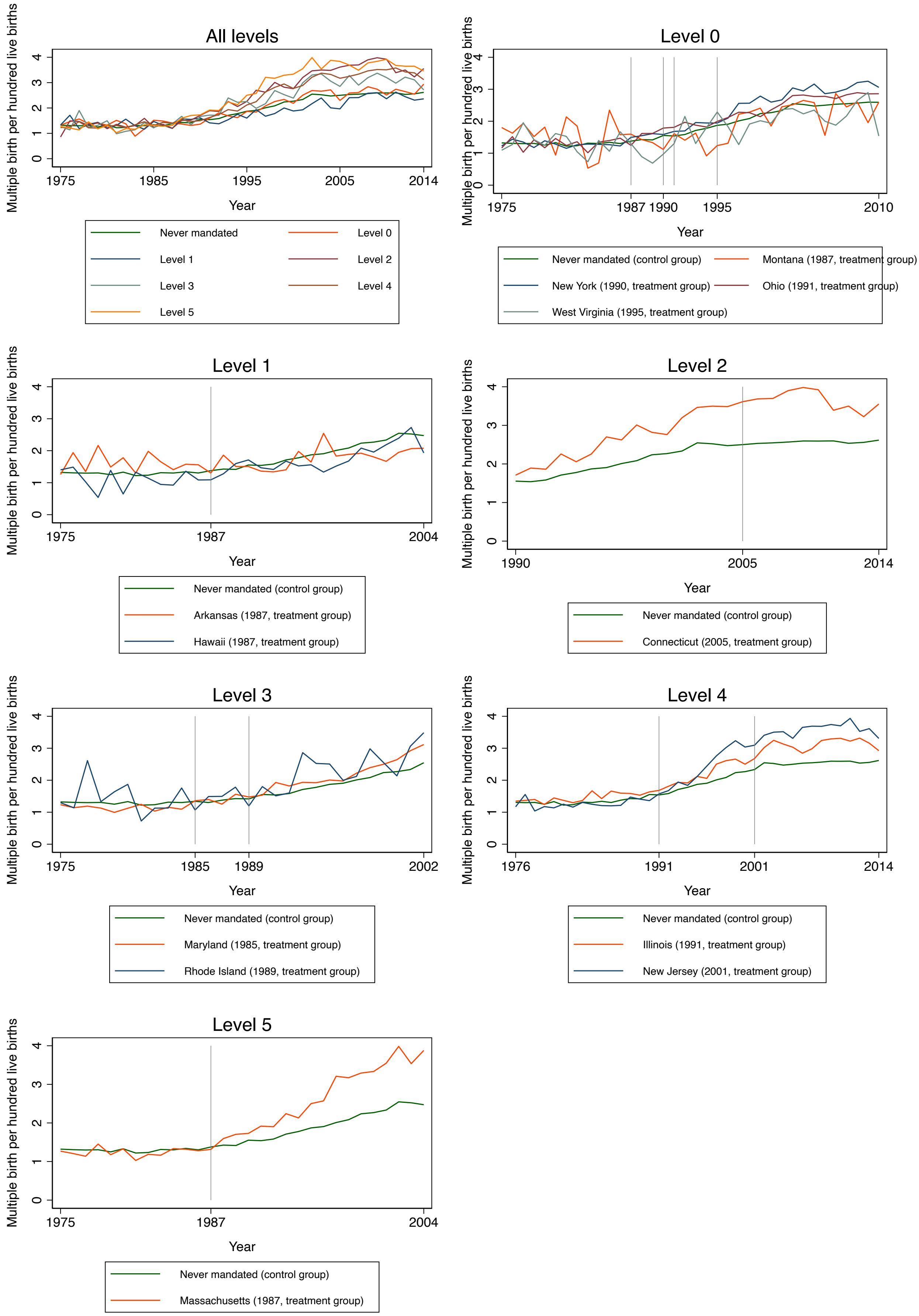
Figures

Figure 1: Multiple births per hundred live births by IVF coverage generosity level

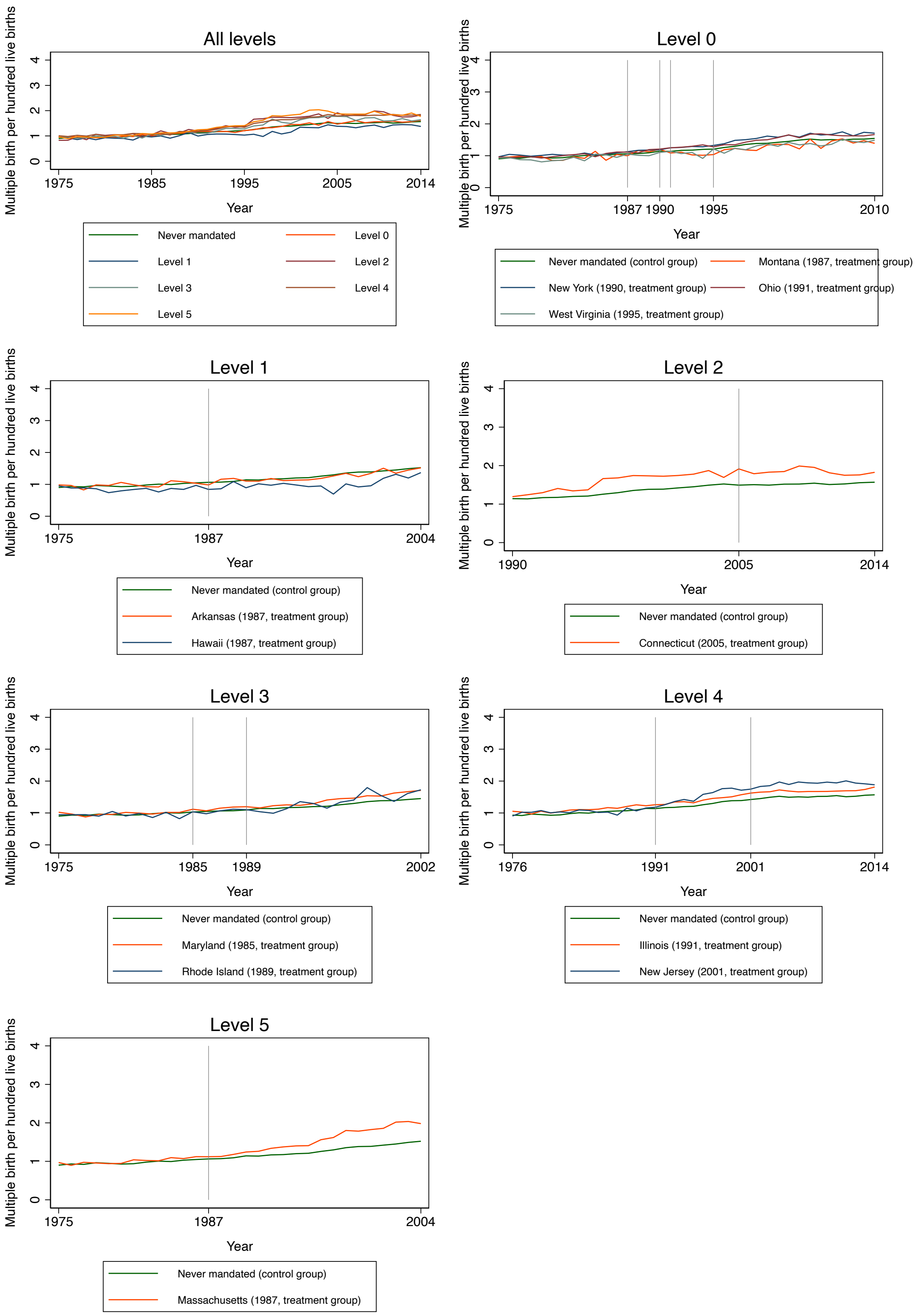
(a) All women



(b) Women 35 and older

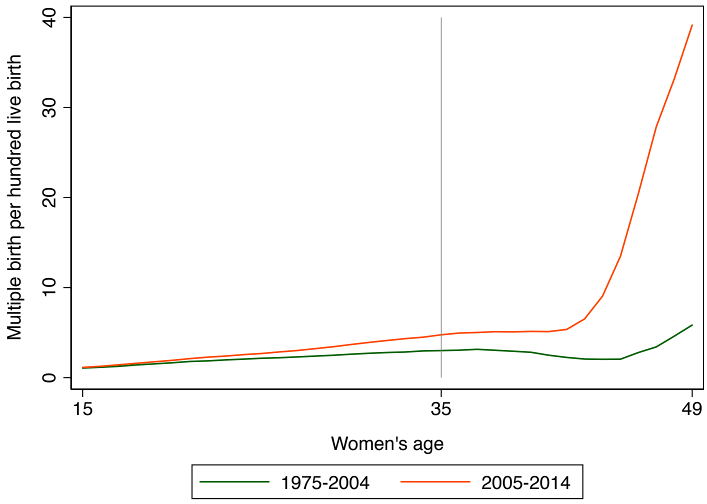


(c) Women under 35



Note: The sample includes all births from National Vital Statistics Detail Natality Data from 1975–2014. Multiple births are defined as births that are not singletons.

Figure 2: Multiple births per hundred live births by women's age

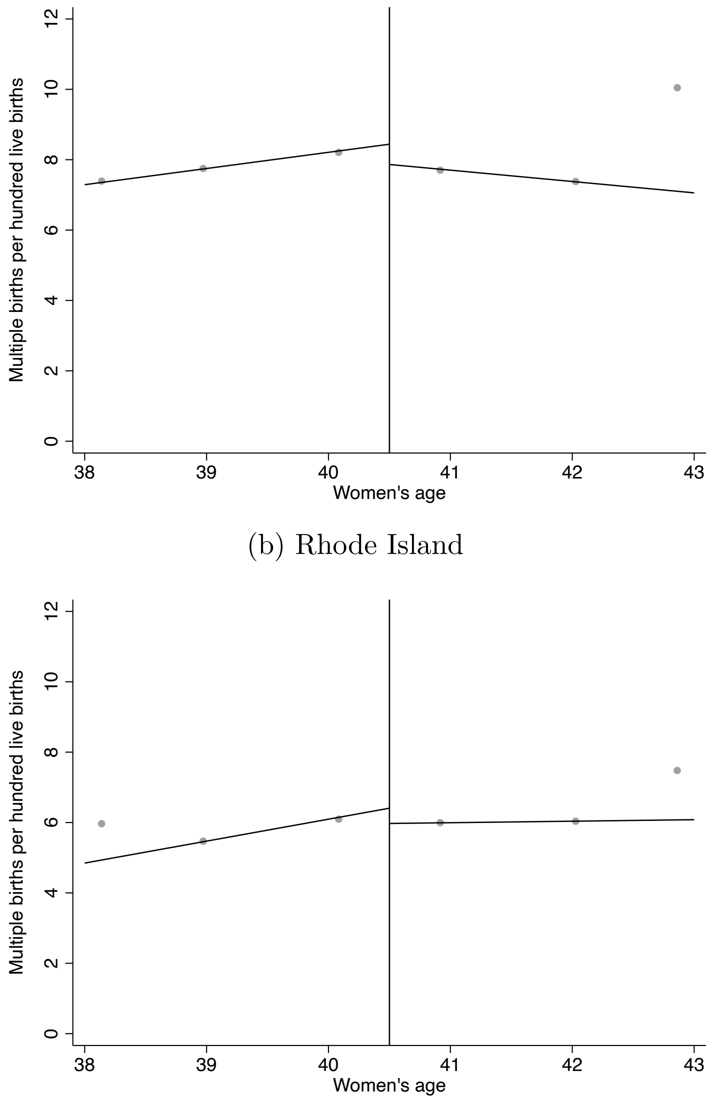


Note: Authors' calculations from the Detail Natality data. Multiple births are defined as births that are not singleton.

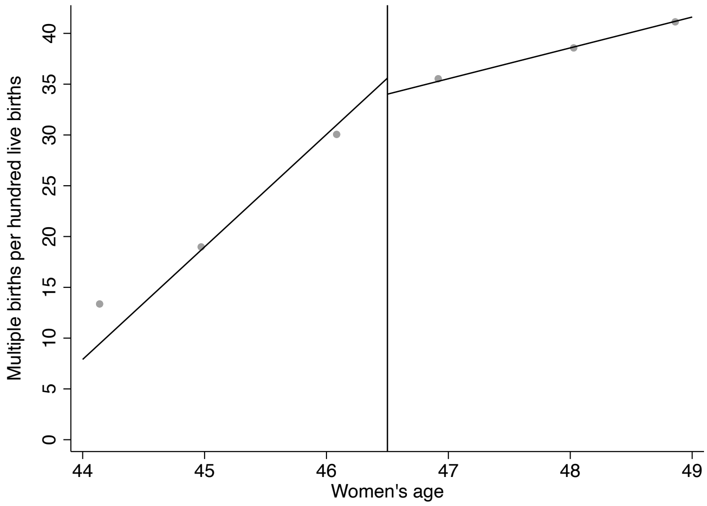
Figure 3: Multiple births per hundred live births by women's age

(a) Connecticut

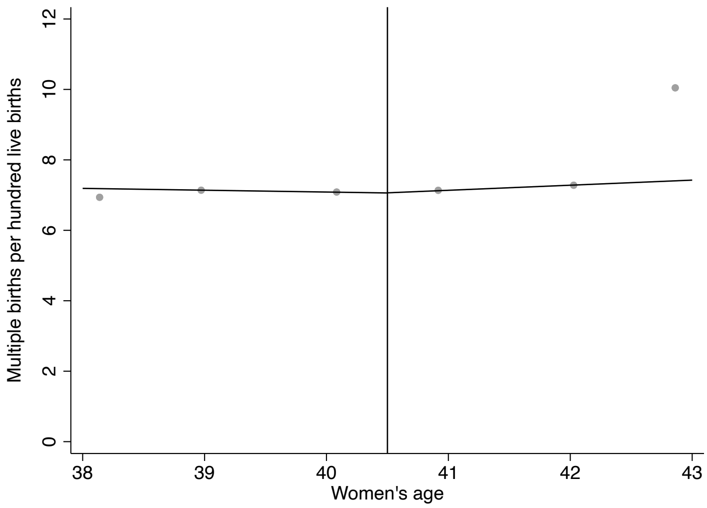
(b) Rhode Island



(c) New Jersey



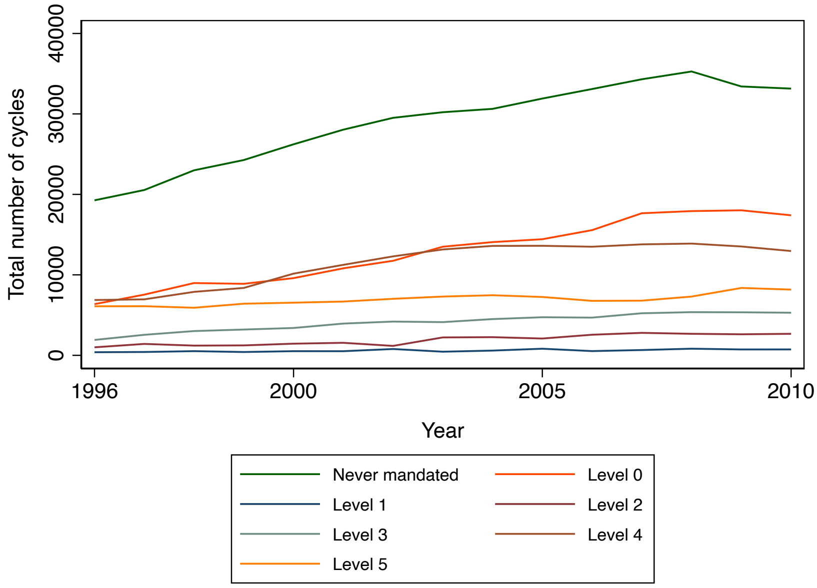
(d) New Jersey (placebo)



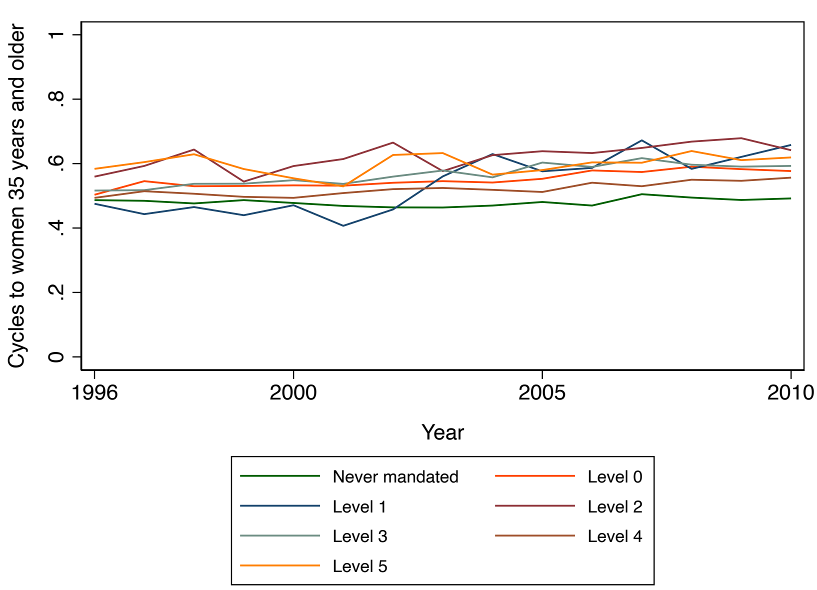
Note: This figure plots the multiple births per hundred live births by women's age two years after mandated IVF coverage in Connecticut (2007–2014), Rhode Island (1991–2014) and New Jersey (2003–2014). There is a sharp change in the incidence of multiple births at age limits for eligibility for IVF coverage.

Figure 4: Patients' IVF utilization behavior, by IVF coverage generosity level

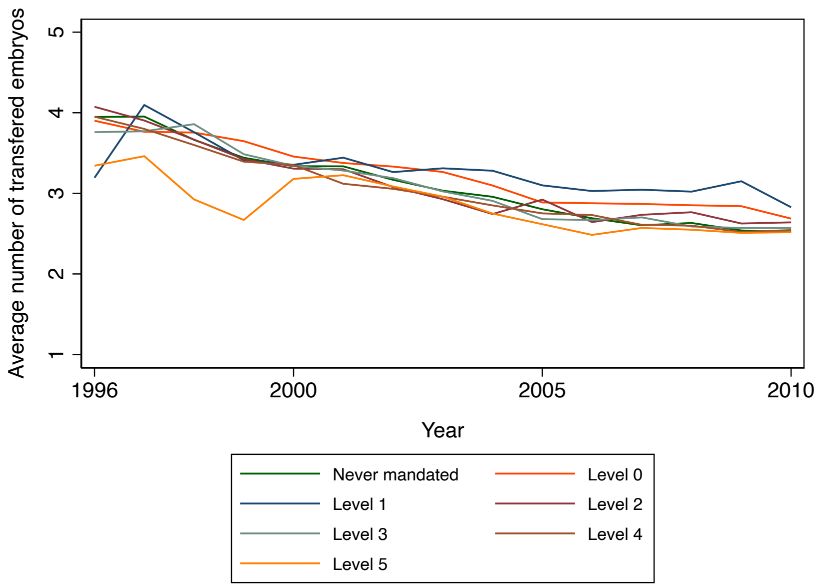
(a) Total number of cycles



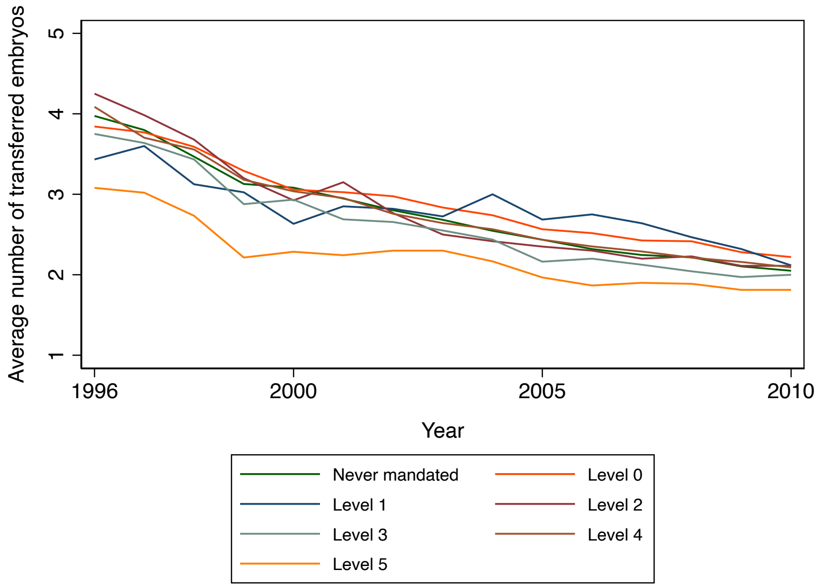
(b) Share of cycles to women 35 and older



(c) Average number of transferred embryos for women 35 and older



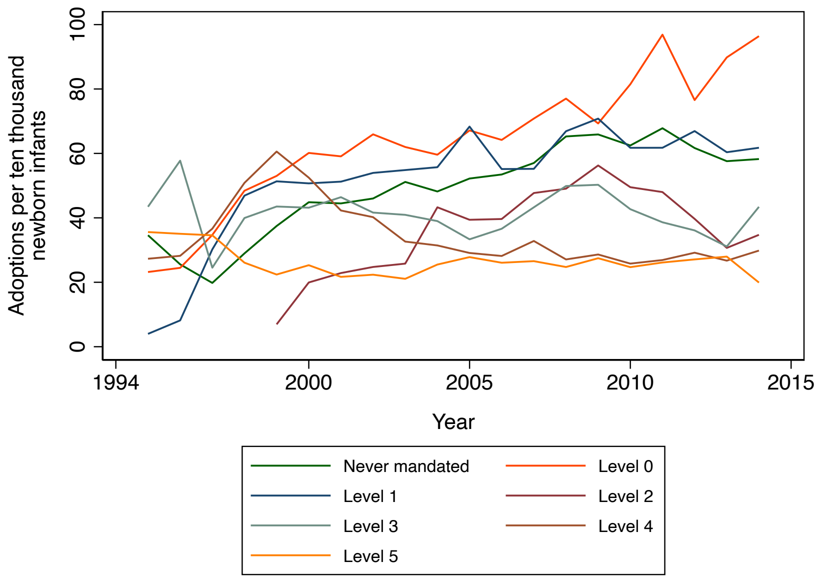
(d) Average number of transferred embryos for women under 35



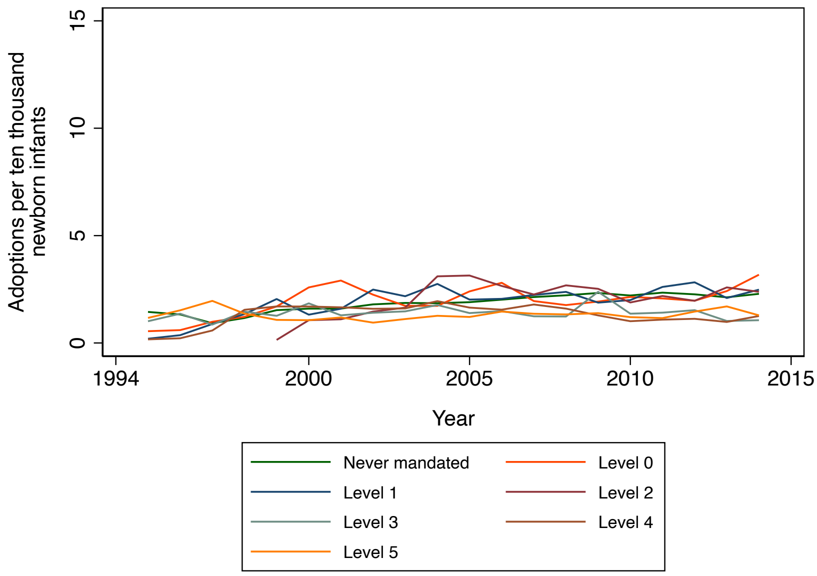
Note: This figure plots trends in patients' utilization behavior using SART's clinic-level data from 1996–2010.

Figure 5: Child adoption rates by IVF coverage generosity level and age of mother

(a) Women 35 and older



(b) Women under 35



Note: The study sample includes all adoptions of children ages 0–6 finalized between 1994–2015 from the National Data Archive on Child Abuse and Neglect (NDACAN). The denominator (total number of births) is from the National Vital Statistics Detail Natality Data.

Appendix

A Estimation procedure of a GSC model

Xu (2017) provides a procedure for estimating a Generalized Synthetic Control (GSC) model specified in Equation (2) as:

$$y_{it} = \delta_{it} D_{it} + X'_{it}\beta + \lambda'_i f_t + \epsilon_{it}. \tag{A.1}$$

The procedure consists of three main steps. The first step includes estimating an interactive fixed effect model using the data only from the control group (i.e., setting $D_{it} = 0$ in Equation (A.1)). Assume that f_t and λ_i are r-vectors where r denotes the number of factors. Also assume that $F = [f_1, f_2, ..., f_T]$ and $\Lambda_{control} = [\lambda_1, \lambda_2, ..., \lambda_{control}]$ where *control* denotes the number of states in the control group and T denotes the time periods in the analysis. To identify β, F and $\Lambda_{control}$ however more constraints are required. Two constraints are imposed. First, all factors are normalized, $\frac{\widehat{F}'\widehat{F}}{|T|} = I_r$, where I_r denotes the identity matrix. Second, loadings are orthogonal to each other, $\widehat{\Lambda}'_{control}\widehat{\Lambda}_{control} = 0$. To obtain the estimated $\widehat{\beta}$, $\widehat{F}$ and $\widehat{\Lambda}_{control}$ then:

$$(\widehat{\beta}, \widehat{F}, \widehat{\Lambda}_{control}) = \underset{\widehat{\beta}, \widehat{F}, \widehat{\Lambda}_{control}}{\arg\max} \sum_{i \in control} (Y_i - X_i\widehat{\beta} - \widehat{F}\widehat{\lambda}_i)'(Y_i - X_i\widehat{\beta} - \widehat{F}\widehat{\lambda}_i), \tag{A.2}$$

$$\text{s.t. } \frac{\widehat{F}'\widehat{F}}{|T|} = I_r \text{ and } \widehat{\Lambda}'_{control}\widehat{\Lambda}_{control} = 0.$$

The number of factors r is unknown and is estimated through a cross validation process that minimizes the prediction error of the model. The estimation process starts with a given r to obtain the corresponding $\widehat{\beta}$, $\widehat{F}$ and $\widehat{\Lambda}_{control}$. For each pre-treatment period $s \in \{1, 2, ..., T_0\}$ (T_0 denotes the number of pre-treatment periods), we hold back data of all treated states at time s. We then run an OLS regression using the rest of the pre-treatment data to obtain factor loadings for each treated unit i, $\widehat{\lambda}_{i,-s}$. We next predict the treated outcome at time s as $\widehat{y}_{is}(0) = X'_{is}\widehat{\beta} + \widehat{\lambda}_{i,-s}\widehat{f}_s$.[1]

We define the prediction error as $e_{is} = y_{is}(0) - \widehat{y}_{is}(0)$. The Mean Square Prediction Error

[1] $y_{it}(1)$ and $y_{it}(0)$ denote the potential outcomes for state i at time t when respectively $D_{it} = 1$ (treated) and $D_{it} = 0$ (not treated).

(MSPE) for a given r is defined as:

$$MSPE(r) = \sum_{s=1}^{T_0} \sum_{i \in T} \frac{e_{is}^2}{T_0} \tag{A.3}$$

This process is repeated for different values of r (we try $r \in \{1, 2, ..., 5\}$). Then, r^* corresponding to the smallest prediction error is chosen.

The factor loadings for the treated states are estimated in the second step. This is done by minimizing the MSPE of the predicted treated outcome in pretreatment periods:

$$\widehat{\lambda}_i = \arg\max_{\widehat{\lambda}_i} (Y_i^0 - X_i^0\widehat{\beta} - \widehat{F}^0\widehat{\lambda}_i)'(Y_i^0 - X_i^0\widehat{\beta} - \widehat{F}^0\widehat{\lambda}_i) \tag{A.4}$$

where "0" superscripts denote the pre-treatment time periods and $\widehat{\beta}$ and $\widehat{F}^0$ are estimated from the first step.

Finally, the third step estimates the treated counterfactual based on $\widehat{\beta}$, $\widehat{F}$ and $\widehat{\lambda}_i$. That is:

$$\widehat{y}_{it}(0) = X_{it}'\widehat{\beta} + \widehat{\lambda}_i'\widehat{f}_i \quad \text{for } i \in Treated,\ t > T_0 \tag{A.5}$$

The estimated average treatment effect on the treated at time t, ATT_t then is:

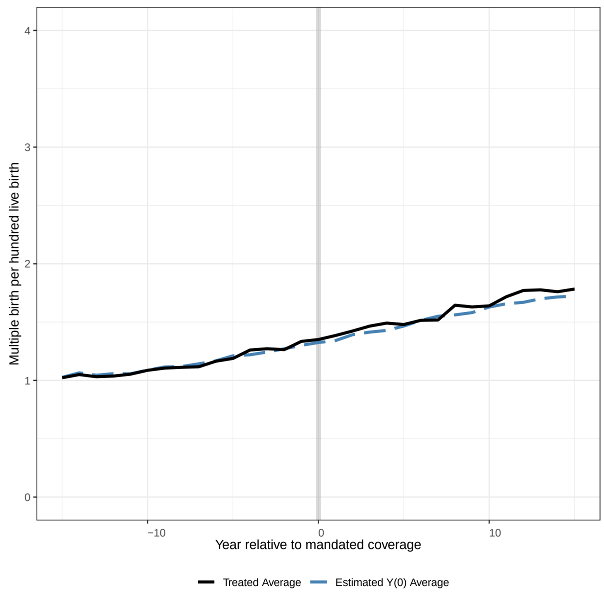
$$\widehat{ATT}_t = \frac{1}{|Treated|} \sum_{i \in Treated} [y_{it}(1) - \widehat{y}_{it}(0)] \quad \text{for } t > T_0 \tag{A.6}$$

B GSC figures

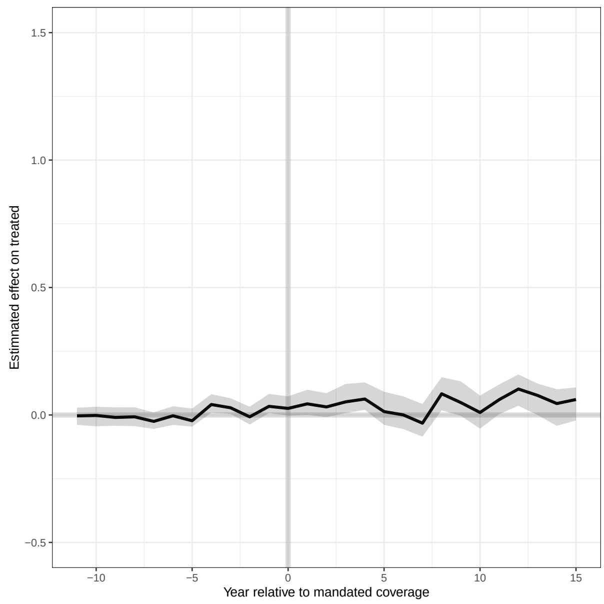
Figure B.1: Effects of IVF coverage generosity level on multiple births per hundred live births, GSC model for all women

(a) All levels

(1) Treated average and estimated average for treated states

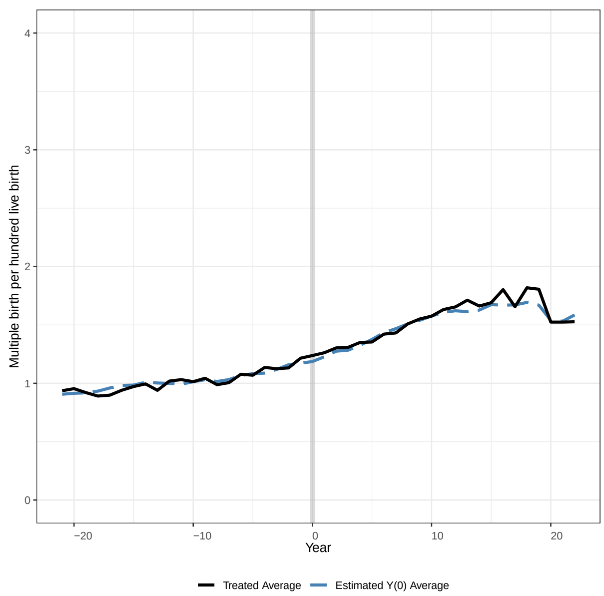


(2) Estimated treatment effect on treated

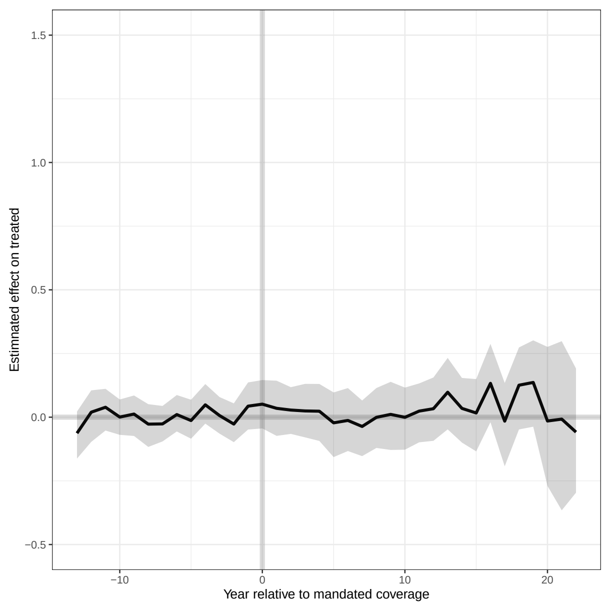


(b) Level 0

(1) Treated average and estimated average for treated states

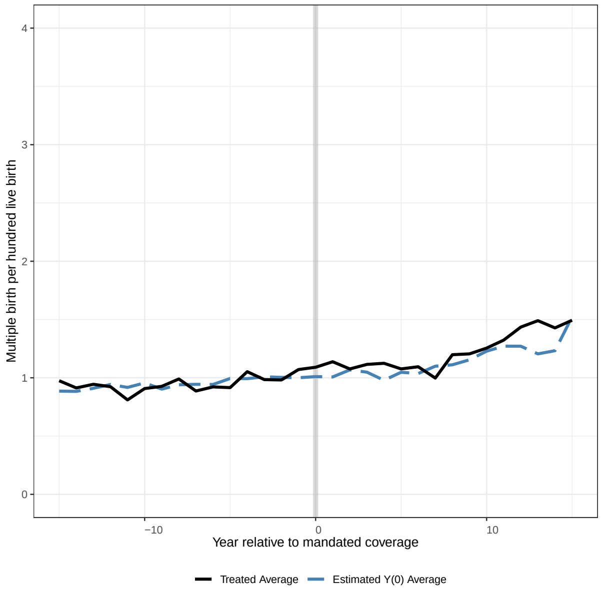


(2) Estimated treatment effect on treated

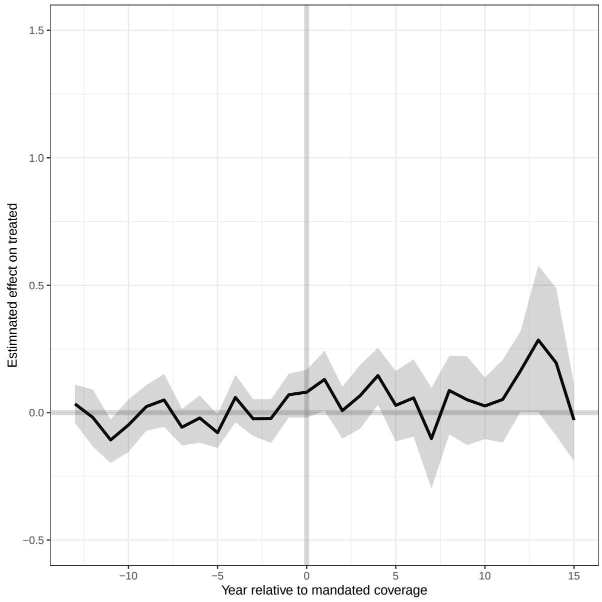


(c) Level 1

(1) Treated average and estimated average for treated states

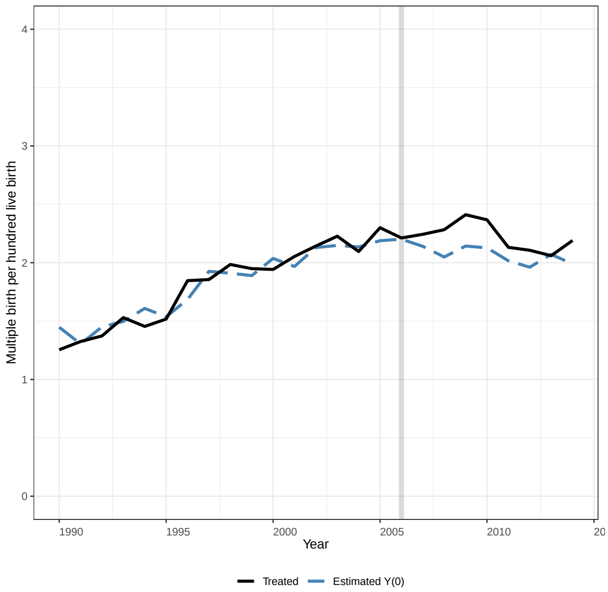


(2) Estimated treatment effect on treated

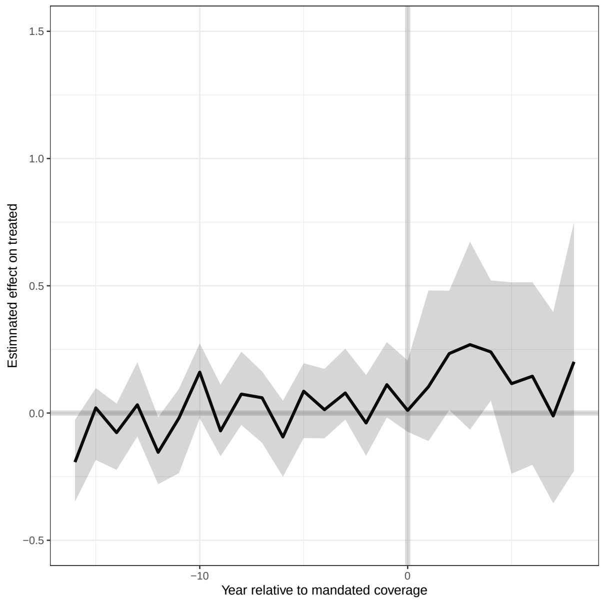


(d) Level 2

(1) Treated average and estimated average for treated states

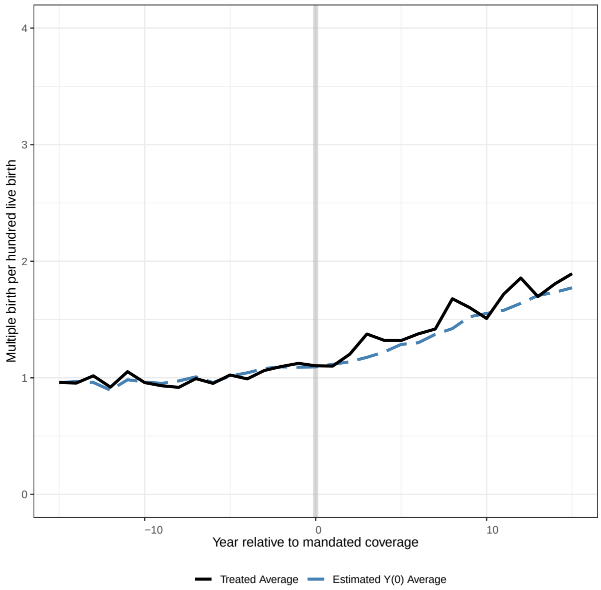


(2) Estimated treatment effect on treated

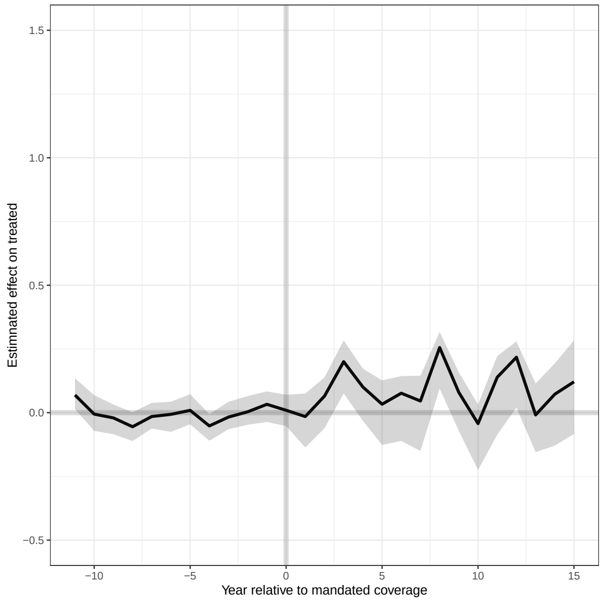


(e) Level 3

(1) Treated average and estimated average for treated states

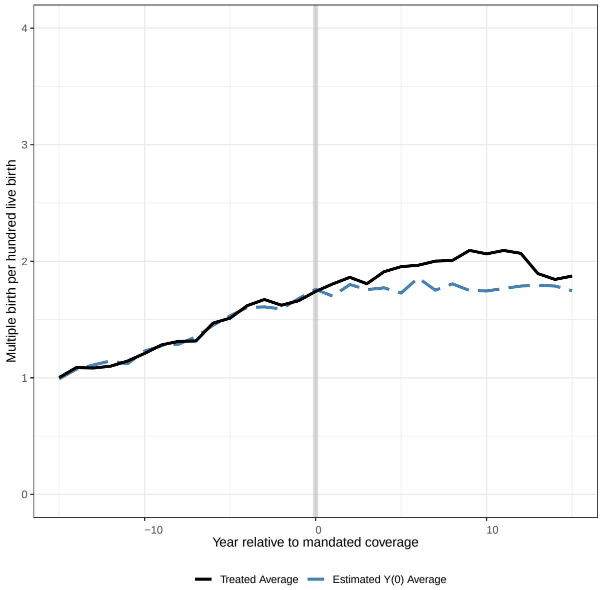


(2) Estimated treatment effect on treated

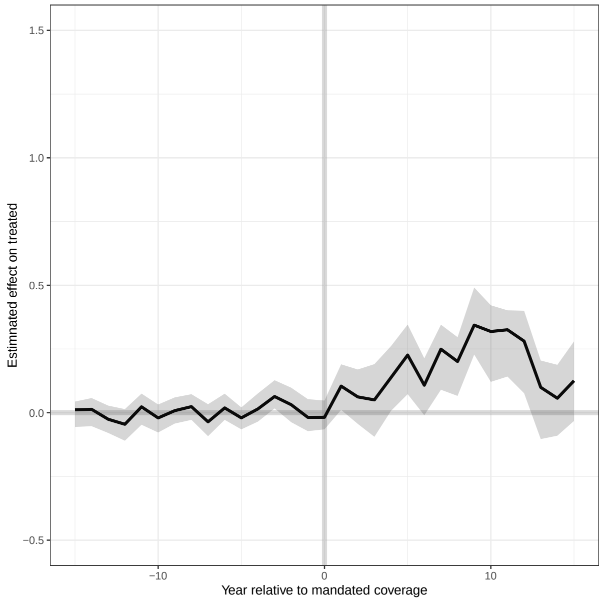


(f) Level 4

(1) Treated average and estimated average for treated states



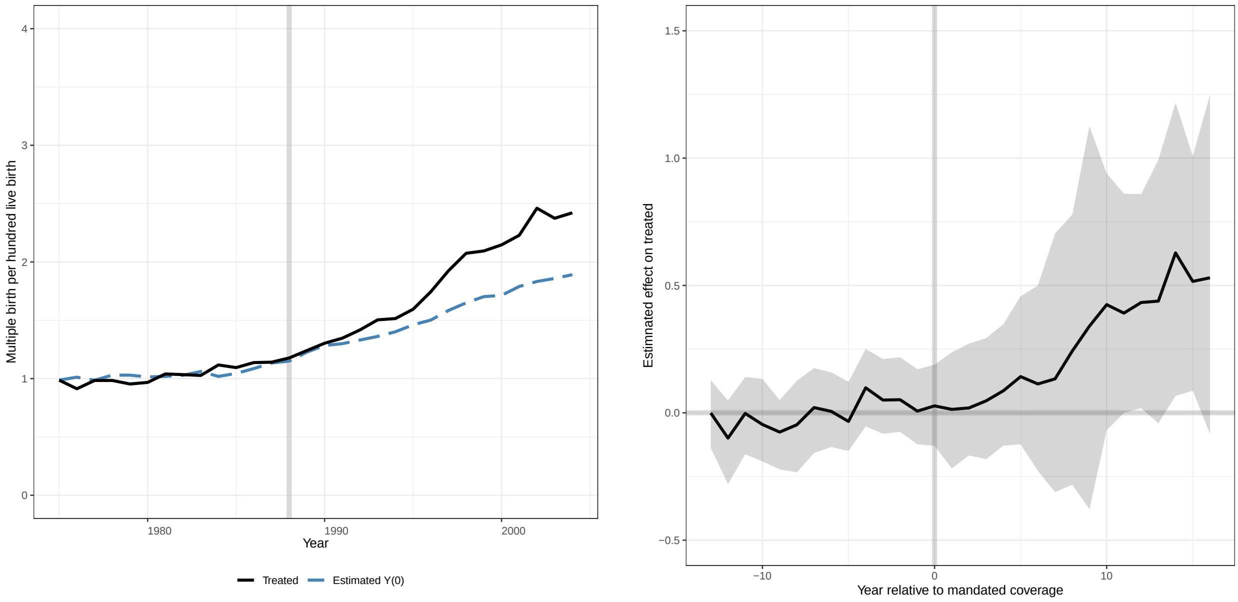
(2) Estimated treatment effect on treated



(g) Level 5

(1) Treated average and estimated average for treated states

(2) Estimated treatment effect on treated

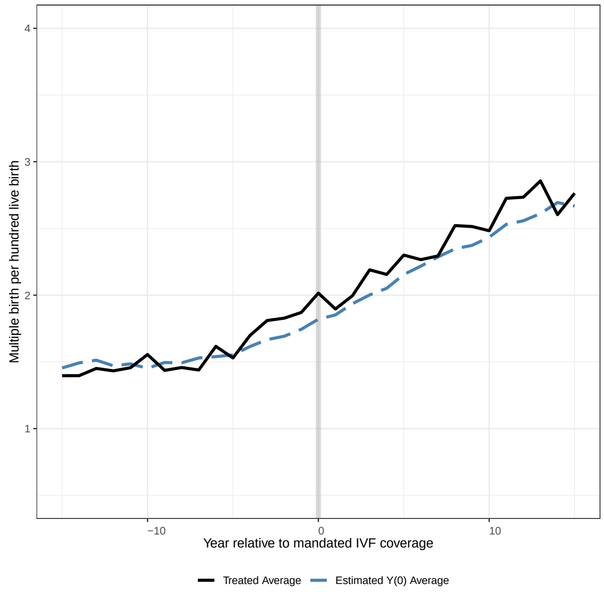


Note: This figure plots the estimated counter-factual outcome $Y(0)$ and the treatment effect on the treated on multiple births per hundred live births using the GSC model specified in Equation (2). The sample includes all births in the US from 1975-2014 from the National Vital Statistics, aggregated by state-year. The included covariates in the model are listed in the Notes to Table 7. The gray shade shows the %95 confidence intervals for the estimated effects.

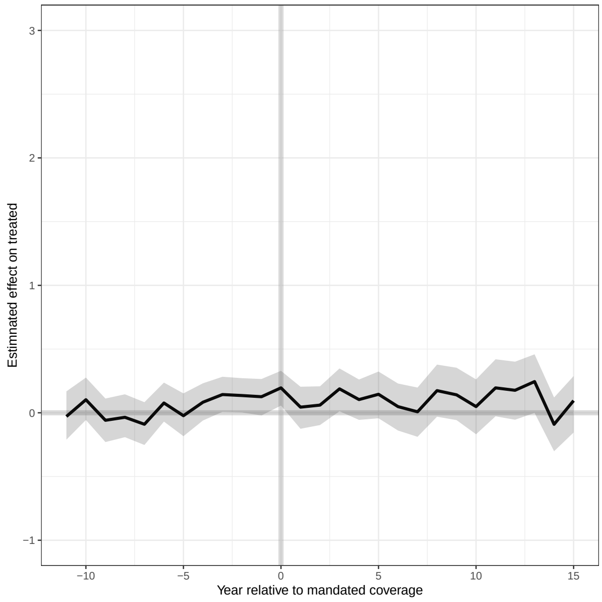
Figure B.2: Effects of IVF coverage generosity level on multiple births per hundred live births, GSC model, women 35 and older

(a) All levels

(1) Treated average and estimated average for treated states

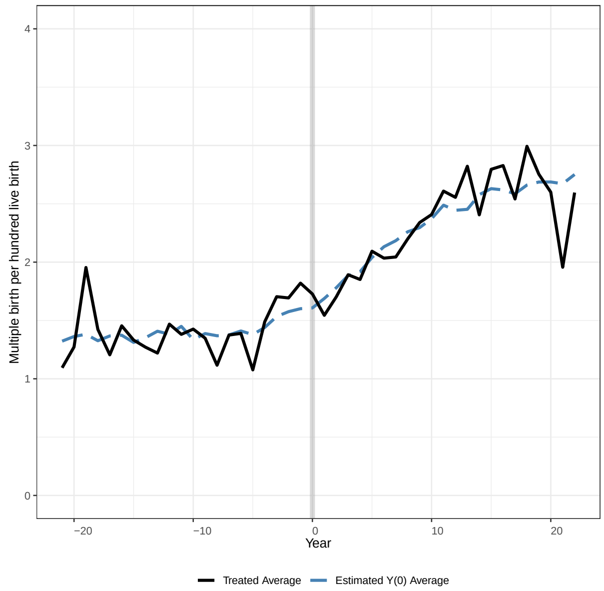


(2) Estimated treatment effect on treated

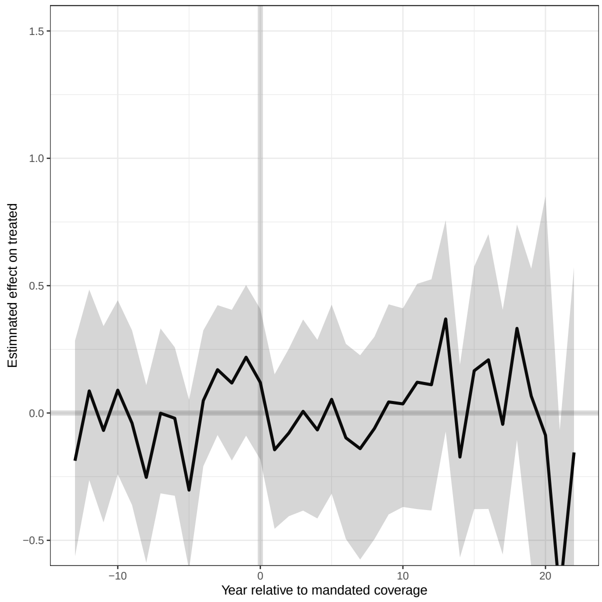


(b) Level 0

(1) Treated average and estimated average for treated states

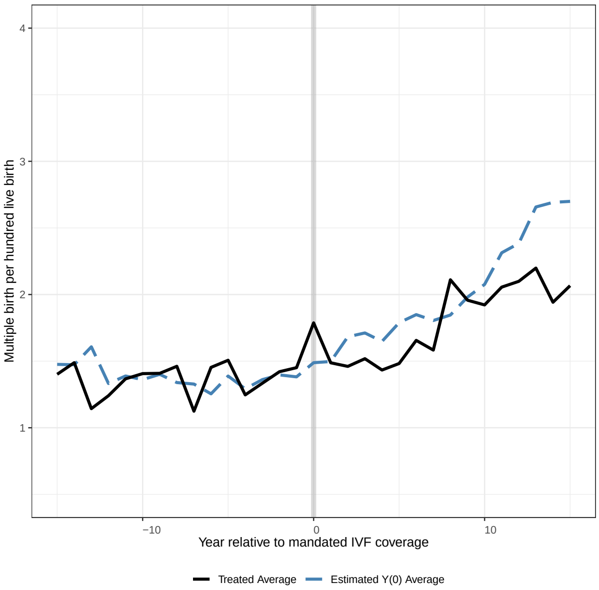


(2) Estimated treatment effect on treated

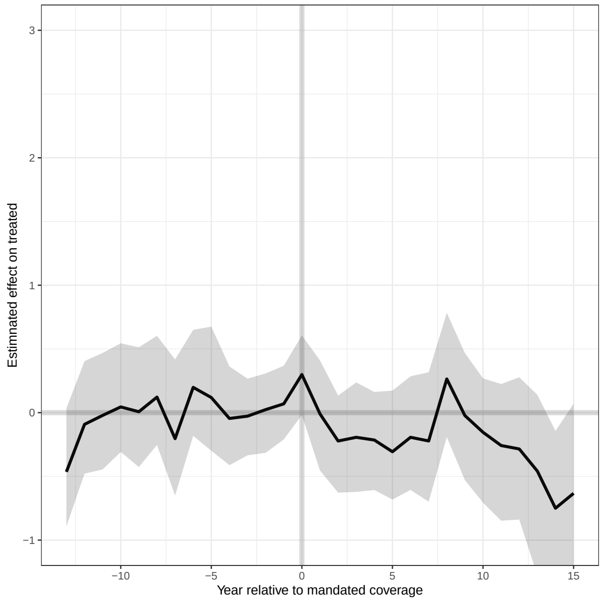


(c) Level 1

(1) Treated average and estimated average for treated states

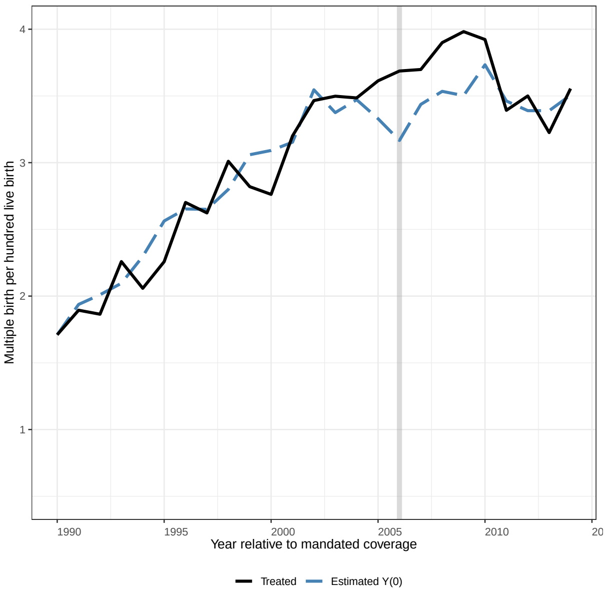


(2) Estimated treatment effect on treated

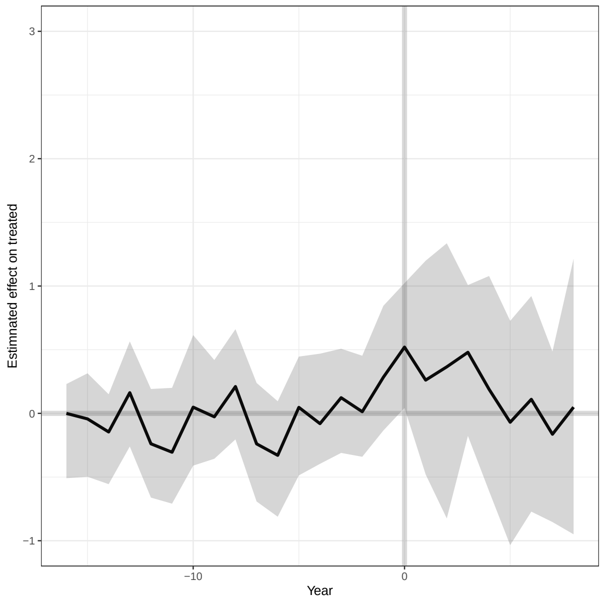


(d) Level 2

(1) Treated average and estimated average for treated states

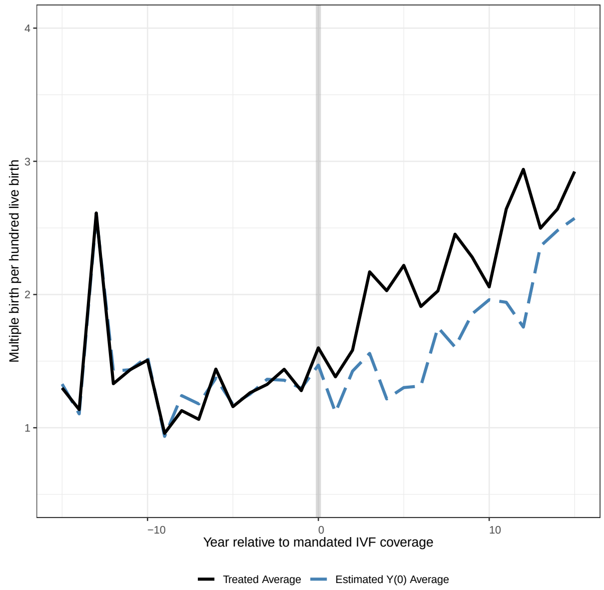


(2) Estimated treatment effect on treated

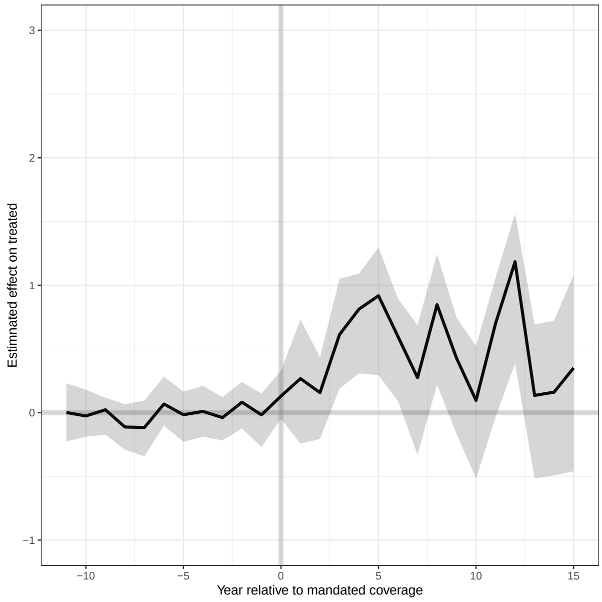


(e) Level 3

(1) Treated average and estimated average for treated states

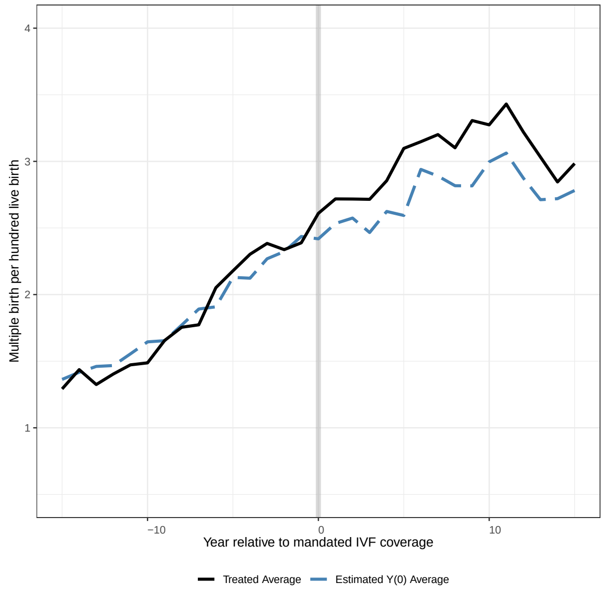


(2) Estimated treatment effect on treated

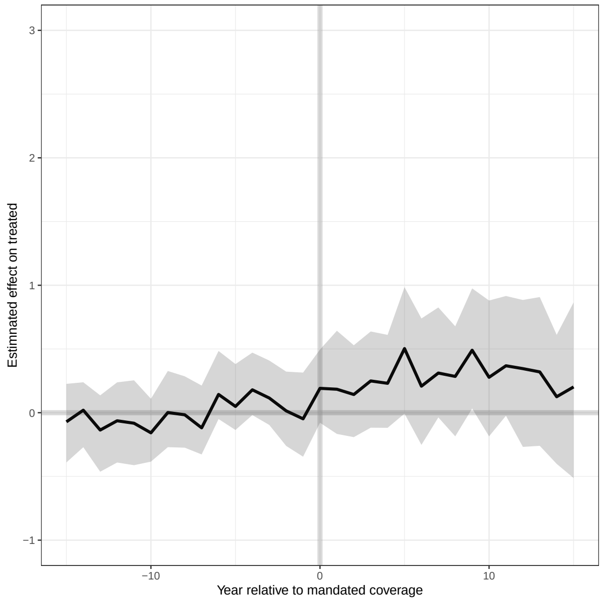


(f) Level 4

(1) Treated average and estimated average for treated states

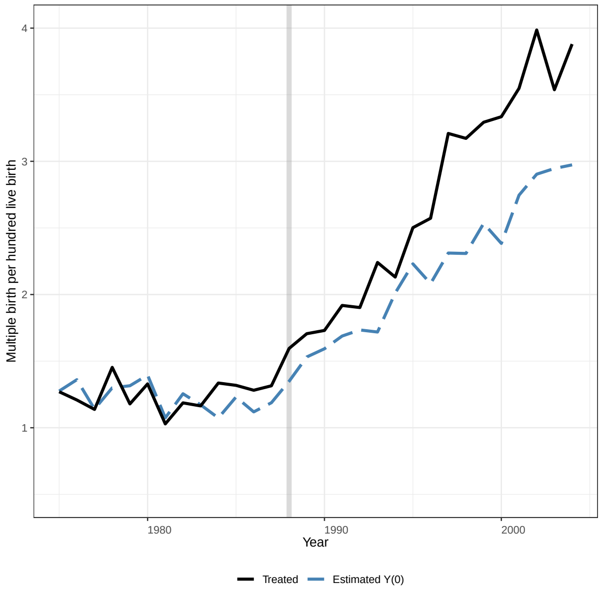


(2) Estimated treatment effect on treated

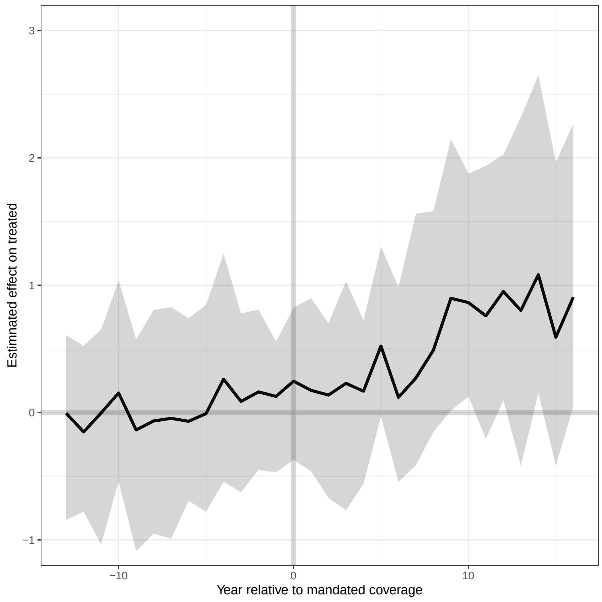


(g) Level 5

(1) Treated average and estimated average for treated states



(2) Estimated treatment effect on treated

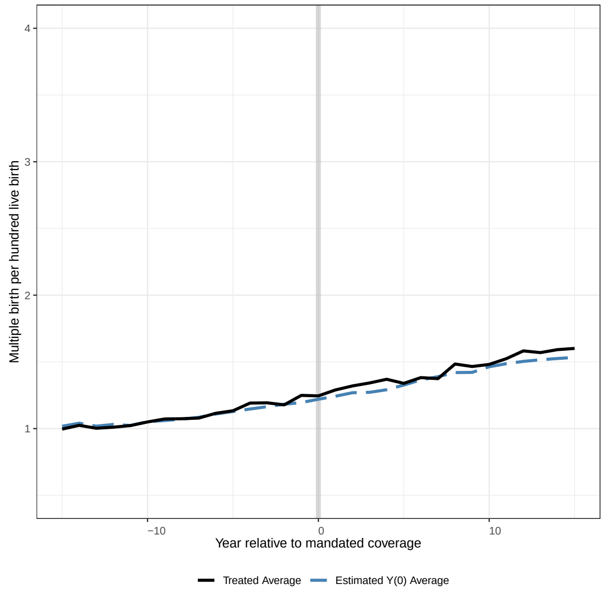


Notes: See notes for Figure B.1.

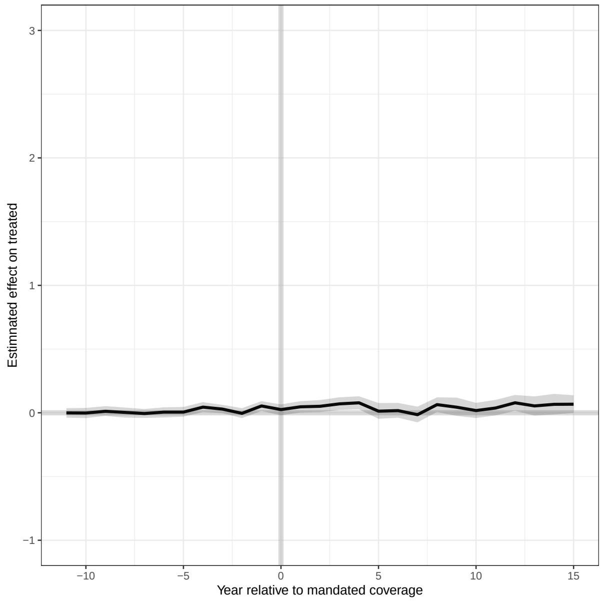
Figure B.3: Effects of IVF coverage generosity on multiple births per hundred live births, GSC model, women under 35

(a) All levels

(1) Treated average and estimated average for treated states

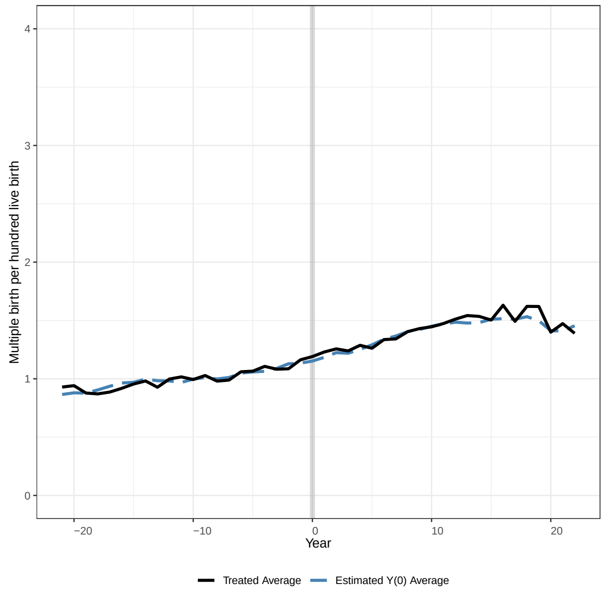


(2) Estimated treatment effect on treated

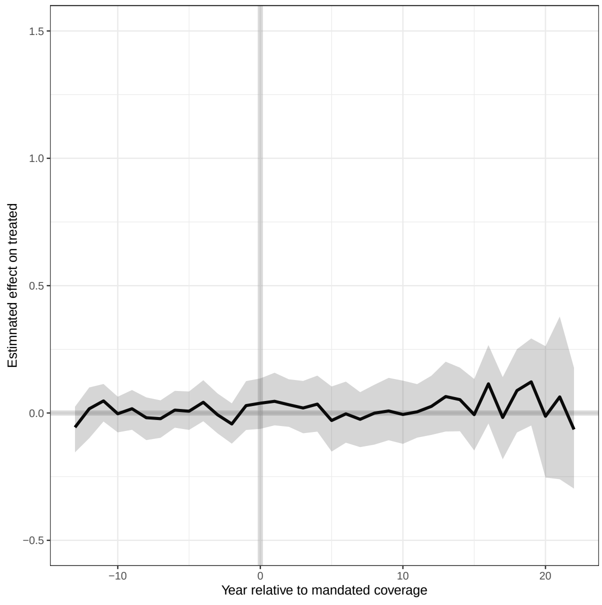


(b) Level 0

(1) Treated average and estimated average for treated states

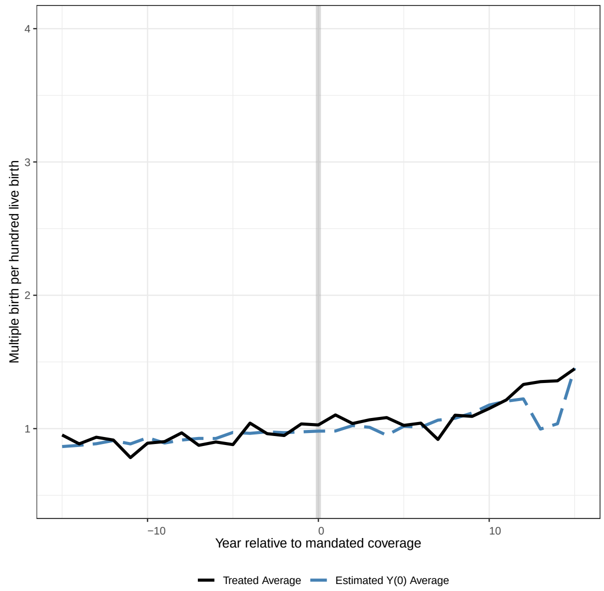


(2) Estimated treatment effect on treated

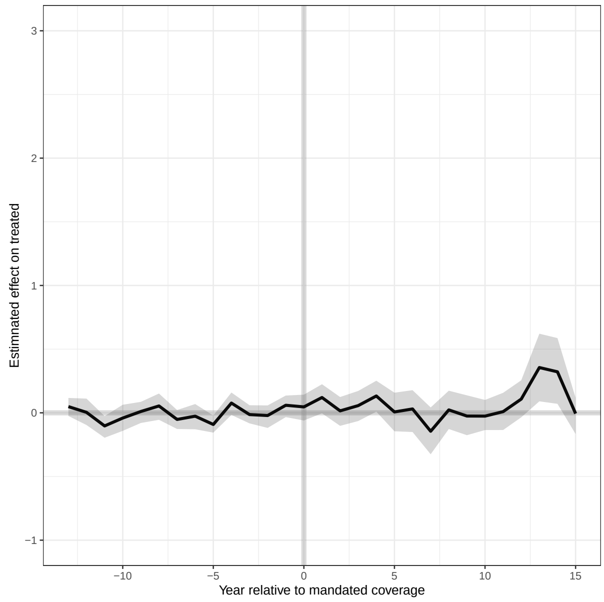


(c) Level 1

(1) Treated average and estimated average for treated states

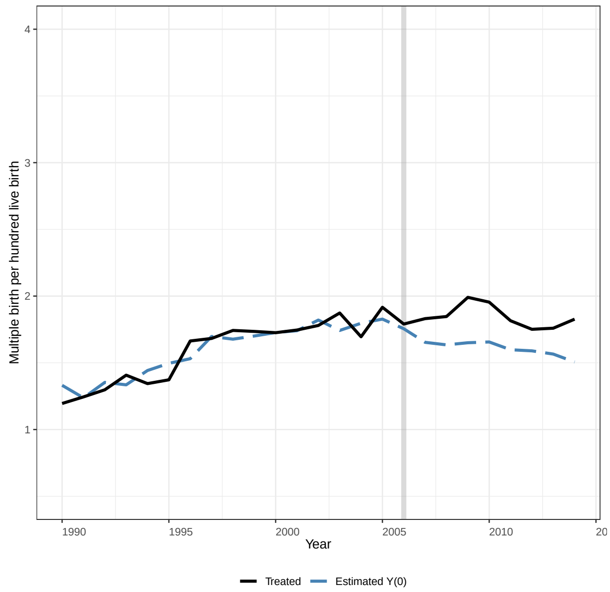


(2) Estimated treatment effect on treated

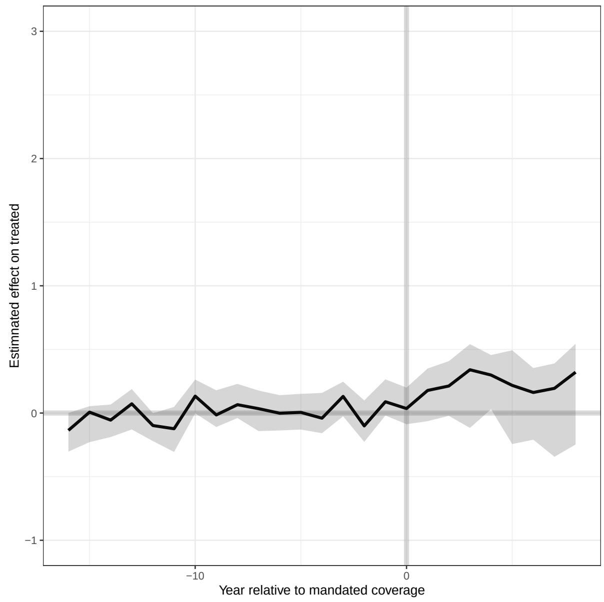


(d) Level 2

(1) Treated average and estimated average for treated states

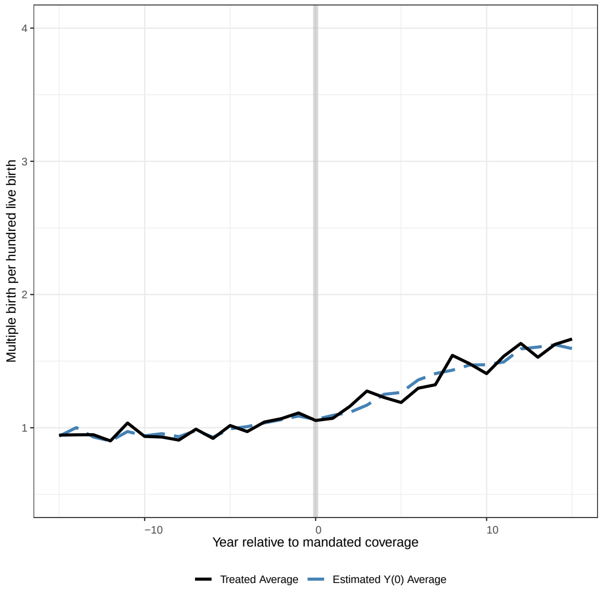


(2) Estimated treatment effect on treated

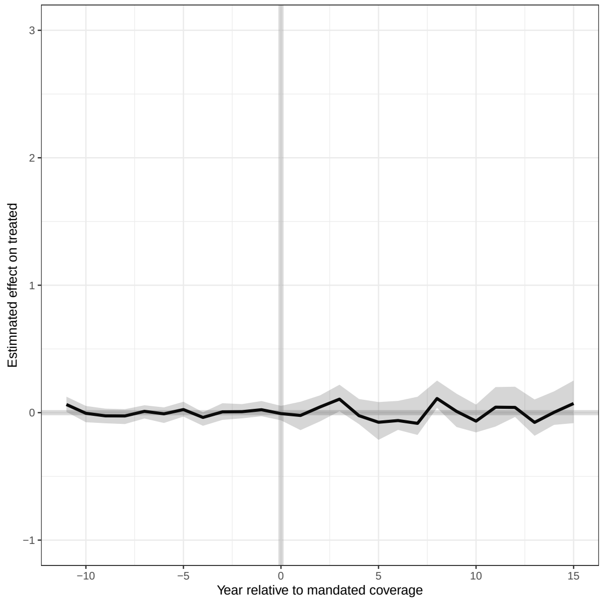


(e) Level 3

(1) Treated average and estimated average for treated states

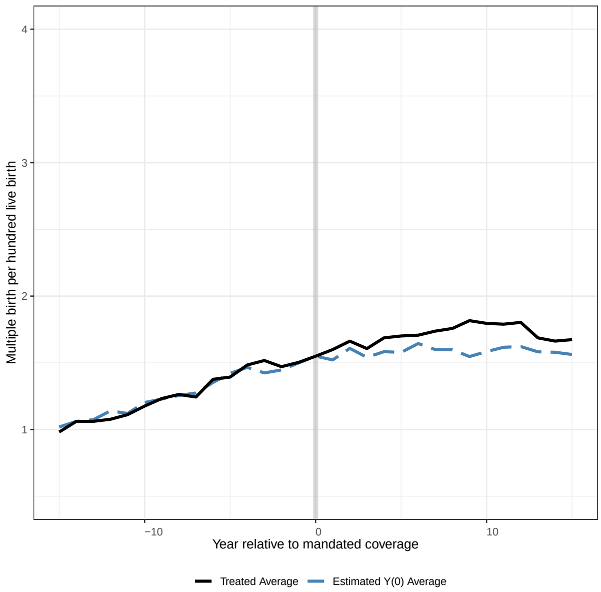


(2) Estimated treatment effect on treated

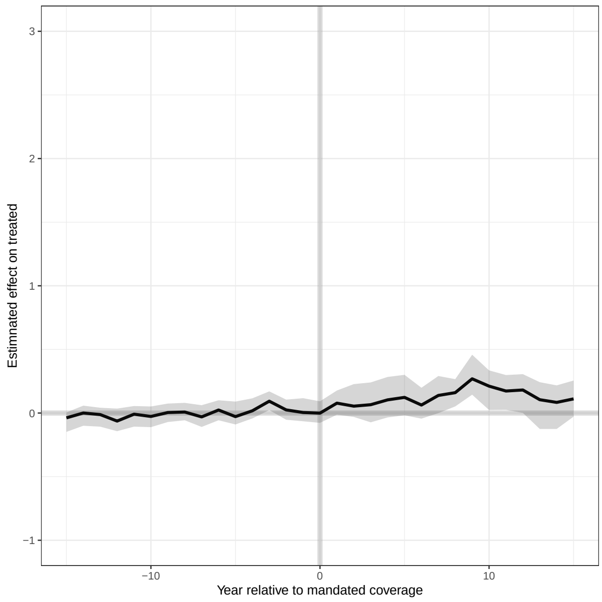


(f) Level 4

(1) Treated average and estimated average for treated states

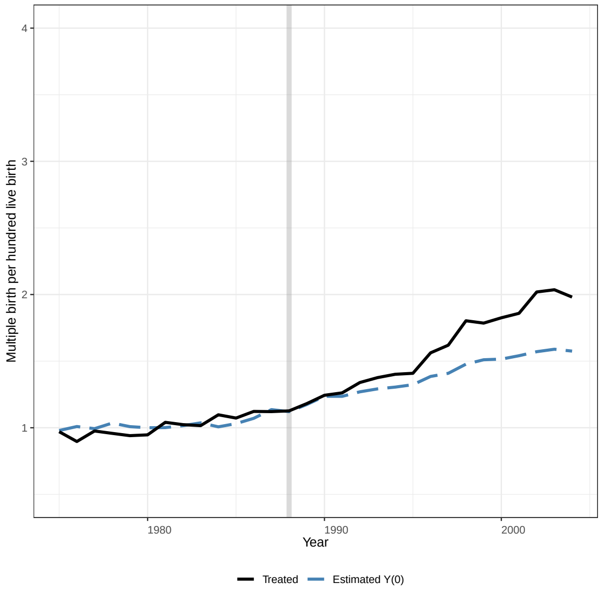


(2) Estimated treatment effect on treated

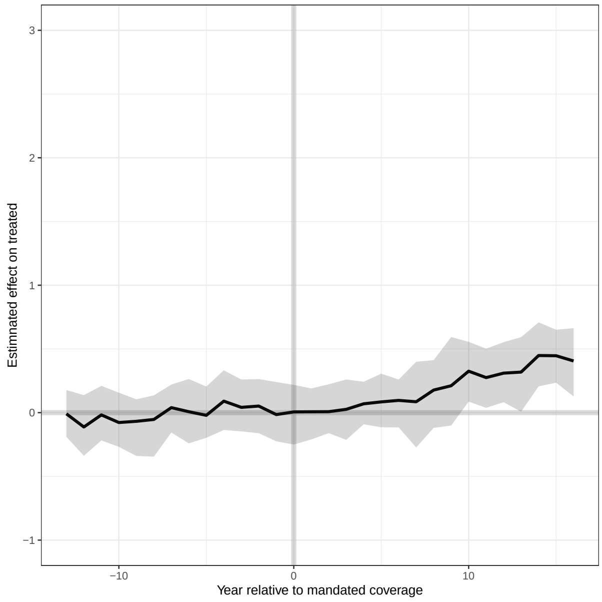


(g) Level 5

(1) Treated average and estimated average for treated states



(2) Estimated treatment effect on treated



Notes: See notes to Figure B.1.

C DD and DDD estimates

To investigate robustness of our findings from the GSC framework, we estimate the effects from mandated IVF coverage on incidence of multiple births using DD and DDD frameworks. We estimate an equation of this form for our DD model:

$$y_{it} = \alpha_0 + \alpha_1(Level_{it} \times Post_t) + \alpha_2 Level_{it} + \lambda_i + \lambda_t + \epsilon_{it} \tag{C.1}$$

where i and t denote state and time respectively. y_{it} denotes the outcome variable, which is the multiple birth rate per hundred live births and the number of infants per thousand live births. $Level_{it}$ includes indicators that denote the generosity level of the mandated coverage. It is set to zero for the never mandated states. $Post_{it}$ is a dummy variable switching on two years after the mandated coverage is enacted. It is set to zero for never mandated states. The vector X_{it} includes the same set of state level time-varying covariates used in the GSC analysis. λ_i and λ_t are respectively state and time fixed effects. ϵ_{it} captures any remaining unobserved factors affecting the outcome variable. The coefficient of interest is α_1, which captures the effect from the generosity of mandated coverage on the incidence of multiple births.

We estimate the following equation in our DDD model:

$$\begin{aligned} y_{ita} =& \alpha_0 + \alpha_1(Level_{it} \times Plus35_a \times Post_{it}) + \alpha_2(Level_{it} \times Plus35_a) \\ &+ \alpha_3(Post_{it} \times Plus35_a) + \alpha_4(Level_{it} \times Post_{it}) + \alpha_5 X'_{ita} \\ &+ \lambda_i + \lambda_t + \lambda_a + \epsilon_{ita} \end{aligned} \tag{C.2}$$

where a denotes women's age. $Plus35_a$ is a dummy indicating women 35 years and older. λ_a is the age fixed effects. The coefficient of interest is α_1 which captures the effect of the number of covered cycles on mothers of 35 years and older in mandated states relative to mothers younger than 35 years.

We aggregate the birth data into state-year and state-year-age cells for estimating the DD and DDD models, respectively. The estimation results are presented in Table C.1 and Table C.2.

Table C.1: Effects of IVF coverage generosity level on multiple births per hundred live births, DD and DDD models

	Difference-in-Differences												Difference-in-Difference-in-Differences			
	All women				Women 35 and older				Women under 35							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
All levels	0.10*	0.07***			0.17	0.12			0.06	0.05***			0.49***	0.25***		
	(0.05)	(0.02)			(0.12)	(0.08)			(0.04)	(0.02)			(0.09)	(0.09)		
Level 0			0.01	0.01			-0.04	-0.03			0.01	0.01			0.45***	0.23**
			(0.06)	(0.03)			(0.15)	(0.10)			(0.04)	(0.03)			(0.12)	(0.11)
Level 1			-0.11***	-0.02			-0.30*	-0.30**			-0.10**	-0.01			0.22	-0.13
			(0.02)	(0.03)			(0.16)	(0.11)			(0.04)	(0.02)			(0.22)	(0.13)
Level 2			0.15***	0.17***			0.39***	0.31***			0.04***	0.11***			0.64***	0.40***
			(0.01)	(0.03)			(0.03)	(0.06)			(0.01)	(0.02)			(0.00)	(0.04)
Level 3			0.20***	0.06			0.37***	0.31***			0.14***	0.05			0.58***	0.39***
			(0.03)	(0.05)			(0.03)	(0.10)			(0.02)	(0.04)			(0.06)	(0.08)
Level 4			0.23**	0.20**			0.45***	0.33***			0.13**	0.16***			0.78***	0.54***
			(0.10)	(0.08)			(0.16)	(0.10)			(0.06)	(0.05)			(0.06)	(0.03)
Level 5			0.42***	0.19***			0.84***	0.62***			0.27***	0.12***			0.94***	0.73***
			(0.02)	(0.04)			(0.03)	(0.10)			(0.01)	(0.04)			(0.00)	(0.04)
Constant	1.00***	-3.23	0.99***	-1.75	1.34***	-1.45	1.33***	4.80	1.00***	-1.93	1.00***	-0.90	0.84***	7.14	0.84***	15.10***
	(0.02)	(2.22)	(0.01)	(2.51)	(0.06)	(7.54)	(0.06)	(7.60)	(0.01)	(2.06)	(0.01)	(2.43)	(0.04)	(5.58)	(0.04)	(3.42)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covars	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of cells	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	3,616	3,276	3,616	3,276

Note: Study sample includes all births in the US from 1975-2014. Data aggregated into state-year cells for DD analysis and state-year-age cell for DDD analysis. All models include state- and year-fixed effects. Included covariates listed in notes for Table 7. Standard errors are clustered in state level and appear in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table C.2: Effects of IVF coverage generosity level on the number of infants per thousand births, DD and DDD models

	Difference-in-Differences												Difference-in-Difference-in-Differences			
	All women				Women 35 and older				Women under 35							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
All levels	1.07*	0.71***			1.72	1.22			0.59	0.57***			5.35***	2.75***		
	(0.55)	(0.26)			(1.23)	(0.89)			(0.39)	(0.20)			(0.95)	(0.93)		
Level 0			0.14	0.05			-0.45	-0.37			0.09	0.06			4.99***	2.57**
			(0.64)	(0.40)			(1.61)	(1.15)			(0.43)	(0.30)			(1.30)	(1.22)
Level 1			-1.26***	-0.20			-3.33**	-3.26***			-1.15***	-0.07			2.50	-1.22
			(0.18)	(0.30)			(1.58)	(1.19)			(0.39)	(0.23)			(2.22)	(1.33)
Level 2			1.38***	1.77***			3.79***	3.25***			0.33***	1.11***			6.29***	3.91***
			(0.12)	(0.27)			(0.31)	(0.66)			(0.10)	(0.22)			(0.00)	(0.38)
Level 3			2.23***	0.72			3.90***	3.30***			1.56***	0.65			6.31***	4.19***
			(0.36)	(0.54)			(0.37)	(1.12)			(0.25)	(0.42)			(0.59)	(0.75)
Level 4			2.33**	2.09***			4.60***	3.44***			1.38**	1.70***			8.19***	5.63***
			(0.90)	(0.74)			(1.37)	(0.92)			(0.54)	(0.50)			(0.31)	(0.32)
Level 5			4.60***	2.18***			9.03***	7.10***			2.96***	1.36***			10.28***	7.95***
			(0.17)	(0.47)			(0.38)	(1.01)			(0.15)	(0.38)			(0.00)	(0.44)
Constant	1010.11***	966.90***	1010.10***	984.36***	1013.55***	994.75***	1013.52***	1064.81***	1010.21***	979.11***	1010.20***	991.29***	1008.39***	1077.56***	1008.38***	1166.04***
	(0.16)	(23.51)	(0.16)	(26.30)	(0.65)	(79.62)	(0.66)	(79.25)	(0.15)	(21.29)	(0.14)	(24.97)	(0.38)	(61.43)	(0.38)	(35.75)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covars	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Number of cells	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	1,768	3,616	3,276	3,616	3,276

Note: See notes for Table C.1. Standard errors are clustered in state level and are presented in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

D Effects of the SART's guideline publication

SART uses voluntary reporting system for IVF clinics to collect information on service utilization and their outcomes, but it does not regulate clinic's practice. However, in January 1998, the SART published guidelines recommending the maximum numbers of embryos for transfer based on a woman's age and quality of embryos. These guidelines have been revised since then with more specified and restrictive changes in 2004. Table D.1 provides more information on the guidelines.

We use SART's clinic level data from 199 to 2010 to investigate the effects of the guideline published in 2004 on the average number of transferred embryos. We estimate an event study model specified as:

$$y_{ist} = \alpha + \rho Post_t \times Level_{is} + \beta X'_{ist} + \lambda_i + \lambda_t + \epsilon_{ist} \tag{D.1}$$

where i, s and t denote clinic, state and year respectively and y_{ist} denotes the outcome variable. We use the average number of transferred embryos as the outcome variable. $Post_t$ is a dummy switching on for years following the published guidelines.[2] $Level_{is}$ denotes generously level of the mandated coverage. X_{st} denotes a set of time-varying state level characteristics from the CPS described in the main text. λ_t and λ_i denote time and clinic fixed effects. ϵ_{ist} captures any remaining unobserved components affecting the outcome variable. The coefficient of interest is ρ, which captures changes in the average number of transferred embryos post publishing the guidelines compared to before publishing the guidelines.

Table D.2 presents the estimated effects. The average number of transferred embryos after publishing guidelines is smaller, and the estimated effects are quite similar within all generosity levels and women's age.

[2] Similar to our previous analysis, we allow published guidelines in 2004 to affect multiple births with a two-year delay.

Table D.1: SART guidelines on the maximum number of embryos to transfer

Women's age (years)	1998	1999	2004	2006, 2008[a]	2009, 2013[a]
< 35 ($favourable^b$)	-	2	1-2	1-2	1-2
< 35	3	3	2	2	2
35-37 ($favourable^b$)	-	-	2	2	2
35-37	4	4	3	3	3
38-40 ($favourable^b$)	-	-	3-4	3	3
38-40	5	4	4	4	4
> 40 ($favourable^b$)	-	-	-	-	-
> 40	5	5	5	5	-
41-42 ($favourable^b$)	-	-	-	-	5
41-42	-	-	-	-	5

Note: This borrowed table from Lee et al. (2016) presents the SART's guidelines on the maximum number of embryos to transfer in an IVF cycle by women's age.
a In these years, guidelines were republished, but the recommended number of embryos to transfer per age group did not change.
b favorable: first cycle of IVF, good embryo quality, excess embryos available for cryopreservation, or previous successful IVF cycle.

Table D.2: Estimated effects from publishing SART guideline at 2004

	All women		Women over 35 years		Women under 35 years	
	(1)	(2)	(3)	(4)	(5)	(6)
All levels	-1.51***		-1.32***		-1.67***	
	(0.12)		(0.11)		(0.15)	
Level 0		-1.58***		-1.40***		-1.69***
		(0.16)		(0.15)		(0.22)
Level 1		-1.51***		-1.31***		-1.67***
		(0.10)		(0.09)		(0.14)
Level 2		-1.49***		-1.31***		-1.60***
		(0.13)		(0.12)		(0.18)
Level 3		-1.54***		-1.36***		-1.70***
		(0.11)		(0.11)		(0.15)
Level 4		-1.51***		-1.33***		-1.64***
		(0.14)		(0.13)		(0.18)
Level 5		-1.46***		-1.27***		-1.64***
		(0.10)		(0.09)		(0.13)
Constant	4.63***	4.78***	4.62***	4.77***	4.93***	4.87***
	(0.78)	(0.78)	(0.87)	(0.87)	(0.98)	(1.09)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clinic fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Covars	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,520	1,520	1,520	1,520	1,723	1,723

Note: This table presents the estimated effects (β_1 in Equation (D.1)) on the average number of transferred embryos in mandated to cover states form publishing SART guidelines in 2004. The study sample includes all clinics in mandated to cover states form SART's data from 1996–2010. See notes to Table 7 for a list of included covariates. Standard errors are clustered in state level and are presented in parenthesis.
$*p < 0.10, **p < 0.05, ***p < 0.01$