Another Baby Boom? How Same-Sex Marriage and the Affordable Care Act Increased Births in the US

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Abstract

Assistive Reproductive Treatment clinics use various procedures to help patients facing infertility issues, or same-sex couples, have children. Using CDC Data, I find that in states with ART insurance mandates, the Affordable Care Act caused an increase of 114-119 frozen births per clinic, due to frozen births being the cheapest procedure. Additionally, same-sex marriage legalization boosted frozen donated births by 6-10 births per clinic, and is driven by same-sex couples uptake of ART. However, these effects diminish at the clinic level due to an increase in the number of clinics following these policy changes, and an exhaustion of the demand.

1 Introduction

With the current composition of the United States Supreme Court, the importance of examining the impacts of policies that could be rolled back or overturned is imperative. In this paper, I look into two laws/policies through their effects on Assistive Reproductive Technology (ART) clinics. ART is a family of procedures with the goal to help those with a uterus conceive by implanting embryos. This process is necessary for the percentage of the population who are unable to or struggle to conceive due to various reasons related to infertility. The first of these laws is the Affordable Care Act (ACA) which occurred in 2010 and was responsible for expanding insurance accessibility through Medicaid to states which already had laws which mandated insurance coverage of ART treatments. The second law is Same-Sex Marriage (SSM) legalization, which occurred on a state-by-state level, but was nationally passed in 2015. This law allowed same-sex individuals to get married and, by extension, likely influenced their ability, desire, and affordability (through their partner's insurance or the ability to have both parents be listed on the child's birth certificate) to have children. One possible reason for infertility is having a same-sex partner, making it impossible for them to conceive a child naturally. Instead, couples may use ART clinics to help them get reproductive material donated from individuals who are of a different sex to be implanted into themselves, or have someone else carry the child with their reproductive material, referred to as surrogacy. Clinics facilitate conception using these methods, but these procedures are expensive, often needing aid from insurance coverage. Some states also mandate that these treatments are covered by insurance, which promotes the quantity of treatments in these states. This study uses yearly data from the CDC to explore the impact that two laws have on the usage of these clinics in the US. Overall, I aim to use both of these policies to analyze whether they impact the quantity of births and transfers,[1] and the strength of this impact for ART clinics in the US. This is important, as the US experiences falling birth rates, and state/federal government officials discuss expanding the definition of

[1] A transfer is the procedure of implanting a number of embryos into a uterus.

infertility to include same-sex individuals, and argue about policies such as medicare for all. Both of which are policies that could offset a portion of the falling birth rates.

I first begin, by calculating the impact from the policies by combining all ART methods to see whether there is an impact in the number of births in the years following the policy. After this I analyze the four different types of births to see if the types of births experience different changes and contrast the differences across the two policies. The first method is thawed, donated births/transfers, which refers to procedures which use embryos/reproductive material which has been frozen previously to later be implanted into the uterus directly. Since this uses donated materials and does not require a person of another gender to be there at the time of the procedure, this is the case most likely to be used for same-sex couples, as donated material is necessary for conception for same-sex couples. The next method is thawed, non-donated births/transfers. These are similar to the previous category, except these embryos/reproductive materials have not been donated. This often refers to someone who has stored eggs or embryos for use at a later date. The third category is fresh, donated births/transfers. These are eggs that are donated from another individual who is not carrying the child, but has never frozen these eggs. These can also be used by same-sex couples, but would need a donation from a friend or relative at the time of the procedure. Finally, there are fresh, non-donated births/transfers. These are eggs which have been harvested and then implanted as an embryo into the same person from whom they are harvested and have never been frozen. These four categories include all births that are available through an ART clinic.

The results from testing each method of birth separately, show that only frozen births per clinic experience an increase in the years after the ACA. My results make sense since when comparing frozen with fresh births, there are a number of differences in these procedures. The primary differences are in price and in ease of use. For frozen procedures, considerably fewer harvests are usually needed, since you can collect and freeze as many eggs as necessary. This can make this type of procedure much cheaper, as you do not need to have as many separate procedures to harvest eggs, and is considered less stressful on the individual from whom the eggs are being harvested. In contrast, fresh procedures are more expensive, must have a harvest each transfer, and can be considerably more stressful on the individual from whom the eggs are being harvested. On top of this, many states only mandate a specific amount of monetary coverage towards ART procedures. These results make sense for a number of different reasons through direct monetary impacts. Firstly, frozen procedures are much more cost effective when compared to Fresh procedures due to a smaller number of necessary cycles (Elite IVF: A Global IVF Agency, n.d.). Secondly, health plan expenditures are higher in states with insurance mandates and are higher for both self-insured and fully-insured plans which indicates uptake of insurance mandates programs (Boulet et al., 2019). Mandated insurance coverage is also associated with higher ART usage, but not excessive increases in consumer costs (Griffin and Panak, 1998). Finally, the risk of negative impacts on individuals who want these procedures, but cannot obtain them may also influence these results. For example, women who want to have children, but are unable to have negative impacts and are 48% more likely to deal with mental health issues, and are 6 percentage points more likely to divorce. Their partners are also likely to have mental health issues and experience a loss of income in the long run (Bogl et al., 2024). This shows that the effect on the increase in frozen, and not fresh procedures is mainly driven by the limits on the finances of the households recieving these procedures.

With those results for the ACA showing increases, I then investigate the effect of SSM on these clinics. The results from my tests using the timing of SSM on the separate four birth types end up showing increases in births using thawed, donated embryos. This makes sense, as donated material is necessary for same-sex couples to conceive a child through non-adoptive measures. The actual mechanism for this effect is less directly clear. Most states have laws that restrict coverage of infertility issues to same-sex couples by defining infertility as having a certain number of months of unprotected sex with the goal of having a child[2].

[2] The definition of infertility has been changing in recent years to be more inclusive and to include same-sex couples, though that does not effect state-level mandates in this study.

There are two likely mechanisms at play. It's likely that bonuses to same-sex households through SSM legalization saved them a significant amount of money that could then be allocated towards ART procedures, essentially constituting an income effect for same-sex households. These bonuses included significant tax breaks and savings through taking their partner's health insurance (Downing and Cha, 2020; Friedberg and Isaac, 2024; Piano, Behr and West, 2023). The effects of these bonuses are evidenced through changes in labor supply and greater financial investments for same-sex households, of which ART would constitute a large financial investment (Hansen, Martell and Roncolato, 2019). The second possibility also has to do with private health insurance coverage. With the expansion of public health insurance, in order to compete, private or employer-provided insurers may have expanded their definition of infertility to include same-sex couples as a method of competition with the public options. This is evident, as increases in specifically employer-sponsored health insurance coverage rose for both men and women after SSM (Downing and Cha, 2020). This effect would be similar to the rise of partnership benefits before the legalization of SSM in the US.

The effect seen in SSM legalization returns to zero two to 3 years after the event. This is likely a result of an increase in the number of clinics. This is supported by testing how many clinics are in a city and how that cheanges after the two policy changes. This can be seen through an increase per city two years after same-sex marriage is legalized, and a general increase per city after the ACA is passed, causing the per clinic births not to permanently change. Unfortunately, it is not possible to entangle which policy specifically caused a rise in total clinics, though it is likely a combination of the two policies.

I run the same tests to look at the effects of each type of birth, but I now control for transfers. This was performed with the intention of seeing whether births would still increase after controlling for the number of transfers at that individual clinic. This should only occur in the case that the individuals getting ART were suddenly healthier. This is backed up by multiple papers that have done tests, and show that positive birth outcomes from ART are more likely if the patient is healthier or does not have fertility issues compared to individuals who were less healthy or had various fertility issues (Gaskins et al., 2023; Libby et al., 2021; Stern et al., 2015; Declercq et al., 2015; Liang et al., 2022). As expected, when controlling for transfers I only see any statistically significant level of increase in thawed, donor births, and a non-statistically significant decrease in fresh donated births. This points to a more healthy group of individuals having births using the thawed, donated methods, with some small movement from fresh donated births to the frozen method. This is likely mostly attributable to same-sex couples deciding to use ART birth methods more often.

The final tests attempt to combine the two policies by looking at the effects of states with insurance mandates using the timing of SSM[3]. These results are similar to the full model, but has much less significant values, which indicates changes after same-sex marriage were more significant when including states without insurance mandates.

In the sections below are my results and more information on these policies. I feel these combinations of tests show that same-sex marriage caused an increase in usage of ART by same-sex couples in the US and that the ACA caused an increase in more cost effective birth methods due to insurance coverage increases for the procedure. The effects of SSM only lasts a couple years after legalization, likely due to a combination of an exhaustion of pent up demand and an increase in the number of clinics per city to handle the increased demand from both SSM and the ACA.

2 Background

I begin by defining the two different treatments analyzed in this paper. This is because their implementation and creation are a product of two very different set of events, but occur at similar times.

[3]Unfortunately, due to the timing of SSM legalization, there are not enough states to test this for only states without insurance mandates.

2.1 Affordable Care Act (ACA)

First, I examine the legalization of the ACA in the United States passed in 2010. The Affordable Care Act is a law that increased the health insurance coverage for uninsured individuals and implemented reforms into the health insurance market. Under this law, individuals who were uninsured due to pre-existing conditions or limited finances were now able to obtain affordable health plans through the health insurance markets in their states. One way it accomplished this is through the expansion of Medicaid to the individuals with limited finances. This is important, because states had laws that mandated that insurance covered different procedures. In this case, some states that previously mandated coverage of IVF now were required to cover individuals through Medicaid as well. This caused a new group of individuals who previously could not afford IVF to now have an opportunity to have these procedures covered.

I use this timing by researching which states mandate coverage and what years they passed these laws(Resolve: The National Infertiity Association, 2023).

One potential complication in this timing was that a supreme court challenge to the ACA led to it being unable to be upheld in some states until 2012. Despite this, I still set the level of legalization to 2010 to avoid issues with anticipation leading to the 2012 decision. Along with this, full access to many of the of the laws did not begin until 2014, though there is no comprehensive list of when ART coverage was instituted by which states. This does cause some estimates to not be treated until approximately two or four years later. Therefore, these results could be caused by private companies being more likely to cover the procedure, ahead of the anticipated changes to IVF for public insurances. This makes it difficult to fully untangle where the full effect comes from, with the possibility of the results being some combination of the ACA and SSM legalization, both of which are explored in detail in this paper.

Also, to keep this a balanced event study, I use the data 6 years before and after the legalization, so I only look between 2004-2016. In this time frame, no individual states changed their insurance mandate laws on IVF through legislation other than the ACA. Unfortunately, in 2017 the CDC combined all births into one variable. This was probably in preparation for how they presented the data in later years when they made the data more anonymous for clinics that had fewer than 5 of any type of procedure or outcome. As a result, data past 2016 is not available.

Below is the table which shows the states that were impacted by the ACA. Luckily, no states in the time-frame of my data changed their laws relating to insurance coverage of IVF. In this chart the treated states are the states that had mandated coverage while untreated states did not have mandated insurance coverage:

Table 1: Affordable Care Act Treated vs. Untreated

Treated	Arkansas, California, Connecticut, Hawaii, Illinois, Louisiana, Maryland, Massachusetts, Montana, New Jersey, New York, Ohio, Rhode Island, Texas, West Virginia
Untreated	Alabama, Alaska, Arizona, Colorado, Delaware, Florida, Georgia, Idaho, Indiana, Iowa, Kansas, Kentucky, Maine, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Hampshire, New Mexico, North Carolina, North Dakota, Oklahoma, Oregon, Pennsylvania, South Carolina, South Dakota, Tennessee, Utah, Vermont, Virginia, Washington, Wisconsin, Wyoming

The usage of the ACA in this paper is very straight forward, where a state is treated if the state mandated coverage of IVF was expanded to Medicaid through the ACA.

2.2 Same-Sex Marriage (SSM) Legalization

Same-Sex Marriage (SSM) legalization is defined as the passage of laws, or constitutional interpretation, that require marriages and marriage licenses between individuals of the same-sex to be recognized as the same as those of opposite-sex couples. As a result of this law changing, a large amount of same-sex couples decided to quickly get married. This also quickly changed the composition of same-sex households including two topics relevant to this paper; children, and insurance coverage through their new partner's benefits.

Therefore, I use the timing of SSM legalization to test whether the states that have legalized SSM have an increase in the number of births using IVF methods brought on from the increase in new marriages and possibly from the ability of a partner with fertility issues to use the other partner's insurance to obtain fertility treatments.

SSM was also legalized using three major categories. The first being legislative which was through the passage of a law at a state legislature. The second was judicial, in which it became legal through the outcome of a court case. The final was a referendum, where individuals voted to change their state's laws directly. On top of this, SSM legalization has a staggered timing effect, which happened over a number of years. By 2015 a supreme court decision forced all states that had not yet done so to legalize SSM immediately at that time. This means the years used for this analysis are from 2003-2014, since by 2015 all states are considered treated. Below is a table that shows the legalization timing by state, and includes an overlay that signifies which states had IVF coverage mandated in their state and is broken down by which method SSM was legalized..

Table 2: Year of Treatment by Same-Sex Marriage and Method of Legalization Passed

Year	Judicial	Legislative	Referendum
2004	Massachusetts*		
2008	Connecticut*		
2009	Iowa	Vermont	
2010		New Hampshire, District of Columbia	
2011		New York*	
2012		Washington	Maine
2013	California*, New Jersey*, New Mexico	Delaware, Hawaii*, Minnesota, Rhode Island*	Maryland*
2014	Alaska, Arizona, Colorado, Indiana, Montana*, Nevada, North Carolina, Oklahoma, Oregon, Pennsylvania, South Carolina, Utah, Virginia, West Virginia*, Wisconsin, Wyoming	Idaho, Illinois*	
2015	Alabama, Arkansas*, Florida, Georgia, Kansas, Kentucky, Louisiana*, Michigan, Mississippi, Missouri, Nebraska, North Dakota, Ohio*, South Dakota, Tennessee, Texas*		

Note: Those with * have insurance coverage for IVF that is mandated to some extent in that state. This chart is made using information from (Hansen, Martell and Roncolato, 2019).

3 Literature Review

3.1 Affordable Care Act (ACA)

The main impact of the ACA is that it increased insurance coverage, which in turn increased the usage of treatments that had mandates that insurance companies must follow. Now I look at the general impact of insurance mandates and their impacts on the economics of mothers and motherhood, which is a central part of this paper. Many papers find that insurance mandates such as these can cause women to delay marriage and child birth (Abramowitz, 2013, 2016; Machado and Sanz-de Galdeano, 2015). These declines are most substantial among younger cohorts of women, with a decline in marriage, and an increase in tax filings of these individuals (Heim, Lurie and Simon, 2017).

Along with this, there is some evidence that future universal mandates would increase treatment and birth costs, and that instead, an embryo cap would in turn lower these costs (Hamilton et al., 2018). Most states though have a maximum amount they cover, which would have a similar effect to an embryo cap, which leads that we should see increases in the usage of ART.

Other papers have similarly dealt with the ACA more directly to view whether it has an impact through the states with mandated insurance coverage. One such paper showed that an IVF procedure called intracytoplasmic sperm injection used in fresh non-donated births had lower rates of use in states after IVF insurance mandates between 2000 and 2015 (Dieke et al., 2018). Mandates in New Jersey and Connecticut showed greater uses of ART without a significant change in birth outcomes (Crawford et al., 2015). States with mandated insurance coverage also experienced lower rates of discontinuation in treatments after unsuccessful treatments (Lee et al., 2022). Insurance mandated states also had higher rates of ART use and lack of infertility insurance mandate was associated with adverse perinatal outcomes (Boulet et al., 2015). There is also a lot of debate on whether the ACA, through expansion of Medicaid, will have an impact on these values (Devine, Stillman and Decherney, 2014), which is one of the primary points of interest that I will look into in this paper.

3.2 Same-Sex Marriage (SSM) Legalization

Overall the literature that examines SSM legalization in relation to ART and child procurement of LGBT+ individuals is scarce.

Most previous papers looking into changes in SSM that relate to this paper examine the expanded access to the insurance of their partners. Though not incredibly likely, usage of

ART may have increased in a similar way after SSM legalization. Other papers have also raised similar questions relating to birth rates of same-sex couples after SSM legalization. There is evidence that both the number of children in same-sex households did not change after SSM legalization (Hansen, Martell and Roncolato, 2019) and that there is a downward trend in the number of adoptive same-sex lesbian households after SSM legalization, though these results may violate pretrends (Bielsa, 2024). These papers show a possibility for SSM legalization to have an impact on increasing ART births after legalization, since ART and adoption are the only access to children that same-sex couples have available to them.

Firstly, a couple of studies have looked into whether same-sex individuals have better health outcomes in comparison to straight women with infertility issues using ART. Swedish data shows that same-sex lesbian couples had similar birth outcomes to heterosexual individuals not using ART and better outcomes than heterosexuals using ART (Goisis, Cederstrom and Martikainen, 2023). When comparing shared motherhood IVF and artificial insemination with donor sperm, pregnancy rate was higher, but health outcomes were similar (Matorras et al., 2023). These papers show that outcomes of ART are more favorable for lesbian women, primarily because they largely do not have issues with fertility.

4 Data

My data comes from the CDC's yearly reporting from ART clinics through their National ART Surveillance System (Centers for Disease Control and Prevention, US Dept of Health and Human Services, 2023). This is a legally mandated program, which requires clinics that do ART to report their results and procedures to the government. There are a couple of limitations with this data. This data set includes 91.4% of clinics in the US and approximately 98% of all ART cycles [4] performed in the US, and reporting is legally mandatory for all clinics. This data was hand-linked at a clinic-level, matching by name (and previous names), city, and medical director and includes approximately 750 clinics.

[4] A cycle is the procedure for harvesting eggs to be implanted with sperm to become embryos

The first limitation is that after 2016, the data values were replaced with a * for clinics that have fewer than 5 births per age group, to protect individuals from being identified.

Additionally, there are reporting issues with fresh, non-donated births. Transfers for this procedure are not reported until 2011, with only cycles recorded before then. This could be due to the CDC not requesting the information or poor reporting practices. As a result, clinics might deprioritize outcomes from this procedure, leading to other issues. Testing indicates significant pretrend issues for this birth method, suggesting the possible presence of such problems. Therefore, models using these outcomes are included in the appendix (substituting cycles for transfers where needed since with fresh non-donated cycles usually you need one cycle per transfer) but the results are not reported as a primary part of the analysis.

Finally, below are summary statistics of the data used in this analysis:

Table 3: Summary Statistics for IVF Clinics

		(1)	
	count	mean	sd
ThwDnrTrans	5929	15.40057	30.2149
ThwNDTransfers	5929	75.99039	140.9175
FshDnrTransfers	5929	20.42098	39.62973
FshNDTransfers	5929	66.48794	179.3784
ThwDnrLvBirths	5929	5.458593	12.35556
ThwNDLvBirths	5929	28.85478	66.52833
FshDnrBirths	5929	11.12515	21.62076
FshNDLvBirths	5929	62.11537	94.58518
FshNDCycle	5929	216.5365	328.0796
SingleWomenBinary	5929	.9357396	.2452369
AccreditationBinary	5929	.920054	.2712325
AccreditationPendingBinary	5929	.0234441	.1513219
DonorEmbryoBinary	5929	.6790353	.4668867
DonorEggBinary	5929	.9274751	.2593769
SurrogatesBinary	5929	.8330241	.3729858
insuranceable	5929	.5242031	.499456

Here it is clear that the most commonly used type of IVF is the fresh non-donated, followed by thawed non-donated, then by fresh donated, and finally thawed donated. This is possibly influenced by not all clinics having cryopreservation available, and higher usage of non-donated eggs as the primary historical usage of ART is for couples with fertility issues.

5 Empirical Strategy

With these established set ups for the ACA and SSM legalization, I use the Borusyak, Jaravel, and Spiess (BJS) difference in difference with staggered treatment timing's imputation estimator (Borusyak, Jaravel and Speiss, 2024) and the Callaway Sant'anna (CS) difference in difference with staggered treatment timing's estimator (Sant'Anna and Callaway, 2021). The decision to use these estimators and how to use these estimators, comes from a trio of papers (Roth et al., 2023; Roth, 2022, 2018). The first paper is a note on interpretation of the new difference-in-difference models when using non-staggered treatment and parallel trends fails. This paper explains that the validity of the post-treatment event study estimates holds as long as the parallel trends assumption also holds, yielding results even under heterogeneous treatment effects for a non-staggered treatment effect design. Results for the event study for the ACA fall under this definition, but for robustness, the classic difference-in-difference model with fixed effects is also run, and shows consistent results. The second paper explains when it is optimal to use the new staggered timing difference-in-difference estimators. In this paper they state that "BJS estimator may be preferable in settings where the outcome is not too serially correlated and the researcher is confident in parallel trends across all periods". Most models have pretrends that are very consistent over longer time periods, where some analyses have issues with pretrends in the CS models. This, coupled with a fairly high level of serial correlation, is why both models are reported, as I feel that together they form a fairly strong set of bounds, especially when including OLS. I feel this is supported by both models generally having similar results, with the CS model having fairly consistently larger standard errors and being closer to zero, which can be explained by the efficiency loss for requiring pretrends to hold only approximately, and through the construction of the model not using all available pretrends. My conclusions will be reached using the results that best follows these rules for the individual model in question. [5]

On top of this, all models used additional pre-testing constructing a hypothesized trend with a 0.80 beta, with some results displayed in the appendix according to the pretrends package (Roth, 2022). The Likelihood Ratio Test and Bayes Test results for each model are reported in the appendix. For the Bayes test, in the presense of a significant pretrend in the model, the smaller the value, the more likely that pretrends hold. If the Likelihood Ratio Test is small, it means the coefficients in the data are more likely under parallel trends than under the hypothesized trend. In this case, I want both of these coefficients to be small if parallel trends has a threat to be violated. These tests can only be completed for the CS and OLS models, since the method requires a normalization based on a pre-period, which by the construction the BJS model does not have.

While there definitely is some serial correlation in outcomes due to the possibility of treatment failing, these treatments are able to be repeated again after about 4 weeks. With this in mind, a successful treatment means the individual is pregnant, in which case they are no longer in the population of individuals looking to get ART treatments. Additionally, with each time period being a year, I feel there is low overlap across years. Births in all cases denotes either the total births in a clinic, or the total births of an individual method, depending on the test run.

Both models below use individual and time treatment effects of delta, and have individual clinic-level controls denoted by X.

Below is the first model, using the ACA legalization:

$$Births_{i,s(i),t(i)} = \sum_{k=-6}^{K} \beta_k (1)\{t - t^* = k\}(ACA_{st}) + \delta_i + \delta_t + \Gamma X_i + \varepsilon_{it} \tag{1}$$

This model's variable of interest is the beta at time k in relation to the treatment. This model uses binary controls for whether the clinic used/had donated embryos, used/had donated eggs, was an accredited clinic, whether the clinic's accreditation was pending, whether

[5] BJS and OLS results will also be reported for all equations, but due to lower sample size, equation 3 results cannot report CS results

they allowed surrogacy, and whether they used any type of cryopreservation. ACA is a variable that is 1 after the ACA is passed in the states that have an insurance mandate to cover IVF, and is 0 otherwise.

The next model uses the differentiation by state of the timing of the legalization of same-sex marriage shown above:

$$Births_{i,s(i),t(i)} = \sum_{k=-3}^{K} \beta_k(1)\{t - t^*(s) = k\}(SSM_{st}) + \delta_i + \delta_t + \Gamma X_i + \varepsilon_{it} \tag{2}$$

This model's variable of interest is the beta at time k in relation to the time of the treatment in that state. This model uses the variables listed above, along with whether the state had mandated insurance coverage of IVF, and the type of legalization method in that state (whether that be legislative, judicial, or through referendum). SSM is 1 in the state and time of and after SSM is legalized.

Model 1 and 2 are run additionally while controlling for the type of transfers relative to those births. This normally would be a bad control if I actually wanted to estimate the actual change in births. Instead I want to see whether the amount of births changes, controlling for changes in the number of transfer. Changes to the amount of births relative to how many transfers indicates one thing: the average population of those receiving IVF treatments have become healthier. In the context of SSM, if someone without fertility issues received IVF, such as a lesbian woman, the likelihood of a birth occurring would increase, as a result increasing the number of births relative to transfers.

The final model below uses both legalization methods and is collapsed to the city level:

$$\#ofClinics_{c,s(c),t(c)} = \sum_{k=-K}^{K} \beta_k(1)\{t - t^*(s) = k\}(Legal_{st}) + \delta_c + \delta_t + \varepsilon_{it} \tag{3}$$

In this case, Legal refers to SSM legalization, or the passage of the ACA depending on the policy I aim to look into at that time. This model is designed to estimate how the separate impact of both the ACA and SSM legalization changes the number of clinics in a city. This model is basic, with city and time fixed effects, and finds the coefficient of interest in Beta.

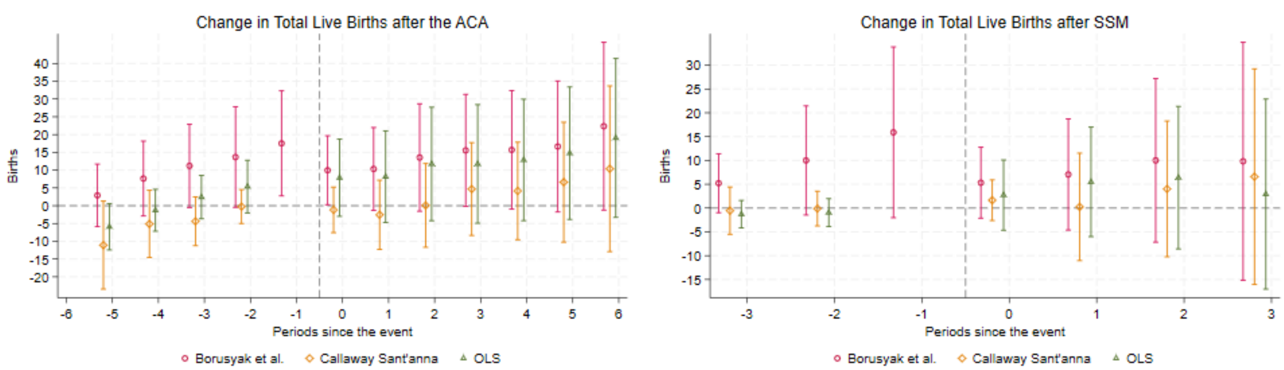
Along with these models, tests are completed to find the overall effect across the periods the event happened and the periods after to obtain an overall effect following the policy. I do this because the sample size of clinics is not very large, and the timing for SSM legalization does not allow for many years, so having an overall effect would give a good idea if there was an actual change in the case where there is not significance in the individual years. These are done by doing a hypothesis test for the sum of the year of the event and all the years after the event used in these event studies and whether that is equal to no effect.

Through these models I test my hypothesis on the magnitude of the impact that the ACA and SSM legalization had on ART clinics in the United States.

6 Results

The first figure shows the results of total births

Figure 1: Births increase in all three categories two years after the ACA is passed

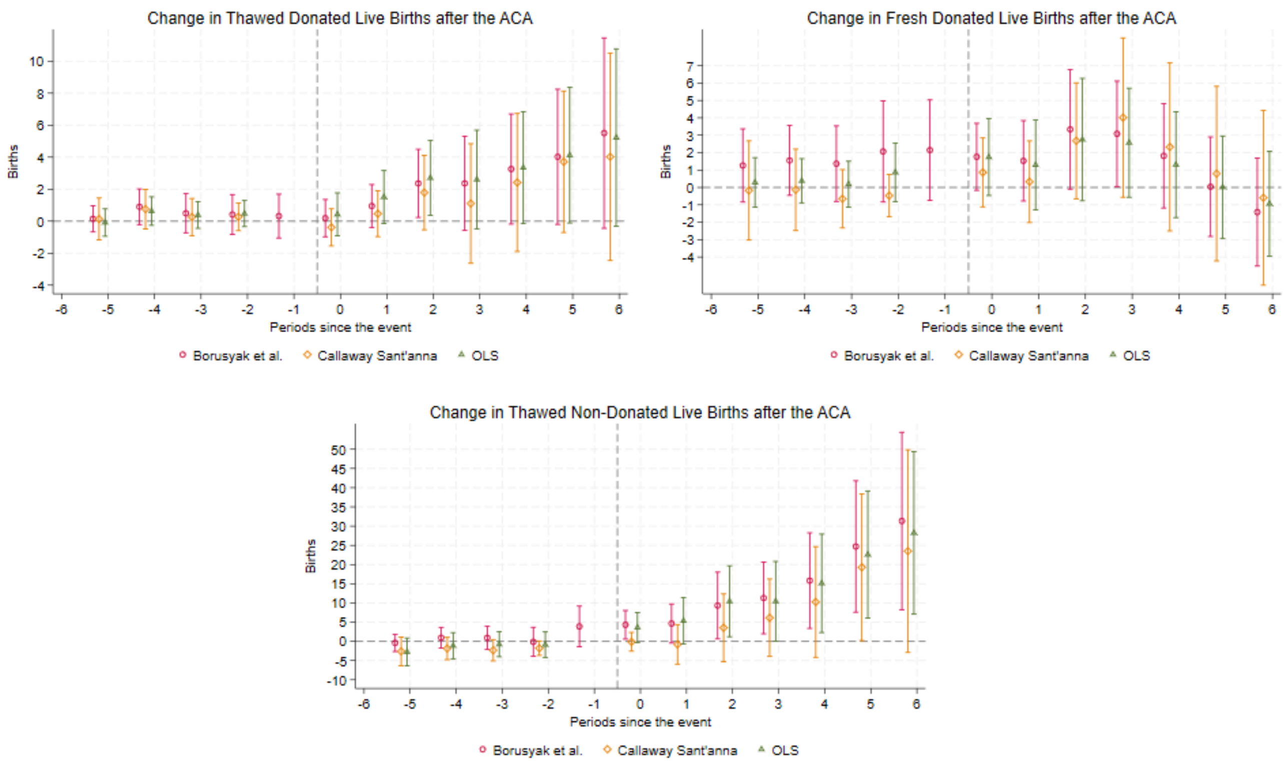


Note: These event study graphs display the results from equation 1 and 2 on total births. These charts display the information using a 95% confidence interval.

The graphs show that there is a general trend upward of estimates after the events, but none being individually statistically significant. Checking the group test, we can see that births in the BJS model seem to have increased, but there are some issues with pretrends present. The pretrends issue is likely due to the issues with the fresh, non-donated births that was discussed earlier and their inclusion in this model. From here I decide to split based on procedure type, beginning with a breakdown of the ACA.

Figure 2 below first looks at the results from equation 1, focusing on the primary three types of births:

Figure 2: Births increase in all three categories two years after the ACA is passed

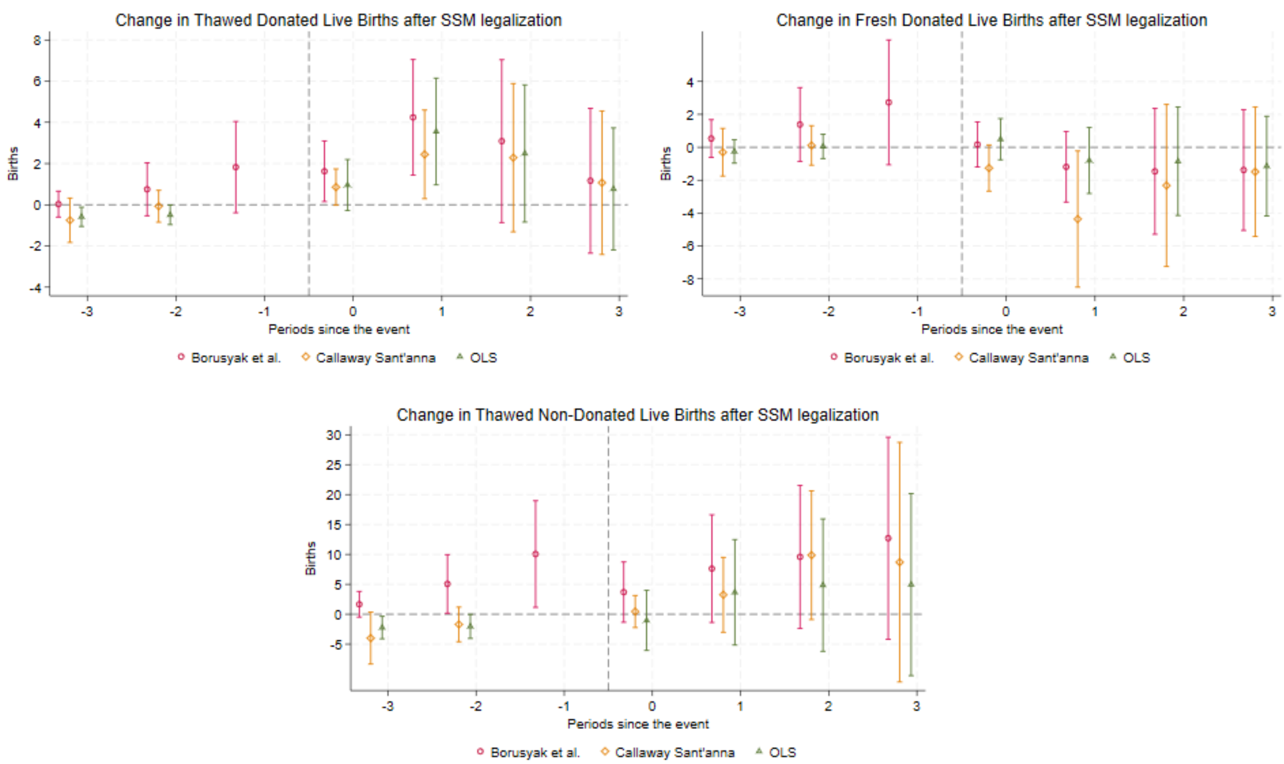


Note: These event study graphs display the results from equation 1 on each different type of births. These charts display the information using a 95% confidence interval.

The first chart in Figure 2 shows that thawed donated births increased approximately two years after the passage of the ACA and had a continual increase in the coming years. BJS and OLS also show cumulative increases of 18-20 births per clinic over the seven years. The second chart shows similar results using fresh donated live births. This chart has an increase two years after, then starts a downward trend four years after the legalization that seems to be a return to zero. The third chart, focusing on thawed non-donated live births, reveals an immediate increase in births after the ACA, with an increase that seems to get larger after each additional year. The BJS and OLS again show a cumulative increase, this time of about 96-99 births per clinic across the seven years. These findings point to a significant increase two years after the passage of the ACA for all three listed types of births, with sustained growth in births that are from thawed embryo. This is likely due to thawed treatments being cheaper than fresh IVF treatments and being much less stressful for those undergoing cycles for each procedure. Overall, these findings indicate that the ACA's insurance coverage had a significant impact on births facilitated by ART.

Now I test equation 2 to see the impact after SSM legalization to compare any differences and results. Below Figure 3 tests this for the three primary types of births using SSM legalization:

Figure 3: Births only increase for thawed donated births after SSM legalization



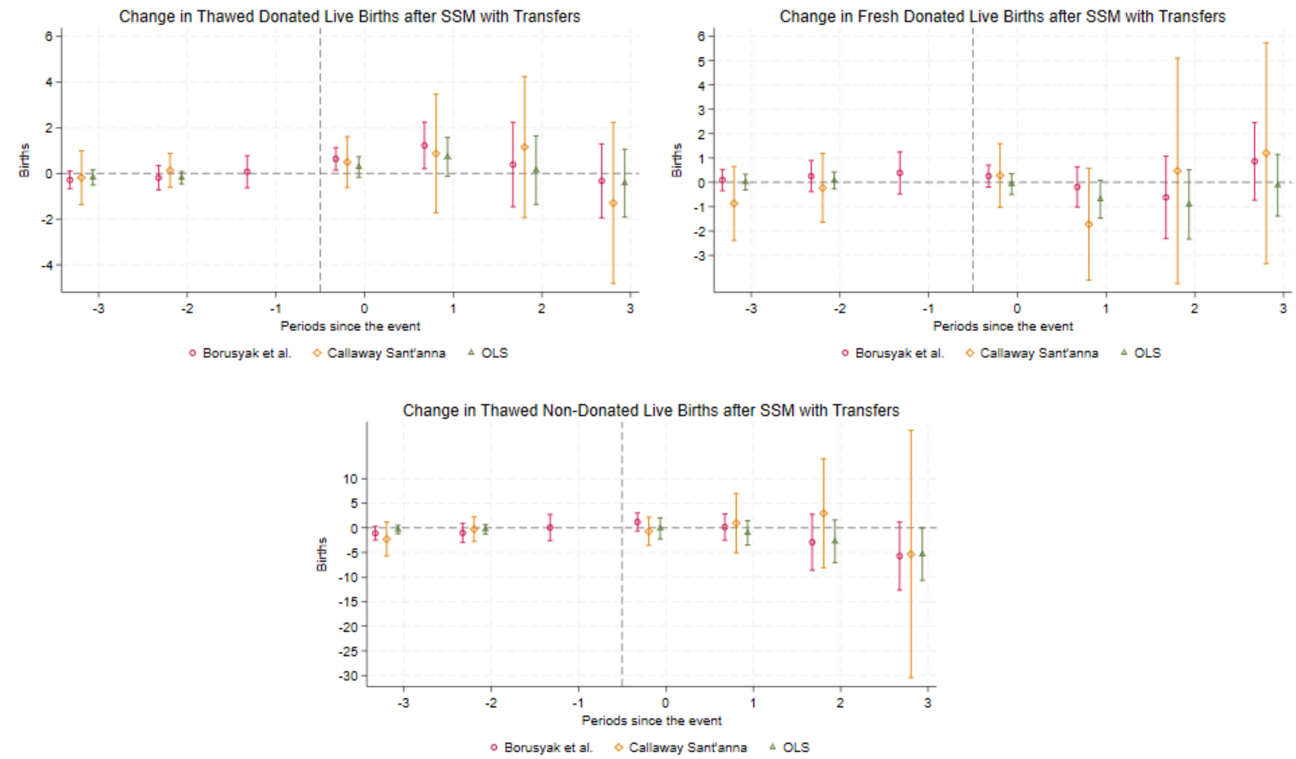
Note: These event study graphs display the results from equation 2 on each different type of births. These charts display the information using a 95% confidence interval.

Here there some issues with pretrends using BJS although only T-1 is significant at the 10% level, and the joint pretrends test fails. Even with this difficulty, all three models indicate an immediate increase on thawed donor births that lasts about two years and returns to zero. The overall cumulative increase in these births is between 6.65-10.1 births per clinic across four years. For the model using fresh donor births, I see these decrease slightly, in the year after the event, which could be caused by some individuals switching to frozen donor births as well as overlap with the ACA and how these births decreased in the later years of the ACA. This effect is only statistically significant both individually and at the cumulative level for the CS model, which also has significant issues with their joint pretrend test. Finally, I can see that thawed non-donor births have some issues with pretrends, but overall seem to show an increase and do not show issues through the Likelihood Ratio, and Bayes testing. Though, at the individual level, only the BJS and CS each have one (different) period that is significant, and only the BJS model has a significant cumulative effect all of which are at the 10% level. These results indicate that SSM caused some changes to the ways ART is used.

Next, equations 1 and 2 were used similarly as before, but with a control for the type of transfer associated with the live birth. This essentially means I am controlling for the number of procedures to implant embryos into the prospective parent. Typically, this would be a bad control if trying to prove the impact on just births, but my aim is to interpret this model slightly differently. The purpose here is to determine if births still increase when controlling for the number of transfers after the implementation of SSM and the ACA. This would indicate improvements in outcomes of births, essentially meaning that more births end up occurring from fewer transfers, since transfers and births should be highly correlated. If births increase while controlling for transfers, it indicates better outcomes of ART, which primarily only happens if more healthy individuals use it and/or users do not have issues with fertility.

Below I can display the impact before and after SSM legalization from using equation 2 in Figure 4:

Figure 4: Thawed donated live births is the only one to show an increase that is statistically significant



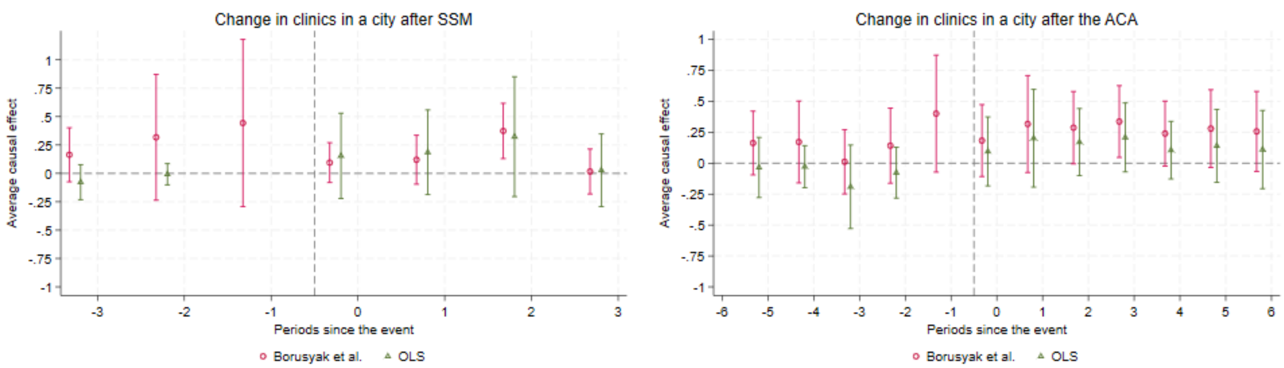
Note: These event study graphs display the results from equation 2 on each different type of births. Including the control of transfers for their respective type of birth/procedure. These charts display the information using a 95% confidence interval.

I can see from the above impact that this model has none of the same pretrends issues I was dealing with from Figure 3. Looking at the thawed donor births model, I can still see a significant impact for the year of and year after in the BJS model, with significance the year after for the OLS model as well. These models do not seem to have significant cumulative effects due to the return to zero and the large confidence intervals for the T+2 and T+3 periods. At the same time, fresh donated births decreased at a much lower rate in the year after and seems to be much closer to not having a significant effect. I can also see that thawed non-donated births no longer seemed to have any impact.

This can be even further shown in the appendix, where equation 1 is run with transfers as a control, showing that there is no longer statistical significance for any type of births when looking at the ACA instead. This makes sense, as outcomes for births compared to transfers should not be influenced by insurance coverage for infertile individuals, which is the primary impact of the ACA. Meanwhile, many same-sex couples often do not have an issue with fertility and are often not guaranteed insurance coverage. This indicates that the impact of SSM legalization caused an increase in births in the US that is likely separate from the ACA and that an increase in birth outcomes for thawed donor births occured as a result.

Now using equation 3, I attempt to see why the positive impact of SSM legalization stopped after one year. Below are the results of those models with both SSM legalization and passage of the ACA:

Figure 5: The number of clinics in a city increase two years after each policy



in

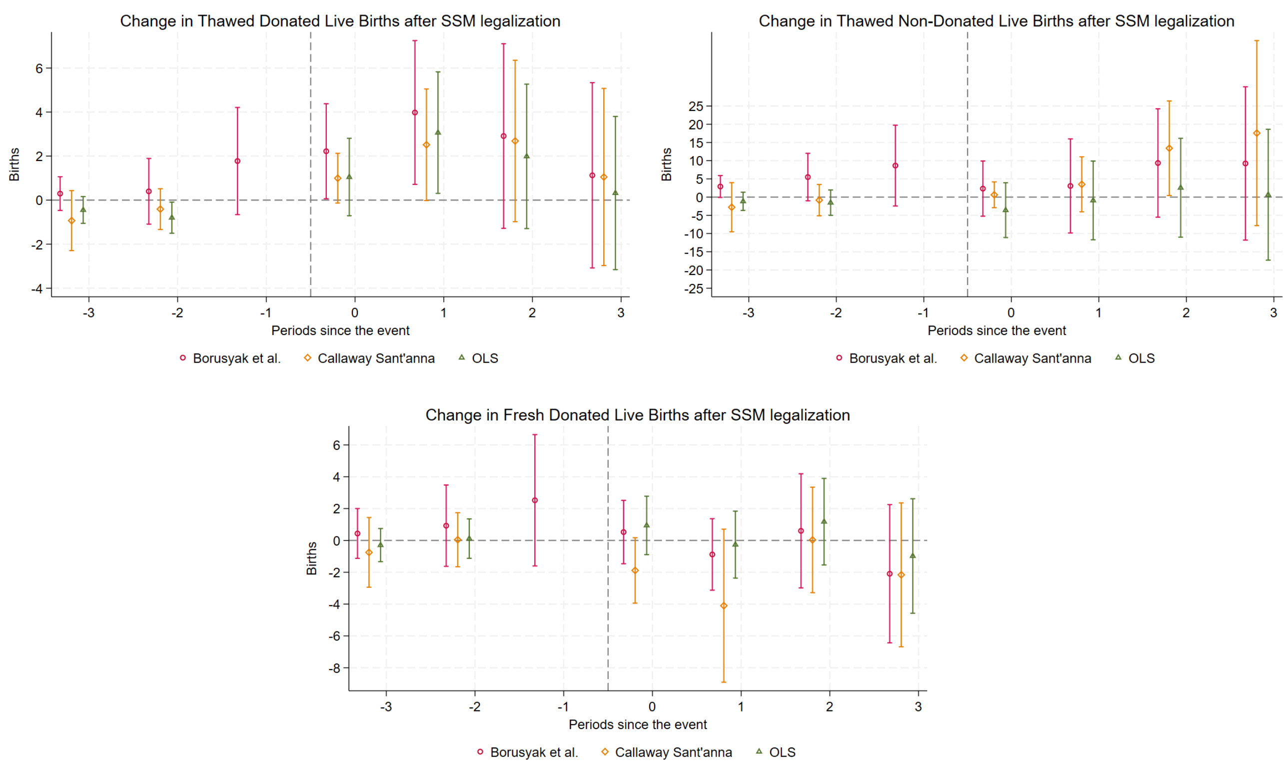
Note: These event study graphs display the results from equation 3 on each type of legalization. These charts display the information using a 95% confidence interval.

These event studies show the change in the number of clinics within a city after the two events I am looking towards. These models had issues with being run at a city level with CS, so only BJS and OLS are reported. I can see that for SSM legalization there appears to be an increase in the number of clinics two years later, and the ACA seems to show an almost immediate increase in the number of clinics a year after that sustains, though many of the individual timings are not significant. The cumulative effects from the BJS model show at the 10% level that the ACA caused the number of clinics in a city to increase. This can lead to the conclusion that these two policies likely influenced the number of clinics per city to keep up with the demand of more procedures and births.

This is even more evidenced in the Apendix, where a test was done at the city level, showing increases that were about the same, but having more significant individual post-time periods.

After this I finally looked at the clinics using equation 2 except restricting to only states that had insurance already mandated. This is an attempt to look at the two policies in conjunction to the best extent possible. It would be preferable to test whether there was an impact in states that did not have insurance mandates, but unfortunately, the states without insurance mandates had very late legalization of same-sex marriage, and those that legalized it early had a very small amount of clinics. As a result this makes it difficult to run a difference in difference estimator with any power due to the limits on the pretrends. For example, BJS is unable to impute enough values to even run. The results are in Figure 6:

Figure 6: Thawed donor live births increase even more in states with mandated insurance coverage.



Note: These event study graphs display the results from equation 2 on each type of birth, except it has been limited to only states with insurance coverage that is mandated. These charts display the information using a 95% confidence interval.

Here I can see the data is still consistent with the previous results, where thawed donated births increase, thawed non-donated births do not change, and fresh donated births either decrease or do not change. The cumulative effect range across the three models is also almost the same; the only change is that OLS for thawed donated births is no longer cumulatively significant. That being said, it seems to support that likely the states that had insurance mandates experienced very similar effects than those without.

All of these tests combine to indicate that same-sex individuals likely drove usage of ART after the legalization of SSM and that the ACA itself had an impact on the quantity of births in the US that likely included same-sex couples.[6]

7 Conclusions

ART and IVF are crucial for increasing birth rates and the number of children among older women, infertile women, and same-sex couples. I find that in the years after the Affordable Care Act (ACA), there was an increase of about 16-17 births per year per clinic in states that mandated insurance coverage when compared to those that did not after it's passage. This was mainly driven by increases in procedures using frozen embryos. The increase in specifically frozen procedures is likely brought along, due to the price-based restrictions on ART coverage by states. Many states only cover a certain amount for ART procedures, and frozen procedures are not only significantly cheaper, but they are also considerably less stress-inducing for the donating individual.

At the same time, I also find that following Same-Sex Marriage (SSM) legalization, thawed donated live births increased by between 6-10 births per clinic in that year and three years after it's legalization. This increase seems to be due to a short-term increase in demand by same-sex couples immediately after the legalization of SSM, which seems to return to zero as more clinics enter the market and the demand is satisfied. This increase is only explainable

[6] Other event studies, robustness checks and the numerical results of these event studies are located in the appendix for more detail. They show support towards the conclusion of my hypothesis and results from testing things like pretrends.

by the population of individuals getting ART treatments becoming healthier in the few years after SSM is legalized, which points towards the uptake of ART by same-sex couples.

These results are relevent as a federal decision to overturn the ACA or SSM will likely cause decreases in births through ART, and could lead to clinic closures as a result.

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A Appendix

Here I have the charts for the results listed above and extra robustness checks:

Table 4: Results For Total Births after the ACA

	(1) BJS	(2) CS	(3) OLS
	totbirths	totbirths	totbirths
T+0	9.974**	-1.171	7.857
	(4.942)	(3.269)	(5.531)
T+1	10.34*	-2.553	8.165
	(5.941)	(4.963)	(6.575)
T+2	13.56*	0.0887	11.74
	(7.707)	(6.008)	(8.139)
T+3	15.57*	4.690	11.75
	(8.035)	(6.656)	(8.506)
T+4	15.71*	4.159	12.87
	(8.509)	(6.990)	(8.710)
T+5	16.66*	6.613	14.77
	(9.396)	(8.605)	(9.499)
T+6	22.35*	10.39	19.05*
	(12.03)	(11.89)	(11.40)
T-1	17.53**		
	(7.533)		
T-2	13.68*	-0.238	5.379
	(7.210)	(2.426)	(3.776)
T-3	11.21*	-4.374	2.412
	(5.978)	(3.505)	(3.109)
T-4	7.642	-5.126	-1.288
	(5.373)	(4.820)	(2.999)
T-5	2.905	-11.08*	-5.930*
	(4.484)	(6.309)	(3.319)
T-6	2.078	-16.04**	-6.177
	(3.264)	(7.291)	(3.823)
N	5575		5840
Joint Pretrends Tests	0.1689	0.3208	-
Cummulative Effect	104.1583**	22.21912	86.19871
	(52.55189)	(41.78959)	(55.04626)
Likelihood Ratio Test	-	6.3057	0.0038
Bayes Test	-	0.4840	0.2433

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 5: Results For Total Births after SSM

	(1) BJS totbirths	(2) CS totbirths	(3) OLS totbirths
T+0	5.321	1.644	2.718
	(3.796)	(2.176)	(3.763)
T+1	7.051	0.247	5.494
	(5.955)	(5.756)	(5.866)
T+2	10.01	4.020	6.383
	(8.761)	(7.274)	(7.635)
T+3	9.823	6.588	2.932
	(12.74)	(11.55)	(10.18)
T-1	15.90*		
	(9.149)		
T-2	10.000*	-0.104	-0.960
	(5.847)	(1.859)	(1.498)
T-3	5.217*	-0.551	-1.284
	(3.158)	(2.534)	(1.472)
N	4872		4923
Joint Pretrends Tests	0.3789	0.6125	-
Cummulative Effect	32.20412	12.49935	17.52784
	(25.40994)	(20.72567)	(23.11163)
Likelihood Ratio Test	-	0	0.0655
Bayes Test	-	0	0.2183

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 6: Results For Thawed Donor Births after the ACA

	(1) BJS	(2) CS	(3) OLS
	ThwDnrLvBirths	ThwDnrLvBirths	ThwDnrLvBirths
T+0	0.150	-0.384	0.414
	(0.595)	(0.591)	(0.679)
T+1	0.916	0.465	1.501*
	(0.684)	(0.730)	(0.840)
T+2	2.305**	1.787	2.698**
	(1.084)	(1.186)	(1.182)
T+3	2.343	1.103	2.620*
	(1.496)	(1.907)	(1.563)
T+4	3.223*	2.422	3.360*
	(1.747)	(2.200)	(1.776)
T+5	3.982*	3.714*	4.157*
	(2.145)	(2.255)	(2.151)
T+6	5.474*	3.988	5.284*
	(3.016)	(3.297)	(2.817)
T-1	0.373		
	(0.701)		
T-2	0.437	0.268	0.468
	(0.638)	(0.439)	(0.416)
T-3	0.557	0.265	0.385
	(0.627)	(0.590)	(0.426)
T-4	0.962*	0.749	0.632
	(0.576)	(0.626)	(0.458)
T-5	0.221	0.159	-0.0501
	(0.422)	(0.665)	(0.438)
T-6	-0.0904	-0.760	-0.496
	(0.330)	(0.709)	(0.490)
N	5581		5841
Joint Pretrends Tests	.8347	0.1848	-
Cummulative Effect	18.39235*	13.09651	20.03574**
	(9.682403)	(10.59257)	(10.05511)
Likelihood Ratio Test		0.4951	0.0038
Bayes Test		0.3529	0.246

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 7: Results For Thawed Non-Donor Births after the ACA

	(1) BJS	(2) CS	(3) OLS
	ThwNDLvBirths	ThwNDLvBirths	ThwNDLvBirths
T+0	4.119**	-0.107	3.544*
	(1.909)	(1.243)	(1.977)
T+1	4.539*	-0.788	5.333*
	(2.599)	(2.624)	(3.050)
T+2	9.061**	3.541	10.38**
	(4.422)	(4.500)	(4.680)
T+3	11.17**	6.155	10.48**
	(4.735)	(5.144)	(5.262)
T+4	15.62**	10.25	15.16**
	(6.317)	(7.347)	(6.509)
T+5	24.40***	19.29**	22.74***
	(8.685)	(9.738)	(8.417)
T+6	31.09***	23.23*	28.53***
	(11.72)	(13.43)	(10.77)
T-1	4.318		
	(2.724)		
T-2	0.140	-1.774*	-0.878
	(1.962)	(0.956)	(1.695)
T-3	1.342	-2.338*	-0.676
	(1.564)	(1.406)	(1.660)
T-4	1.373	-1.885	-1.047
	(1.428)	(1.472)	(1.742)
T-5	0.0747	-2.594	-2.503
	(1.216)	(1.895)	(1.854)
T-6	-0.0170	-2.494	-3.279
	(1.021)	(2.293)	(2.017)
N	5581		5841
Joint Pretrends Tests	0.2073	0.5922	-
Cummulative Effect	99.99452***	61.57119	96.17569**
	(36.26123)	(40.37081)	(37.54813)
Likelihood Ratio Test	0	0.7665	0.01268
Bayes Test	0	0.4404	0.2313

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 8: Results For Fresh Donor Births after the ACA

	(1) BJS FshDnrBirths	(2) CS FshDnrBirths	(3) OLS FshDnrBirths
T+0	1.499	0.864	1.512
	(1.013)	(1.011)	(1.157)
T+1	1.273	0.327	1.063
	(1.210)	(1.197)	(1.336)
T+2	3.046*	2.680	2.533
	(1.766)	(1.700)	(1.806)
T+3	3.095**	4.015*	2.475
	(1.539)	(2.336)	(1.598)
T+4	1.837	2.327	1.206
	(1.523)	(2.463)	(1.552)
T+5	0.0740	0.792	-0.0771
	(1.452)	(2.560)	(1.496)
T+6	-1.377	-0.578	-1.046
	(1.573)	(2.570)	(1.533)
T-1	2.024		
	(1.473)		
T-2	1.670	-0.470	0.613
	(1.534)	(0.621)	(0.899)
T-3	1.209	-0.696	0.0278
	(1.115)	(0.852)	(0.685)
T-4	1.404	-0.194	0.224
	(1.031)	(1.188)	(0.659)
T-5	1.220	-0.236	0.344
	(1.070)	(1.447)	(0.728)
T-6	0.209	-2.263*	-0.461
	(0.767)	(1.192)	(0.723)
N	5581		5841
Joint Pretrends Tests	0.6751	0.4381	-
Cummulative Effect	9.447882	10.42816	7.665327
	(8.133509)	(11.07373)	(8.97804)
Likelihood Ratio Test	0	3.3397	0.0199412
Bayes Test	0	0.2870	0.2473777

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 9: Results For Fresh Non-Donor Births after the ACA

	(1) BJS FshNDLvBirths	(2) CS FshNDLvBirths	(3) OLS FshNDLvBirths
T+0	2.793	-1.544	1.048
	(3.411)	(2.379)	(3.574)
T+1	2.045	-2.557	-1.025
	(3.708)	(3.046)	(3.797)
T+2	-2.502	-7.920**	-5.077
	(4.276)	(3.734)	(4.263)
T+3	-0.606	-6.582	-4.104
	(4.031)	(4.485)	(4.186)
T+4	-4.569	-10.84**	-7.166
	(4.271)	(4.842)	(4.354)
T+5	-11.51**	-17.19***	-12.14**
	(5.006)	(6.350)	(4.925)
T+6	-12.26**	-16.69**	-13.62**
	(5.796)	(7.190)	(5.448)
T-1	11.16**		
	(5.405)		
T-2	9.807*	1.738	3.770
	(5.428)	(2.330)	(2.994)
T-3	8.011*	-2.127	1.928
	(4.505)	(2.606)	(2.400)
T-4	3.851	-9.012**	-1.830
	(3.854)	(3.505)	(2.097)
T-5	2.053	-4.402	-2.886
	(3.158)	(4.444)	(2.170)
T-6	2.660	-11.06**	-1.191
	(2.377)	(5.190)	(2.592)
N	5581		5841
Joint Pretrends Tests	0.0547	0.1782	-
Cummulative Effect	-26.60312	-63.32017**	-42.08082
	(24.92165)	(26.74444)	(26.32262)
Likelihood Ratio Test	0	10.27119	0.0037
Bayes Test	0	0.4195415	0.2447

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 without transfers

Table 10: Results For Thawed Donor Births after the ACA controlling for Transfers

	(1) BJS ThwDnrLvBirths	(2) CS ThwDnrLvBirths	(3) OLS ThwDnrLvBirths
T+0	-0.178	-0.705	-0.197
	(0.323)	(0.501)	(0.287)
T+1	0.0630	0.0579	-0.0243
	(0.300)	(0.673)	(0.282)
T+2	-0.0885	1.153	0.0516
	(0.537)	(1.097)	(0.405)
T+3	0.00204	0.239	0.0400
	(0.577)	(1.601)	(0.459)
T+4	-0.164	1.088	0.0533
	(0.658)	(1.806)	(0.495)
T+5	-0.536	2.516	0.00617
	(0.972)	(1.957)	(0.715)
T+6	-1.004	2.853	-0.214
	(1.117)	(2.912)	(0.758)
T-1	-0.653		
	(0.466)		
T-2	-0.842**	0.364	-0.400
	(0.390)	(0.501)	(0.245)
T-3	-0.288	0.431	0.0768
	(0.388)	(0.652)	(0.261)
T-4	-0.0555	0.833	0.326
	(0.313)	(0.706)	(0.276)
T-5	-0.747***	0.231	-0.403
	(0.280)	(0.729)	(0.257)
T-6	-0.297	-0.618	-0.0493
	(0.295)	(0.883)	(0.268)
Transfers	0.472***		0.432***
	(0.0410)		(0.0180)
N	5581		5841
Joint Pretrends Tests	0.0196	0.4217	-
Cummulative Effect	-1.904853	7.201279	-0.2836922
	(3.697067)	(7.963718)	(2.582304)
Likelihood Ratio Test	-	0.1244	1.9049
Bayes Test	-	0.4051	0.2499

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with transfers

Table 11: Results For Thawed Non-Donor Births after the ACA controlling for Transfers

	(1) BJS ThwNDLvBirths	(2) CS ThwNDLvBirths	(3) OLS ThwNDLvBirths
T+0	-0.358	-1.704	-0.301
	(0.861)	(1.696)	(0.770)
T+1	-1.163	-4.362	-0.842
	(1.418)	(3.539)	(1.089)
T+2	0.441	-3.059	0.323
	(1.533)	(5.563)	(1.268)
T+3	0.542	-2.842	0.361
	(1.728)	(6.955)	(1.462)
T+4	-1.218	-1.477	-0.458
	(2.187)	(8.848)	(1.665)
T+5	-2.546	7.071	-1.514
	(2.959)	(9.972)	(2.102)
T+6	-1.130	9.277	-0.350
	(3.506)	(12.35)	(2.370)
T-1	-2.411**		
	(1.153)		
T-2	-2.981***	-2.306**	-1.361*
	(1.118)	(1.096)	(0.741)
T-3	-1.935*	-2.301	-0.471
	(1.027)	(1.452)	(0.791)
T-4	-1.531	-1.245	-0.126
	(1.010)	(1.460)	(0.883)
T-5	-1.311	-2.146	0.00105
	(0.938)	(1.962)	(0.894)
T-6	-0.465	-0.227	0.620
	(0.749)	(2.343)	(0.871)
Transfers	0.485***		0.476***
	(0.0325)		(0.0172)
N	5581		5841
Joint Pretrends Tests	0.2878	0.2725	-
Cummulative Effect	-5.432205	2.905115	-2.779975
	(11.47867)	(45.04871)	(8.282211)
Likelihood Ratio Test	-	0.0728	2.8733
Bayes Test	-	0.4098	0.2399

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with transfers

Table 12: Results For Fresh Donor Births after the ACA controlling for Transfers

	(1) BJS	(2) CS	(3) OLS
	FshDnrBirths	FshDnrBirths	FshDnrBirths
T+0	0.421	1.326	0.520
	(0.338)	(1.248)	(0.365)
T+1	0.112	0.786	0.161
	(0.369)	(1.579)	(0.359)
T+2	0.290	4.081**	0.501
	(0.445)	(2.038)	(0.412)
T+3	0.0878	6.501***	0.308
	(0.471)	(2.423)	(0.437)
T+4	0.530	6.229**	0.496
	(0.446)	(2.528)	(0.453)
T+5	0.332	4.815**	0.202
	(0.483)	(2.136)	(0.450)
T+6	-0.00435	3.619*	0.00244
	(0.472)	(1.860)	(0.461)
T-1	-0.0622		
	(0.500)		
T-2	-0.102	-0.917	0.0109
	(0.535)	(0.822)	(0.390)
T-3	0.136	-1.233	0.128
	(0.532)	(1.179)	(0.388)
T-4	0.265	-0.317	0.280
	(0.477)	(1.441)	(0.367)
T-5	0.0676	0.169	0.137
	(0.476)	(1.823)	(0.421)
T-6	-0.495	-4.009**	-0.442
	(0.422)	(1.976)	(0.379)
Transfers	0.552***		0.509***
	(0.0239)		(0.0187)
N	5581		5841
Joint Pretrends Tests	0.5302	0.3027	-
Cummulative Effect	1.768343	27.35675	2.190258
	(2.254947)	(11.80615)	(2.274578)
Likelihood Ratio Test	-	0.7553	0.0063
Bayes Test	-	0.3709	0.2467

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with transfers

Table 13: Results for Thawed Donor Transfers after the ACA

	(1) BJS	(2) CS	(3) OLS
	ThwDnrTrans	ThwDnrTrans	ThwDnrTrans
T+0	0.695	-0.546	1.415
	(1.290)	(1.098)	(1.504)
T+1	1.808	1.002	3.534*
	(1.701)	(1.397)	(2.042)
T+2	5.073*	3.865	6.132**
	(2.659)	(2.545)	(2.923)
T+3	4.960	2.455	5.977*
	(3.384)	(3.877)	(3.587)
T+4	7.176*	5.554	7.660*
	(3.812)	(4.504)	(3.953)
T+5	9.573**	9.545**	9.616**
	(4.469)	(4.704)	(4.553)
T+6	13.73**	11.35	12.74**
	(6.608)	(6.964)	(6.108)
T-1	2.174		
	(1.701)		
T-2	2.709*	1.192	2.011**
	(1.554)	(0.812)	(0.902)
T-3	1.790	-0.291	0.714
	(1.528)	(1.149)	(0.943)
T-4	2.155	0.816	0.709
	(1.328)	(1.693)	(1.038)
T-5	2.051**	0.379	0.817
	(1.021)	(1.420)	(0.961)
T-6	0.437	-1.911	-1.035
	(0.825)	(1.577)	(1.091)
N	5581		5841
Joint Pretrends Tests	0.2646	0.0455	-
Cummulative Effect	43.0105**	33.22846	47.07026**
	(21.77236)	(22.13261)	(23.00441)
Likelihood Ratio Test	-	.9367817	.0000512
Bayes Test	-	.3880336	.244934

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with the outcome variable being the number of transfers performed by a clinic

Table 14: Results for Thawed Non-Donor Transfers after the ACA

	(1) BJS	(2) CS	(3) OLS
	ThwNDTransfers	ThwNDTransfers	ThwNDTransfers
T+0	9.235**	-0.834	8.085*
	(4.244)	(2.513)	(4.270)
T+1	11.76*	-0.548	12.98**
	(6.410)	(5.774)	(6.601)
T+2	17.78**	7.162	21.16**
	(8.897)	(8.456)	(9.178)
T+3	21.92**	8.189	21.27**
	(10.06)	(10.48)	(10.66)
T+4	34.73***	23.17	32.84**
	(12.91)	(14.42)	(12.94)
T+5	55.58***	43.42**	51.01***
	(17.63)	(19.50)	(16.89)
T+6	66.47***	51.18*	60.73***
	(23.14)	(26.12)	(21.11)
T-1	13.87**		
	(5.906)		
T-2	6.432	-2.513	1.016
	(4.975)	(2.132)	(3.446)
T-3	6.754*	-5.876*	-0.433
	(4.092)	(3.570)	(3.609)
T-4	5.986	-6.168	-1.936
	(3.723)	(4.246)	(3.915)
T-5	2.857	-8.763*	-5.266
	(3.259)	(5.218)	(4.327)
T-6	0.924	-10.01	-8.200*
	(2.694)	(6.915)	(4.961)
N	5581		5841
Joint Pretrends Tests	0.1886	0.6708	-
Cummulative Effect	217.4763***	131.7352*	208.0846***
	(74.87823)	(79.91915)	(75.78552)
Likelihood Ratio Test	-	2.735011	.006077
Bayes Test	-	.5153427	.2331691

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with the outcome variable being the number of transfers performed by a clinic

Table 15: Results for Fresh Donor Transfers after the ACA

	(1) BJS	(2) CS	(3) OLS
	FshDnrTransfers	FshDnrTransfers	FshDnrTransfers
T+0	1.955	0.821	1.951
	(1.797)	(1.439)	(1.999)
T+1	2.104	0.124	1.771
	(2.439)	(2.041)	(2.622)
T+2	4.995	4.135	3.994
	(3.449)	(2.948)	(3.492)
T+3	5.450*	6.614*	4.258
	(3.203)	(3.816)	(3.264)
T+4	2.367	2.687	1.396
	(2.815)	(3.780)	(2.903)
T+5	-0.468	-0.00260	-0.549
	(2.815)	(4.008)	(2.870)
T+6	-2.487	-2.135	-2.060
	(2.882)	(4.032)	(2.796)
T-1	3.781		
	(2.649)		
T-2	3.212	-0.367	1.183
	(2.757)	(0.968)	(1.540)
T-3	1.945	-1.337	-0.196
	(1.877)	(1.617)	(1.089)
T-4	2.065	-0.941	-0.110
	(1.766)	(1.866)	(1.049)
T-5	2.088	-0.0482	0.407
	(1.661)	(2.213)	(1.046)
T-6	1.274	-2.651	-0.0375
	(1.206)	(2.289)	(1.272)
N	5581		5841
Joint Pretrends Tests	0.8814	0.6935	-
Cummulative Effect	13.91758	12.24232	10.76176
	(16.52966)	(17.34968)	(17.77223)
Likelihood Ratio Test	-	.4902608	.0158524
Bayes Test	-	.402329	.2454293

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with the outcome variable being the number of transfers performed by a clinic

Table 16: Results for Fresh Non-Donor Cycles after the ACA

	(1) BJS	(2) CS	(3) OLS
	FshNDCycle	FshNDCycle	FshNDCycle
T+0	8.056	-7.340	3.290
	(11.37)	(6.159)	(11.15)
T+1	5.172	-10.93	-1.872
	(13.70)	(11.10)	(13.28)
T+2	-7.971	-23.47*	-13.08
	(15.21)	(13.08)	(14.31)
T+3	-4.573	-23.87*	-16.30
	(14.78)	(13.06)	(14.84)
T+4	-6.506	-25.34	-17.13
	(15.55)	(15.74)	(15.40)
T+5	-16.75	-36.34**	-20.93
	(15.28)	(16.23)	(15.18)
T+6	-19.87	-42.06**	-23.47
	(17.91)	(19.19)	(17.15)
T-1	39.17**		
	(16.58)		
T-2	32.51**	4.068	12.47
	(16.11)	(7.253)	(9.020)
T-3	30.77**	-3.467	10.39
	(14.49)	(9.918)	(9.018)
T-4	9.771	-21.88**	-9.592
	(10.70)	(10.73)	(6.956)
T-5	8.995	-23.34*	-8.135
	(8.574)	(13.33)	(6.843)
T-6	10.55	-27.88*	-3.311
	(6.618)	(15.94)	(8.147)
N	5581		5841
Joint Pretrends Tests	0.0165	0.1527	-
Cummulative Effect	-42.43654	-169.3399**	-89.49992
	(89.27934)	(77.92534)	(90.41905)
Likelihood Ratio Test	-	7.230981	.002949
Bayes Test	-	.4569241	.2428077

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 1 with the outcome variable being the number of cycles performed by a clinic

Table 17: Results for Thawed Donor Births after SSM legalization

	(1) BJS ThwDnrLvBirths	(2) CS ThwDnrLvBirths	(3) OLS ThwDnrLvBirths
T+0	1.630**	0.857*	0.965
	(0.751)	(0.449)	(0.633)
T+1	4.245***	2.445**	3.564***
	(1.432)	(1.098)	(1.322)
T+2	3.098	2.285	2.501
	(2.016)	(1.835)	(1.698)
T+3	1.176	1.067	0.779
	(1.794)	(1.777)	(1.510)
T-1	1.877*		
	(1.131)		
T-2	0.793	-0.0719	
	(0.657)	(0.394)	
T-3	0.0537	-0.750	-0.481**
	(0.321)	(0.549)	(0.242)
N	4872		4923
Joint Pretrends Tests	0.1491	0.8230	-
Cummulative Effect	10.14901**	6.654461*	7.809262*
	(4.581325)	(3.91563)	(4.097264)
Likelihood Ratio Test	-	9.20e-24	3.197798
Bayes Test	-	0	.2192322

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 without transfers

Table 18: Results for Thawed Non-Donor Births after SSM legalization

	(1) BJS ThwNDLvBirths	(2) CS ThwNDLvBirths	(3) OLS ThwNDLvBirths
T+0	3.721	0.444	-1.000
	(2.569)	(1.368)	(2.561)
T+1	7.644*	3.242	3.704
	(4.588)	(3.193)	(4.499)
T+2	9.636	9.860*	4.919
	(6.094)	(5.491)	(5.644)
T+3	12.75	8.671	5.002
	(8.616)	(10.21)	(7.760)
T-1	10.30**		
	(4.551)		
T-2	5.262**	-1.703	-1.994*
	(2.503)	(1.474)	(1.030)
T-3	1.769	-4.005*	-2.241**
	(1.099)	(2.212)	(0.956)
N	4872		4923
Joint Pretrends Tests	0.1796	0.0780	-
Cummulative Effect	33.75122*	22.21673	12.62579
	(17.55302)	(16.3046)	(17.01749)
Likelihood Ratio Test	-	.0001726	1.983629
Bayes Test	-	5.29e-06	.2184894

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 without transfers

Table 19: Results for Fresh Donor Births after SSM legalization

	(1) BJS	(2) CS	(3) OLS
	FshDnrBirths	FshDnrBirths	FshDnrBirths
T+0	0.179	-1.260*	0.531
	(0.702)	(0.717)	(0.641)
T+1	-1.183	-4.365**	-0.759
	(1.091)	(2.112)	(1.021)
T+2	-1.412	-2.331	-0.794
	(1.950)	(2.512)	(1.681)
T+3	-1.338	-1.500	-1.095
	(1.872)	(2.004)	(1.546)
T-1	3.036		
	(1.972)		
T-2	1.644	0.112	0.118
	(1.182)	(0.612)	(0.383)
T-3	0.673	-0.302	-0.249
	(0.609)	(0.739)	(0.363)
N	4872		4923
Joint Pretrends Tests	0.5437	0.0058	-
Cummulative Effect	-3.753989	-9.455572*	-2.117154
	(4.242298)	(5.336288)	(3.769042)
Likelihood Ratio Test	-	2.47e-48	.04115352
Bayes Test	-	0	.21926385

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 without transfers

Table 20: Results for Fresh Non-Donor Births after SSM legalization

	(1) BJS FshNDLvBirths	(2) CS FshNDLvBirths	(3) OLS FshNDLvBirths
T+0	-0.179	1.595	2.485
	(2.078)	(1.400)	(2.665)
T+1	-3.630	-1.087	-0.693
	(2.995)	(3.156)	(3.451)
T+2	-0.952	-5.871	0.166
	(5.481)	(5.556)	(5.019)
T+3	-2.491	-1.772	-1.419
	(8.350)	(8.291)	(6.934)
T-1	2.852		
	(5.632)		
T-2	4.152	1.552	1.852
	(3.914)	(1.546)	(1.370)
T-3	3.740	4.478^{**}	1.842
	(2.413)	(2.226)	(1.176)
N	4872		4923
Joint Pretrends Tests	0.1373	0.2354	-
Cummulative Effect	-7.252714	-7.135121	.5390946
	(15.993)	(14.89641)	(15.72464)
Likelihood Ratio Test	-	0	.0006934
Bayes Test	-	0	.2180094

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 without transfers

Table 21: Results for Thawed Donor Births controlling for Transfers after SSM legalization

	(1) BJS	(2) CS	(3) OLS
	ThwDnrLvBirths	ThwDnrLvBirths	ThwDnrLvBirths
T+0	0.636**	0.493	0.281
	(0.252)	(0.570)	(0.229)
T+1	1.223**	0.872	0.726*
	(0.521)	(1.327)	(0.431)
T+2	0.390	1.154	0.142
	(0.944)	(1.576)	(0.764)
T+3	-0.323	-1.301	-0.427
	(0.826)	(1.798)	(0.759)
T-1	0.0866		
	(0.359)		
T-2	-0.179	0.133	-0.190
	(0.275)	(0.377)	(0.137)
T-3	-0.282	-0.187	-0.177
	(0.198)	(0.601)	(0.168)
Transfers	0.384***		0.399***
	(0.00958)		(0.0149)
N	4872		4923
Joint Pretrends Tests	0.2273	0.8267	-
Cummulative Effect	1.926038	1.217898	.7223082
	2.064874	4.018199	1.768408
Likelihood Ratio Test	-	7.27e-43	1.228136
Bayes Test	-	0	.2209806

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 controlling for the type of transfer used for that birth type

Table 22: Results for Thawed Non-Donor Births controlling for Transfers after SSM legalization

	(1) BJS ThwNDLvBirths	(2) CS ThwNDLvBirths	(3) OLS ThwNDLvBirths
T+0	1.200	-0.718	-0.107
	(0.935)	(1.464)	(1.096)
T+1	0.165	0.962	-1.018
	(1.371)	(3.071)	(1.267)
T+2	-2.918	2.934	-2.753
	(2.892)	(5.641)	(2.223)
T+3	-5.718	-5.390	-5.364**
	(3.525)	(12.82)	(2.719)
T-1	0.114		
	(1.343)		
T-2	-0.995	-0.281	-0.290
	(0.991)	(1.273)	(0.493)
T-3	-1.085	-2.291	-0.345
	(0.708)	(1.769)	(0.429)
Transfers	0.459***		0.442***
	(0.0343)		(0.0360)
N	4872		4923
Joint Pretrends Tests	0.0705	0.0787	-
Cummulative Effect	-7.272831	-2.211717	-9.242689
	7.702858	18.84952	6.221199
Likelihood Ratio Test	-	3.22e-15	.101855
Bayes Test	-	9.92e-15	.2189528

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 controlling for the type of transfer used for that birth type

Table 23: Results for Fresh Donor Births controlling for Transfers after SSM legalization

	(1) BJS	(2) CS	(3) OLS
	FshDnrBirths	FshDnrBirths	FshDnrBirths
T+0	0.261	0.280	-0.0638
	(0.234)	(0.670)	(0.218)
T+1	-0.180	-1.726	-0.681*
	(0.419)	(1.171)	(0.394)
T+2	-0.597	0.463	-0.895
	(0.868)	(2.362)	(0.727)
T+3	0.895	1.189	-0.100
	(0.815)	(2.318)	(0.647)
T-1	0.451		
	(0.451)		
T-2	0.315	-0.230	0.0944
	(0.332)	(0.721)	(0.178)
T-3	0.130	-0.871	0.0133
	(0.227)	(0.776)	(0.165)
Transfers	0.512***		0.502***
	(0.0188)		(0.0199)
N	4872		4923
Joint Pretrends Tests	0.8387	0.0301	-
Cummulative Effect	.3784268	.2055635	-1.739686
	1.911964	4.730347	1.58745
Likelihood Ratio Test	-	9.8e-108	.0055485
Bayes Test	-	0	.219707

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These are the results for equation 2 controlling for the type of transfer used for that birth type

Table 24: Results for Thawed Donor Transfers after SSM legalization

	(1) BJS ThwDnrTrans	(2) CS ThwDnrTrans	(3) OLS ThwDnrTrans
T+0	2.591	0.836	1.712
	(1.704)	(0.954)	(1.417)
T+1	7.874**	2.441	7.111**
	(3.238)	(2.588)	(3.034)
T+2	7.054*	4.748	5.910
	(4.244)	(4.106)	(3.640)
T+3	3.906	2.999	3.022
	(4.351)	(4.252)	(3.750)
T-1	4.668*		
	(2.647)		
T-2	2.535*	-0.0774	-0.728
	(1.533)	(0.729)	(0.525)
T-3	0.875	-1.190	-1.021*
	(0.727)	(1.111)	(0.534)
N	4872		4923
Joint Pretrends Tests	0.3910	0.0157	-
Cummulative Effect	21.42504*	11.02432*	17.75553
	(10.46549)	(9.506868)	(9.577514)
Likelihood Ratio Test	-	3.00e-30	.2538061
Bayes Test	-	0	.2182591

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 with the outcome variable being the number of transfers performed by a clinic

Table 25: Results for Thawed Non-Donor Transfers after SSM legalization

	(1) BJS ThwNDTransfers	(2) CS ThwNDTransfers	(3) OLS ThwNDTransfers
T+0	5.497	0.291	-2.019
	(5.527)	(2.835)	(5.921)
T+1	16.31	8.367	10.68
	(9.956)	(6.394)	(10.15)
T+2	27.37*	26.13**	17.35
	(16.02)	(12.33)	(14.73)
T+3	40.26*	28.08	23.45
	(20.79)	(20.70)	(19.20)
T-1	22.22**		
	(10.27)		
T-2	13.64**	-2.135	-3.855*
	(6.599)	(2.777)	(2.226)
T-3	6.223*	-5.302	-4.288**
	(3.507)	(4.311)	(2.162)
N	4872		4923
Joint Pretrends Tests	0.2129	0.4774	-
Cummulative Effect	89.43508	62.87277*	49.46271
	(44.72415)	(34.54731)	(44.31108)
Likelihood Ratio Test	-	2.67e-57	1.148695
Bayes Test	-	0	.2185228

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 with the outcome variable being the number of transfers performed by a clinic

Table 26: Results for Fresh Donor Transfers after SSM legalization

	(1) BJS FshDnrTransfers	(2) CS FshDnrTransfers	(3) OLS FshDnrTransfers
T+0	-0.160	-3.030**	1.183
	(1.445)	(1.328)	(1.380)
T+1	-1.960	-7.972*	-0.155
	(1.986)	(4.262)	(1.975)
T+2	-1.593	-3.378	0.201
	(3.713)	(4.331)	(3.162)
T+3	-4.364	-5.927*	-1.981
	(3.385)	(3.206)	(2.734)
T-1	5.054		
	(3.776)		
T-2	2.599	-0.416	0.0467
	(2.219)	(0.892)	(0.619)
T-3	1.061	-1.048	-0.522
	(1.043)	(1.270)	(0.655)
N	4872		4923
Joint Pretrends Tests	0.5750	0.3294	-
Cummulative Effect	-8.076784	-20.30662	-.7515251
	(8.058841)	(9.434811)	(7.337556)
Likelihood Ratio Test	-	1.3e-128	.009236
Bayes Test	-	0	.2190947

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 with the outcome variable being the number of transfers performed by a clinic

Table 27: Results for Fresh Non-Donor Cycles after SSM legalization

	(1) BJS	(2) CS	(3) OLS
	FshNDCycle	FshNDCycle	FshNDCycle
T+0	0.0503	5.170	10.11
	(6.722)	(4.264)	(8.517)
T+1	-8.832	-5.468	4.981
	(10.35)	(8.650)	(12.07)
T+2	9.685	-6.984	15.47
	(22.56)	(20.95)	(19.16)
T+3	19.86	2.408	24.56
	(33.23)	(36.89)	(27.74)
T-1	19.82		
	(22.36)		
T-2	24.22	9.820**	7.240*
	(16.06)	(3.978)	(3.923)
T-3	15.79*	9.532	1.705
	(9.389)	(6.077)	(3.503)
N	4872		4923
Joint Pretrends Tests	0.0135	0.0000	
Cummulative Effect	20.76061	-4.873671	55.11734
	(57.45522)	(56.49719)	(52.81132)
Likelihood Ratio Test	-	0	.000104
Bayes Test	-	0	.2188587

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 with the outcome variable being the number of cycles performed by a clinic

Table 28: Results For Thawed Donor Births after SSM using states with insurance mandates

	(1) BJS	(2) CS	(3) OLS
	ThwDnrLvBirths	ThwDnrLvBirths	ThwDnrLvBirths
T+0	2.229**	0.997*	1.064
	(1.103)	(0.576)	(0.901)
T+1	3.990**	2.515*	3.084**
	(1.667)	(1.293)	(1.410)
T+2	2.934	2.690	2.011
	(2.138)	(1.871)	(1.672)
T+3	1.152	1.053	0.345
	(2.146)	(2.051)	(1.774)
T-1	1.900		
	(1.253)		
T-2	0.484	-0.409	-0.782**
	(0.769)	(0.473)	(0.362)
T-3	0.355	-0.931	-0.448
	(0.394)	(0.695)	(0.311)
N	2520		2586
Joint Pretrends Tests	0.1923	0.7347	-
Cummulative Effect	10.23794*	7.245148*	6.42256
	(5.472561)	(4.280774)	(4.433462)
Likelihood Ratio Test		3.30e-14	11.14575
Bayes Test		8.69e-14	.2200774

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and is limited to only the states that had insurance mandates before the ACA

Table 29: Results For Thawed Non-Donor Births after SSM using states with insurance mandates

	(1) BJS	(2) CS	(3) OLS
	ThwNDLvBirths	ThwNDLvBirths	ThwNDLvBirths
T+0	2.421	0.630	-3.488
	(3.862)	(1.807)	(3.845)
T+1	3.181	3.501	-0.795
	(6.582)	(3.852)	(5.517)
T+2	9.516	13.41**	2.695
	(7.584)	(6.623)	(6.921)
T+3	9.428	17.56	0.788
	(10.73)	(12.96)	(9.165)
T-1	9.304		
	(5.682)		
T-2	5.913*	-0.829	-1.463
	(3.345)	(2.192)	(1.782)
T-3	3.201**	-2.776	-1.167
	(1.547)	(3.442)	(1.273)
N	2520		2586
Joint Pretrends Tests	0.3000	0.0089	-
Cummulative Effect	23.99968	35.11832*	-1.268116
	(24.25116)	(19.71655)	(21.6713)
Likelihood Ratio Test	0	.0101971	.3444457
Bayes Test	0	.0206256	.2199504

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and is limited to only the states that had insurance mandates before the ACA

Table 30: Results For Fresh Donor Births after SSM using states with insurance mandates

	(1) BJS FshDnrBirths	(2) CS FshDnrBirths	(3) OLS FshDnrBirths
T+0	0.557	-1.883*	1.032
	(1.023)	(1.048)	(0.947)
T+1	-0.858	-4.098*	-0.175
	(1.142)	(2.453)	(1.071)
T+2	0.700	0.0299	1.284
	(1.826)	(1.690)	(1.387)
T+3	-1.994	-2.164	-0.876
	(2.211)	(2.304)	(1.833)
T-1	3.313		
	(2.307)		
T-2	1.495	0.0438	0.232
	(1.463)	(0.866)	(0.646)
T-3	0.823	-0.753	-0.285
	(0.914)	(1.117)	(0.531)
N	2520		2586
Joint Pretrends Tests	0.5098	0.2653	-
Cummulative Effect	-1.848185	-8.117275	.8763534
	(4.776219)	(5.350508)	(4.054617)
Likelihood Ratio Test	0	5.50e-21	.0176165
Bayes Test	0	0	.2197056

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and is limited to only the states that had insurance mandates before the ACA

Table 31: Results For Fresh Non-Donor Births after SSM using states with insurance mandates

	(1) BJS FshNDLvBirths	(2) CS FshNDLvBirths	(3) OLS FshNDLvBirths
T+0	2.805	2.542	3.972
	(3.042)	(2.092)	(4.362)
T+1	-0.450	0.469	1.730
	(3.887)	(3.720)	(4.554)
T+2	1.367	-5.237	1.789
	(7.672)	(6.649)	(7.159)
T+3	-1.115	-7.323	-0.342
	(9.734)	(9.600)	(8.414)
T-1	4.276		
	(8.442)		
T-2	4.644	2.824	1.705
	(5.909)	(2.177)	(2.461)
T-3	2.537	3.435	0.235
	(4.098)	(3.396)	(1.867)
N	2520		2586
Joint Pretrends Tests	0.7525	0.1378	-
Cummulative Effect	1.843262	-9.564181	5.3635
	(20.83323)	(17.74274)	(21.53066)
Likelihood Ratio Test	0	4.06e-70	.0070579
Bayes Test	0	0	.2188746

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and is limited to only the states that had insurance mandates before the ACA

Table 32: Results For Thawed Donor Births after SSM at the City Level

	(1) BJS ThwDnrLvBirths	(2) CS ThwDnrLvBirths	(3) OLS ThwDnrLvBirths
T+0	1.628**	0.857**	0.958
	(0.714)	(0.433)	(0.615)
T+1	4.243***	2.444**	3.556***
	(1.380)	(1.107)	(1.301)
T+2	3.088**	2.285	2.490
	(1.559)	(1.743)	(1.601)
T+3	1.167	1.070	0.770
	(1.126)	(1.718)	(1.241)
T-1	1.828		
	(1.122)		
T-2	0.752	-0.0719	-0.490**
	(0.667)	(0.400)	(0.226)
T-3	0.0322	-0.750	-0.584**
	(0.314)	(0.582)	(0.241)
N	4872		4923
Joint Pretrends Tests	0.1723	0.0678	-
Cummulative Effect	10.1256***	6.656579*	7.773579**
	3.423213	3.614757	3.679595
Likelihood Ratio Test	-	3.87e-18	6.527875
Bayes Test	-	1.21e-16	.219768

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and are clustered at the City Level.

Table 33: Results For Thawed Non-Donor Births after SSM at the City Level

	(1) BJS	(2) CS	(3) OLS
	ThwNDLvBirths	ThwNDLvBirths	ThwNDLvBirths
T+0	3.695	0.447	-1.041
	(2.592)	(1.346)	(2.543)
T+1	7.620*	3.244	3.657
	(4.401)	(2.927)	(4.487)
T+2	9.584**	9.867*	4.863
	(4.698)	(5.234)	(6.195)
T+3	12.70**	8.697	4.952
	(5.278)	(9.121)	(8.315)
T-1	10.05**		
	(4.247)		
T-2	5.064**	-1.702	-2.037*
	(2.194)	(1.595)	(1.100)
T-3	1.666*	-4.003*	-2.235**
	(0.922)	(2.261)	(0.989)
N	4872		4923
Joint Pretrends Tests	0.1226	0.0000	-
Cummulative Effect	33.59496*	22.25516	12.43046
	12.90555	14.45677	18.45426
Likelihood Ratio Test	-	3.61e-07	2.049473
Bayes Test	-	2.33e-08	.2186581

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and are clustered at the City Level.

Table 34: Results For Fresh Donor Births after SSM at the City Level

	(1) BJS FshDnrBirths	(2) CS FshDnrBirths	(3) OLS FshDnrBirths
T+0	0.173	-1.259*	0.493
	(0.673)	(0.740)	(0.627)
T+1	-1.188	-4.363**	-0.804
	(1.092)	(2.225)	(1.129)
T+2	-1.463	-2.321	-0.850
	(1.934)	(2.893)	(1.978)
T+3	-1.378	-1.488	-1.142
	(1.189)	(1.415)	(1.010)
T-1	2.732		
	(1.789)		
T-2	1.386	0.113	0.0550
	(1.019)	(0.633)	(0.398)
T-3	0.531	-0.300	-0.256
	(0.543)	(0.700)	(0.373)
N	4872		4923
Joint Pretrends Tests	0.4851	0.0007	-
Cummulative Effect	-3.856147	-9.431413*	-2.303694
	3.547228	5.433434	3.709347
Likelihood Ratio Test	-	8.39e-48	.0068264
Bayes Test	-	0	.2184164

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and are clustered at the City Level.

Table 35: Results For Fresh Non-Donor Births after SSM at the City Level

	(1) BJS	(2) CS	(3) OLS
	FshNDLvBirths	FshNDLvBirths	FshNDLvBirths
T+0	-0.174	1.599	2.309
	(1.847)	(1.400)	(1.844)
T+1	-3.625	-1.078	-0.914
	(2.560)	(3.182)	(2.492)
T+2	-1.200	-5.811	-0.120
	(4.604)	(6.237)	(4.744)
T+3	-2.661	-1.691	-1.648
	(7.103)	(9.804)	(6.883)
T-1	1.284		
	(4.447)		
T-2	2.798	1.557	1.513
	(2.970)	(1.529)	(1.077)
T-3	2.988	4.502**	1.790
	(1.965)	(2.151)	(1.092)
N	4872		4923
Joint Pretrends Tests	0.1373	0.0331	-
Cummulative Effect	-7.660301	-6.980973	-.3725018
	13.35514	17.48046	13.00371
Likelihood Ratio Test	-	7.9e-139	.0006288
Bayes Test	-	0	.2187843

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results use equation 2 without transfers and are clustered at the City Level.

Table 36: Results for Number of Clinics in a City after the ACA

	(1) BJS	(2) OLS
	howmanycity	howmanycity
T+0	0.183	0.0941
	(0.149)	(0.142)
T+1	0.317	0.201
	(0.200)	(0.201)
T+2	0.287*	0.170
	(0.150)	(0.138)
T+3	0.337**	0.207
	(0.149)	(0.142)
T+4	0.240*	0.104
	(0.136)	(0.119)
T+5	0.287*	0.146
	(0.162)	(0.151)
T+6	0.265	0.118
	(0.167)	(0.162)
T-1	0.399*	
	(0.241)	
T-2	0.140	-0.0778
	(0.155)	(0.105)
T-3	0.0107	-0.191
	(0.132)	(0.173)
T-4	0.171	-0.0279
	(0.169)	(0.0877)
T-5	0.153	-0.0441
	(0.132)	(0.125)
T-6	0.125	-0.0687
	(0.0808)	(0.0823)
N	5947	6107
Joint Pretrends Tests	0.4336	-
Cummulative Effect	1.9165*	1.0391
	(0.9966)	(0.9366)
Likelihood Ratio Test	-	0.1348
Bayes Test	-	0.2467

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Note: These results display the results from equation 3 for the ACA.

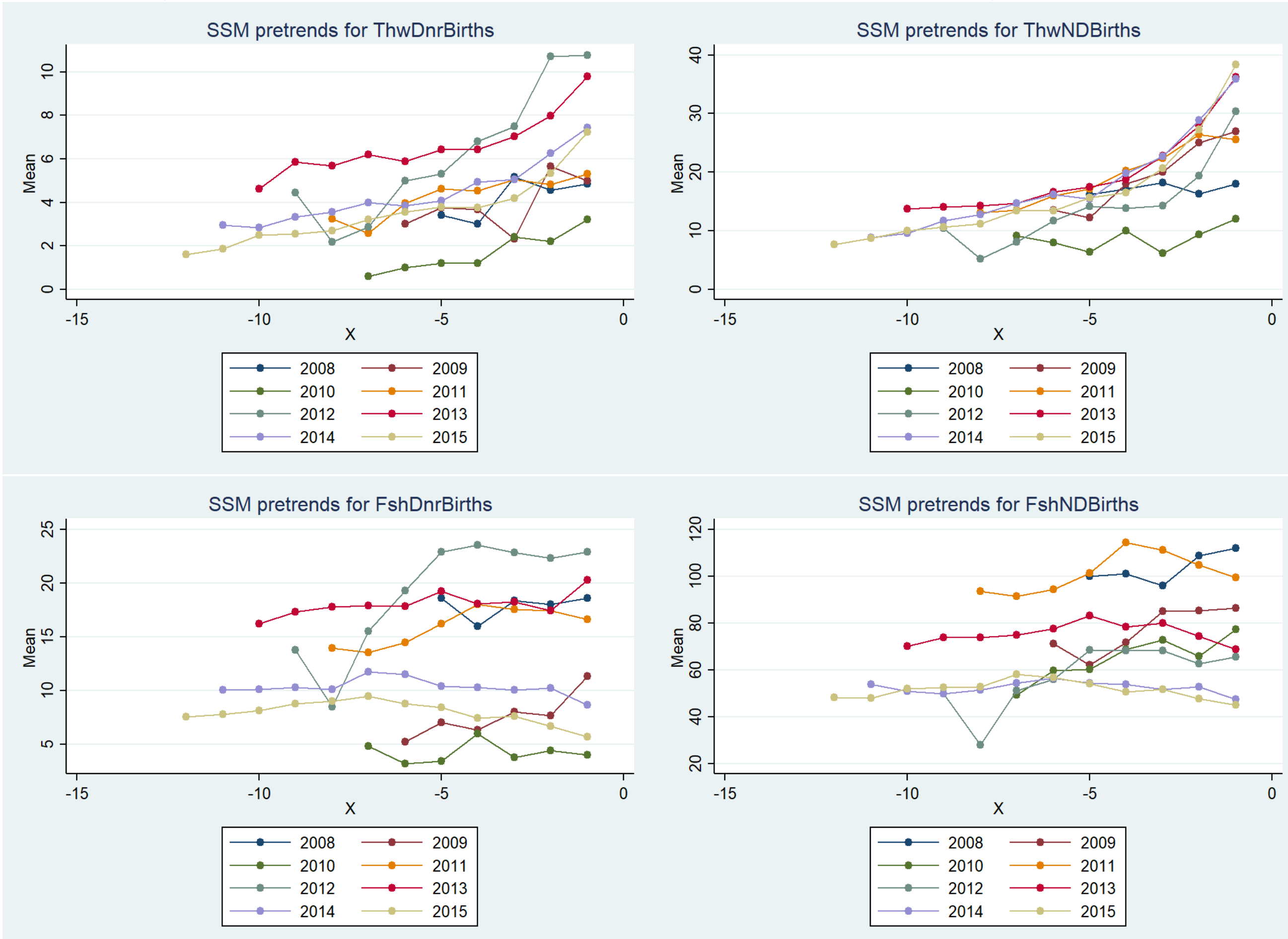
Table 37: Results for Number of Clinics in a City after SSM Legalization

	(1) BJS howmanycity	(2) OLS howmanycity
T+0	0.0956	0.155
	(0.0898)	(0.192)
T+1	0.120	0.185
	(0.110)	(0.190)
T+2	0.373***	0.323
	(0.125)	(0.269)
T+3	0.0162	0.0273
	(0.101)	(0.163)
T-1	0.444	
	(0.375)	
T-2	0.318	-0.00755
	(0.283)	(0.0475)
T-3	0.164	-0.0772
	(0.121)	(0.0787)
N	5089	5183
Joint Pretrends Tests	0.2480	-
Cummulative Effect	0.6043	0.6912
	(0.3751)	(0.7916)
Likelihood Ratio Test	-	0.0716
Bayes Test	-	0.2208

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

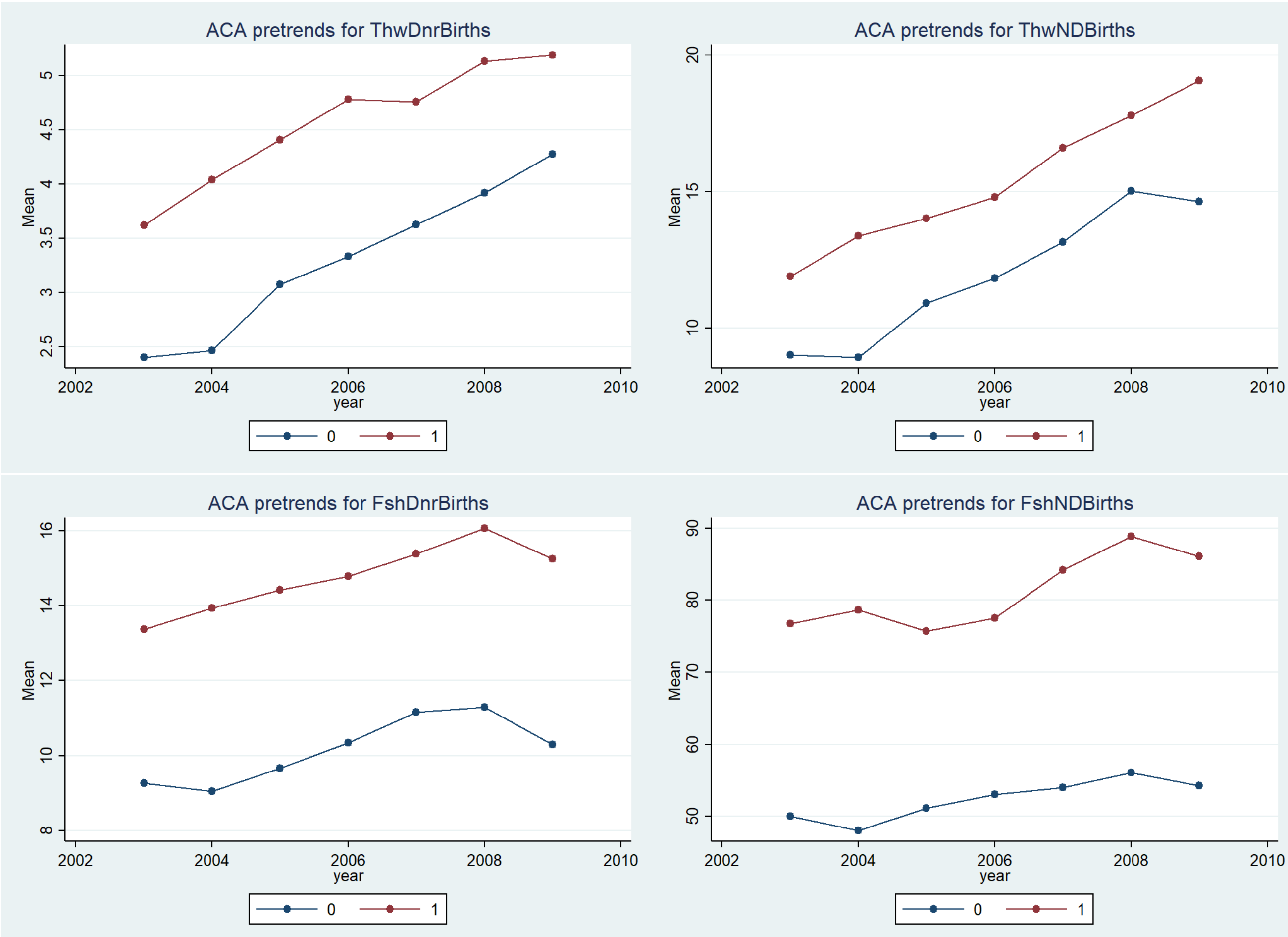
Note: These results display the results from equation 3 for SSM legalization.

Figure 7: Trends for the different types of births before SSM legalization



Note: These charts show the trends by year of legalization before SSM legalization. These show that there are very similar pretrends across the four birth types.

Figure 8: Trends for the different types of births before the ACA



Note: These charts show the trends by whether they have insurance mandates in place or not before passage of the ACA. These show that there are very similar pretrends across the four birth types.