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 (ART) 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

Since the birth of Louise Brown, the first baby born as a result of in vitro fertilization (IVF), IVF has become a cornerstone in the fertility industry. Over the past few decades, the use of IVF has expanded rapidly, now representing over 99% of Assisted Reproductive Technology (ART) procedures in the United States (US Dept of Health and Human Services, 2024). ART is a family of procedures with the goal to help those with a uterus to conceive. This is particularly important, since ART is necessary for the percentage of the population who are unable to conceive due to various reasons related to infertility. In light of declining U.S. fertility rates, the importance of ART in supporting population growth and addressing demographic challenges cannot be understated.

In this paper, I look into two laws/policies through the lense of their effects on Assistive Reproductive Technology (ART) clinics within the United States. 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 that mandated insurance coverage of ART treatments. This will cause an increase in usage of these programs from the individuals that now have coverage. The policy's overall impact can lead to one of two outcomes. The first is that mandated insurance coverage will cause higher ART usage, but will not have excessive increases in consumer costs (Griffin and Panak, 1998). The second possibility is that the increase in insurance coverage will cause an increase in treatment and birth costs (Hamilton et al., 2018). If the pool of individuals recieving ART through insurance is smaller than those who do not use insurance, this can cause those individuals to leave the market in larger numbers than the individuals who are gaining expanded insurance coverage. That being said, most states have a maximum monetary amount they cover, which will likely cap these price increases.

The second law I looked at is Same-Sex Marriage (SSM) legalization, which occurred on a state-by-state level, but was nationally legalized through a supreme court judicial ruling in 2015. This policy enabled same-sex couples to formalize their unions, which may have implications for both their financial capabilities (through their partner's insurance/tax benefits) and their desires to pursue parenthood (the ability to have both parents be listed on the child's birth certificate). By definition, cisgendered same-sex couples are unable to concieve on their own. Therefore, same-sex couples use ART clinics to help them recieve reproductive material that has been donated by individuals who are of a different sex. This material is then implanted into one of the parents, or a surrogate[1]. This is expected to increase the amount of births through one of three mechanisms. The most likely mechanism is from married couples saving through marriage benefits such as tax breaks which gave same-sex couples money to spend on ART procedures. The second mechanism is the extension of private insurance coverage to spouses, potentially offering better ART coverage and thus allowing more individuals to use these procedures. The last mechanism is that married couples are likely to experience an increase in demand for a new child and through this we simply see a rightward shift of demand.

To evaluate the impacts of these policies, I use previously unlinked yearly data obtained from ART clinics mandatory reporting to the Centers for Disease Control (CDC) from 2004 to 2016. This data is a near population of clinics in the US with information on types of procedures used, location of clinics, transfers[2], and births that occured as a result of those transfers. After linking the clinics across years, I can identify which clinics are located in states where SSM had been legalized and which clinics were in states that had their insurance mandates expanded by the ACA.

To quantify both of these policies, I use a difference-in-differences approach tailored to each individual policy. For the ACA, I take advantage of the simple timing that the ACA passed in 2010. Treated states are the states that had insurance mandates for ART before 2010 and then had their mandates expanded to Medicaid, while the control group are states that did not have insurance mandates for ART. This model is to examine the impact of the

[1]Surrogates are individuals who are often paid to carry another couple's child. This is often due to the type of fertility issue that is occuring. Same-sex men (Who are CIS-gendered) must participate in surrogacy to concieve.

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

ACA on births that resulted from procedures in ART clinics.

For this model, I find results that the ACA causes increases of 114-119 births per clinic over 7 years for births that occured from thawed ART procedures. This occurs because thawed procedures are considerably cheaper when compared to fresh procedures in ART clinics (Elite IVF: A Global IVF Agency, 2024). This is because they only need one procedure to harvest the eggs to later be used for these procedures. This is prevalent, because states have caps on the amount of coverage that these insurance mandates are required to provide.

On the other hand, for SSM legalization, I consider a state treated if SSM is legalized and is not later made illegal, and the control states are those in which SSM is not permanently legal. This means that by 2015, due to the supreme court decision, all states become treated at this time. Due to the differential timing of the legalization of SSM I employ a staggered difference-in-difference model to examine the effects of this policy on births that occured from procedures in ART clinics.

I find evidence that after SSM, ART clinics see an increase in thawed donor births of between 6-10 births per clinic over 4 years. This is likely because thawed procedures are cheaper and because donated material is necessary for same-sex couples to give birth to a child. This gives evidence that the increases in births from this legalization is from same-sex individuals. This effect, however, appears transient, with demand for ART treatments returning to pre-policy levels after approximately two years.

From here I rerun both models, and include the type of transfer for each birth method as a control. This was performed with the intention of seeing whether births would still increase after controlling for the number of transfers at that individual clinic.

These models only show increases in thawed donated births for the SSM model, but no results for any other SSM model, or any of the ACA models. Since a transfer is necessary for a birth to occur, increases in births that have smaller increases in transfers 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 in comparison 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). This points to a more healthy group of individuals having birth using the thawed, donated methods which is most likely attributable to same-sex couples deciding to use ART birth methods more often.

After this I exploit the timings of both of these policies again to test whether the number of clinics in a city change after each policy. From this, I see that after the ACA the number of clinics per city does have a general increase of about 2 clinics over seven years. At the same time, two years after SSM there was a one year increase of about 0.3 clinics per city. This may have contributed to the percieved exhaustion of demand, since new clinics opened up to accomodate the new demand.

I also test to see if my results change when I retest the model for SSM using only states that had insurance mandates for ART. [3]The result of this test show the same estimate results as the model with all states, which provides evidence that this impact is not specifically diven by states with insurance mandates.

This paper contributes to the literature on the effect of insurance mandates on individuals using ART which is discussed in more detail in Section 3.1. Other papers look at information adjacent to these insurance mandates which look at changes in health care expenditures (Boulet et al., 2019), and the impact of not allowing insurance coverage to these individuals (Bogl et al., 2024). I complement this literature through my analyses of the ACA which specifically expanded the coverage requirements of states with insurance mandates to cover a larger population of individuals.

My paper also relates to the literature for the intersection of fertility and SSM legalization which is discussed in more detail in Section 3.2. Relating to general SSM papers, most find that SSM led to significant tax breaks and savings through taking their partner's health insurance (Downing and Cha, 2020; Friedberg and Isaac, 2024; Piano, Behr

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

and West, 2023). Papers also find increases in labor supply, large financial investments and increases in employer-sponsored health insurance coverage (Hansen, Martell and Roncolato, 2019; Downing and Cha, 2020). My paper compliments this literature as it looks into whether these impacts to households through this policy encouraged households to make larger financial/health investments in fertility decisions.

The rest of this paper is organized as follows. Section 2 is split into two subsections and discusses the backgrounds of these two policies (ACA in Section 2.1, and SSM in Section 2.2). Section 3 has a more in depth literature review of the two policies (ACA in Section 3.1, and SSM in Section 3.2). In Section 4, I describe the data I use in this study, and Section 5 explains how I use this data to form my research design and estimation strategy. Section 6 examines and explains my results from my data set in depth, and Section 7 concludes the paper and reviews my paper's contributions.

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.

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 this was accomplished 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.

Using variation in timing and across states, I study which states have insurance mandates that have been expanded (Resolve: The National Infertiity Association, 2023).

One potential complication in this timing occured right away. A supreme court challenge to the ACA led to it being blocked until 2012. Despite this, I still set the level of legalization to 2010 to avoid issues with anticipation. Another potential pitfall is that full access to many of the benefits from the ACA did not rollout until 2014. This does cause some states not to rollout these policies until approximately two or four years after the 2010. Therefore, I think some of results are attributed to private companies covering the procedure, ahead of the anticipated changes to IVF for public insurances. Unfortunately, with my data, I cannot fully untangle where the full effect comes from, as another possibility is that the results are simply a combination of the ACA and SSM legalization, both of which are explored in detail in this paper.

I also 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 through 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 in 2010	Arkansas, California, Connecticut, Hawaii, Illinois, Louisiana, Maryland, Massachusetts, Montana, New Jersey, New York, Ohio, Rhode Island, Texas, West Virginia
Never Treated	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. A state becomes treated if the state mandated coverage of IVF, and these benefits were expanded 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 number of same-sex couples decided to quickly get married. This led to changes in insurance coverage for both spouses and the ability to seek insurances which covered IVF.

I use the timing of SSM legalization to test whether the states that have legalized SSM experienced an increased use of IVF.

One more thing to note for estimation purposes is that 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, where some states began legalizing in 2004 while others legalized later. By 2015 a supreme court decision forced all states that had not yet done so to legalize SSM immediately (see table 2). 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. In this paper I study the general impact of insurance mandates on IVF. 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).

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., 2016). 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 adoption of LGBT+ individuals is scarce.

Most previous papers looking into changes in SSM and 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 having 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 as(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.

The first limitation is that after 2016, the data values were censored 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 related to this procedure recorded before then. This could be due to the CDC not requesting the information or poor reporting

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

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 for completeness.

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

Table 3: Summary Statistics for IVF Clinics

Clinic Information	Average	Standard Deviation
Frozen Donor Transfers	15.400	30.215
Frozen Non-Donor Transfers	75.990	140.918
Fresh Donor Transfers	20.421	39.630
Fresh Non-Donor Cycles	216.537	328.080
Frozen Donor Births	5.459	12.356
Frozen Non-Donor Births	28.855	66.528
Fresh Donor Births	11.125	21.621
Fresh Non-Donor Births	62.115	94.585
Allow Single Women	0.938	0.245
Have Accreditation	0.920	0.271
Accreditation Pending	0.023	0.151
Use Donor Embryos	0.679	0.467
Use Donor Eggs	0.927	0.259
Allow Surrogates	0.833	0.373
Follow ACA Insurance Mandates	0.524	0.500
Clinics Total (2003-2016)	5929	

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

In this paper I make use of a difference-in-difference approach to identify the impact of both the ACA and SSM legalization on ART clinics in the US. These approaches vary based on the policy, due to them each occuring in a different way. Below I use the linked ART-clinic data discussed in section 4 to create different models for both policies. I use not yet and never treated clinics together as my control group to look at the effect of these policies.

5.1 Affordable Care Act (ACA)

I begin with the ACA, and I compare the three birth methods before and after the policy is implemented. I use states that have ART coverage insurance mandates that were expanded through passage of the ACA as my treated group and I use states that never had those mandates as the control group. In this setting, treatment occurs in 2010 or does not occur at all. As a result, this test uses a simple OLS event study and the Borusyak, Jaravel, and Spiess (BJS) difference in difference imputation estimator (Borusyak, Jaravel and Speiss, 2024). This uses both, as BJS is consistant with OLS and can be more accurate in a non-staggered setting. The bounds of this event study model are from 2004 to 2016 due to data restrictions. This model can be written as:

$$Births_{i,s,t} = \sum_{k=-6}^{K} \beta_k (1)\{t - 2010 = k\}(ART_s) + \lambda_i + \delta_t + \varepsilon_{it} \quad (1)$$

The independent variable in this model are the births that occur in clinic (i), in state (s) at time (t). This model's variable of interest is the β at time in relation to the treatment (k). ART is a variable that is 1 after the ACA is passed in states with an insurance mandate to cover IVF, and is 0 otherwise. This model also has clinic-level (λ), and time-level (δ) fixed effects.

This model uses a very simple difference-in-difference framework. The methods to estimate these results uses ordinary least squares (OLS) and the Borusyak, Jaravel, and Spiess (BJS) difference in difference imputation estimator (Borusyak, Jaravel and Speiss, 2024). These methods are both consistent with the standard difference in difference methods.

These group treatment effects are reported using an event study approach. These results compare the clinics in states where the ACA has occured (treatment) and the clinics in states where the policy had not yet occured (control) in the years after it's passage in 2010. Section

6 reports the results for this model in more detail and further results. The Appendix also estimates this model while replacing the independent variable births with transfers at the clinic level.

5.2 Same-Sex Marriage (SSM) Legalization

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

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

The independent variable in this model are the births that occur in clinic (i), in state (s) at time (t). This model's variable of interest is the β at time in relation to the treatment (k) which occurs based on when the state legalized SSM. SSM is a variable that is 1 after SSM legalization has occured in that state, and is 0 otherwise. This model also has clinic-level (λ), and time-level (δ) fixed effects.

With this established set up 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). I also use and report OLS, eventhough OLS is biased in a staggered setting.

These group treatment effects are reported using an event study approach. These results compare the clinics in states where SSM has occured (treatment) and the clinics in states where SSM has not yet occured (control). Section 6 reports the results for this model in more detail along with other versions of this model being run. The Appendix also estimates this model while replacing the independent variable births with transfers at the clinic level.

5.3 City-Effects For Both Policies

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

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

In this case, #ofClinics refers to the number of clinics in city (c) in state (s) at time (t). Legal refers to SSM legalization, or the passage of the ACA depending on the policy I aim to look into at that time where it is 1 if the policy has occured and 0 if it has yet to occur. 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 also has clinic-level (λ), and time-level (δ) fixed effects.

This model uses both policies, in the ways mentioned in the previous two sections. This means that when Legal is for the ACA I report BJS and OLS, and when Legal is for SSM legalization, I use BJS, CS, and OLS. Section 6 also reports the results for this model.

5.4 Difference-in-Difference Models

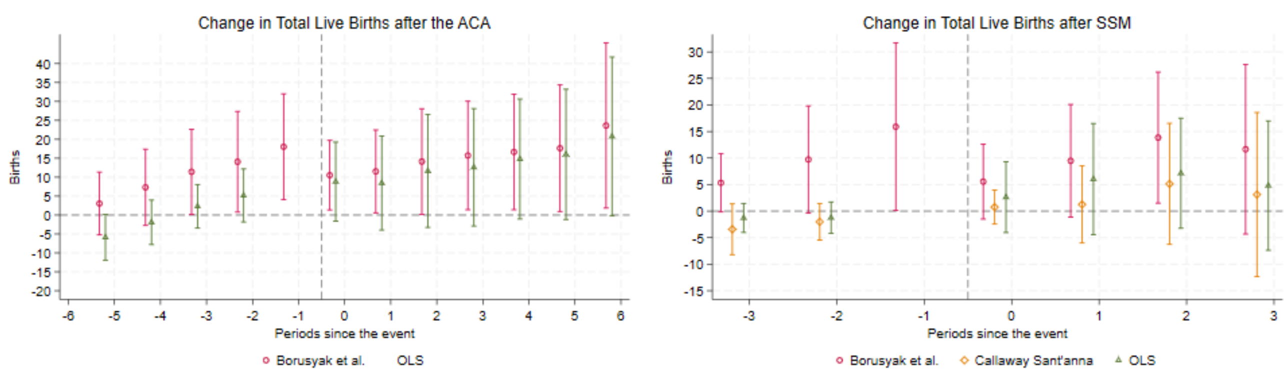
The decision to use these estimators and how to use these estimators, comes from a trio of papers (Roth et al., 2023; Roth, 2022, 2018). The first paper is a note on interpretation of the new difference-in-difference models when using non-staggered treatment and parallel trends fails. This paper explains 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 in the staggered setting, as I feel that together they form a fairly strong set of bounds. 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 approximatelyand through the construction of the model not using all available pretrends or the issues with serial correlation. My conclusions will use all appropriate models for their results.

6 Results

The third figure shows the results of total births added together to look at the total effect.

Figure 1: Total births increase for both policies with pretrends issues



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 and their inclusion in this model.

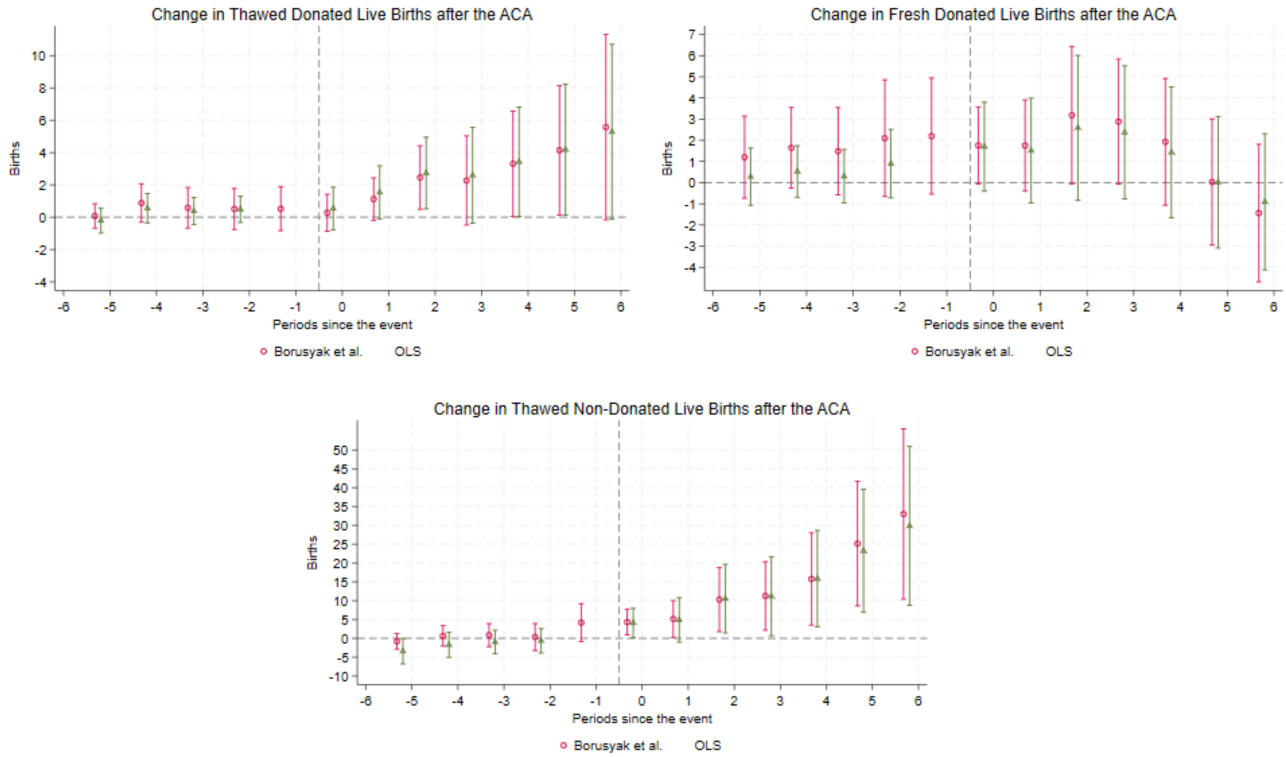
Since pretrends are a worry in difference in difference models as evidenced by this model, I use additional pre-testing according to the pretrends package in (Roth, 2022). This uses a power of 80% and the Likelihood Ratio Test and Bayes Test results for each model are reported in the appendix. For the 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 construction, the BJS model does not have.[5]

Figure 1 also shows results that look substantial, but in individual years do not have a lot of significance. Therefore, a hypothesis test for the sum of the post time periods after the policy for every model is tested and the results are reported in the Appendix. 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.

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

[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

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

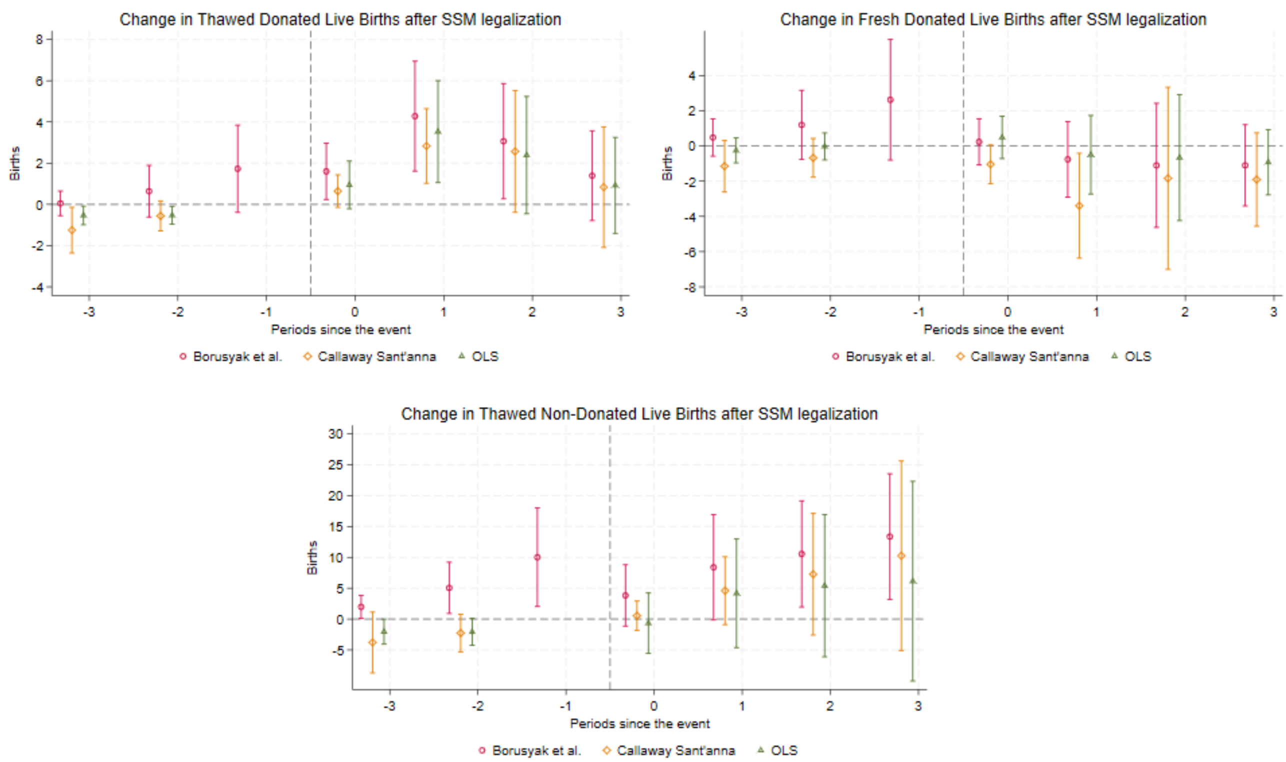


Note: These event study graphs display the results from equation 1 on each different type of births. These charts display the information using a 95% confidence interval.

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 embryos. 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.

Next I study 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.

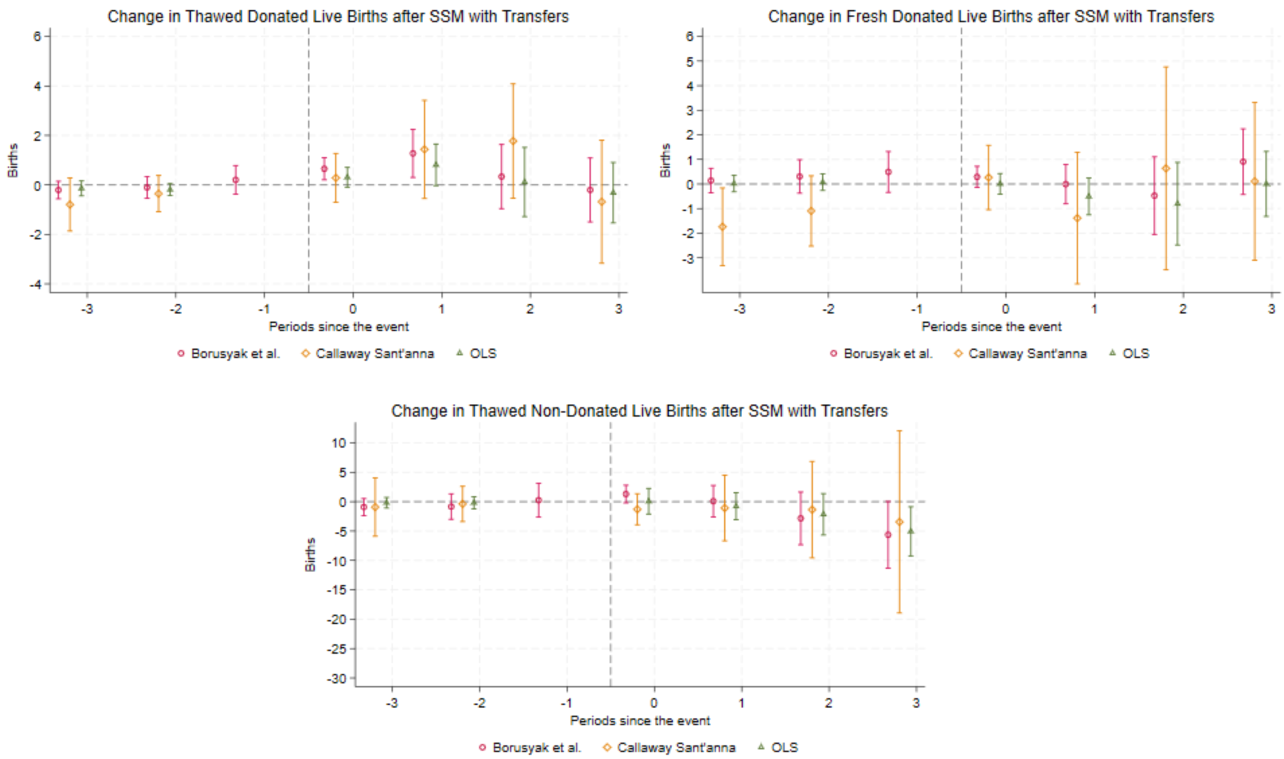
The first graph in Figure 3 indicates an immediate increase on thawed donor births that lasts about two years and returns to zero. The overall cumulative increase in these births is between 6.7-10.1 births per clinic across four years. For the model using fresh donor births, I see these decrease slightly, in the year after the event, which could be caused by some individuals switching to frozen donor births. This may also have some 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, but passes the additional testing for both the Likelihood Ratio, and Bayes tests which are reported in the Appendix. For the third graph, there are some issues with pretrends using BJS although this is only the case with thawed non-donor births model through the model had low values for both the Likelihood Ratio, and Bayes tests reported in the Appendix. These results indicate that SSM caused some changes to the ways ART is used, by increasing the uptake of donated materials and frozen materials.

Next, I control for the type of transfer associated with the live birth. This controls 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. The purpose here is to determine if births increase when controlling for the number of transfers after the implementation of SSM and the ACA. This increase would indicate improvements in birth outcomes, essentially meaning that more births end up occurring from fewer transfers, since transfers and births are highly correlated. If births increase while controlling for transfers, it would indicate better outcomes of ART. This only happens if healthier individuals use ART and/or users do not have issues with fertility.

Due to the legalization of SSM, I expect a large amount of the increase in usage to be coming from lesbian and gay individuals. This is because these individuals are using ART because they are unable to otherwise obtain the other half of the reproductive material needed for the embryos. This in comparison to most heterosexual couples who use ART for infertility that is rooted in a medical condition.

Figure 4 displays the impact before and after SSM legalization from estimating equation 2 in Figure 4:

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



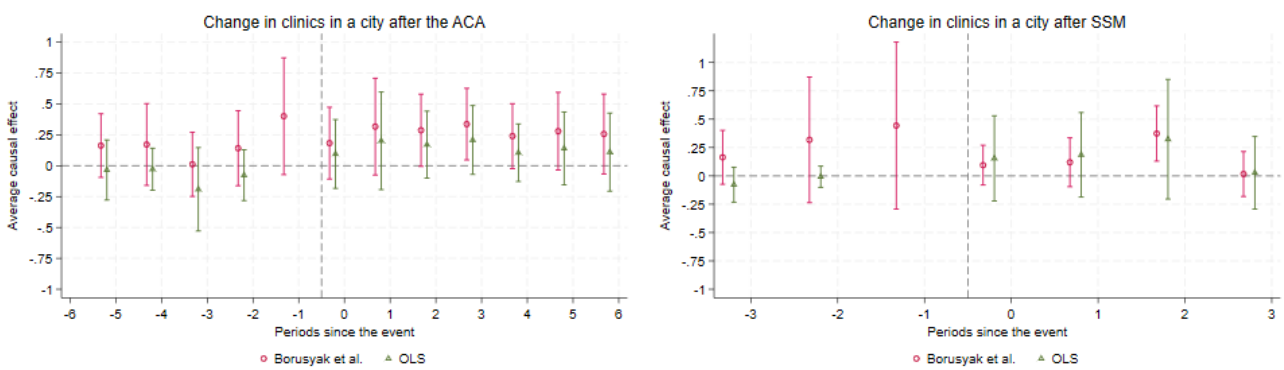
Note: These event study graphs display the results from equation 2 on each different type of births. Including the control of transfers for their respective type of birth/procedure. These charts display the information using a 95% confidence interval.

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. 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 no longer have statistically significant decreases. I can also see that thawed non-donated births no longer 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. Insurance coverage and SSM are incredibly unlikely to effect the fertility of individuals using ART. Therefore, this increase indicates that same-sex couples are the drivers in the increase of demand because their ART usage is not based on medical infertility. This means that the impact of SSM legalization caused an increase in births in the US that is separate from the ACA and that an increase in birth outcomes for thawed donor births specifically occured as a result.

Now using equation 3, I attempt to see why the positive impact of SSM legalization stopped after two years by looking at the number of clinics. 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

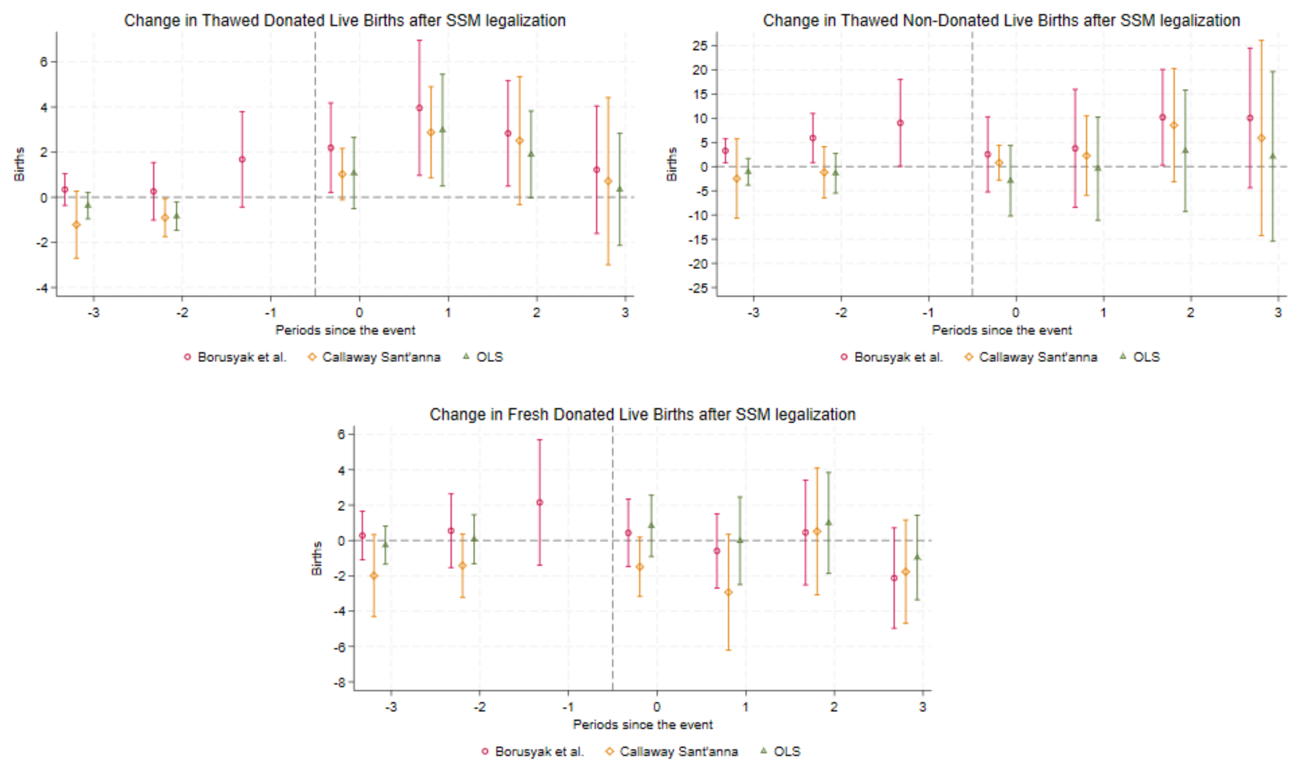


Note: These event study graphs display the results from equation 3 on each type of legalization. These charts display the information using a 95% confidence interval.

These event studies show the change in the number of clinics within a city after the ACA and SSM legalization. There appears to be an increase in the number of clinics two years later for the SSM model. The ACA model shows an increase in the number of clinics a year after the policy goes into effect, though many of the individual timings are not significant other than three years after the policy. This effect is persistent for the full six years though. 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. These results show that the two policies likely influenced an increase in the number of clinics in a city to keep up with the demand of more procedures and births.

After this I use equation 2 to estimate the equation for the impact of SSM on births, but restricting to only states that had insurance mandates for ART that were expended by the ACA. Looking at the two policies in conjunction, I study their joint impact. 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 after SSM



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 (which is biased anyways) 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. This was mainly driven by increases in procedures using frozen embryos. The increase in frozen procedures is likely, due to the state-specific price-based restrictions on ART coverage. 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 an 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 likely due to 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.

[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.

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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 Total Births	(3) OLS Total Births
T+0	10.53**	8.809*
	(4.685)	(5.332)
T+1	11.52**	8.444
	(5.581)	(6.334)
T+2	14.13**	11.65
	(7.113)	(7.616)
T+3	15.72**	12.60
	(7.309)	(7.912)
T+4	16.65**	14.80*
	(7.781)	(8.084)
T+5	17.64**	16.02*
	(8.528)	(8.774)
T+6	23.63**	20.75*
	(11.12)	(10.71)
T-1	18.03**	
	(7.133)	
T-2	14.07**	5.170
	(6.785)	(3.575)
T-3	11.42**	2.300
	(5.729)	(2.934)
T-4	7.312	-1.926
	(5.136)	(3.000)
T-5	3.042	-5.885*
	(4.227)	(3.082)
T-6	2.823	-5.449
	(3.217)	(3.731)
N	5773	6052
Joint Pretrends Tests	0.169	-
Cummulative Effect	109.8275**	93.06861*
	(48.56958)	(51.61761)
Likelihood Ratio Test	-	0.004
Bayes Test	-	0.243

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	0.379	0.613	-
Cummulative Effect	40.554**	10.275	20.619
	(17.947)	(16.260)	(16.378)
Likelihood Ratio Test	-	0	0.141
Bayes Test	-	0	0.218

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	(3) OLS
	ThwDnrLvBirths	ThwDnrLvBirths
T+0	0.274	0.541
	(0.583)	(0.671)
T+1	1.120*	1.539*
	(0.669)	(0.836)
T+2	2.457**	2.732**
	(1.001)	(1.131)
T+3	2.270	2.591*
	(1.407)	(1.510)
T+4	3.308**	3.430**
	(1.661)	(1.724)
T+5	4.143**	4.179**
	(2.042)	(2.061)
T+6	5.571*	5.285*
	(2.926)	(2.762)
T-1	0.521	
	(0.689)	
T-2	0.506	0.488
	(0.646)	(0.413)
T-3	0.581	0.386
	(0.641)	(0.427)
T-4	0.878	0.558
	(0.607)	(0.466)
T-5	0.0779	-0.206
	(0.386)	(0.398)
T-6	-0.236	-0.633
	(0.314)	(0.456)
N	5773	6052
Joint Pretrends Tests	0.835	-
Cummulative Effect	19.14268**	20.29648**
	(9.233787)	(9.758065)
Likelihood Ratio Test	-	0.006
Bayes Test	-	0.245

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 ThwNDLvBirths	(3) OLS ThwNDLvBirths
T+0	4.329**	4.096**
	(1.751)	(1.965)
T+1	5.130**	4.864
	(2.487)	(3.006)
T+2	10.27**	10.53**
	(4.325)	(4.642)
T+3	11.26**	11.15**
	(4.641)	(5.332)
T+4	15.74**	15.83**
	(6.244)	(6.533)
T+5	25.15***	23.21***
	(8.442)	(8.313)
T+6	32.99***	29.83***
	(11.52)	(10.76)
T-1	4.154	
	(2.580)	
T-2	0.355	-0.668
	(1.830)	(1.650)
T-3	0.853	-0.978
	(1.560)	(1.600)
T-4	0.653	-1.720
	(1.381)	(1.686)
T-5	-0.815	-3.416***
	(1.054)	(1.721)
T-6	-0.357	-3.402*
	(0.765)	(1.892)
N	5773	6052
Joint Pretrends Tests	0.207	-
Cummulative Effect	104.885***	99.506***
	(36.195)	(37.745)
Likelihood Ratio Test	-	0.005
Bayes Test	-	0.230

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	(3) OLS FshDnrBirths
T+0	1.757*	1.698
	(0.928)	(1.071)
T+1	1.750	1.513
	(1.099)	(1.263)
T+2	3.185*	2.592
	(1.654)	(1.745)
T+3	2.882*	2.371
	(1.505)	(1.605)
T+4	1.926	1.431
	(1.528)	(1.578)
T+5	0.0301	0.0192
	(1.520)	(1.586)
T+6	-1.438	-0.906
	(1.659)	(1.643)
T-1	2.198	
	(1.399)	
T-2	2.101	0.896
	(1.408)	(0.825)
T-3	1.483	0.300
	(1.053)	(0.644)
T-4	1.642*	0.526
	(0.973)	(0.621)
T-5	1.201	0.282
	(0.991)	(0.690)
T-6	0.214	-0.532
	(0.738)	(0.661)
N	5773	6052
Joint Pretrends Tests	0.675	-
Cummulative Effect	10.091	8.718
	(8.049)	(9.050)
Likelihood Ratio Test	-	0.004
Bayes Test	-	0.247

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	(3) OLS FshNDLvBirths
T+0	4.166	2.475
	(2.895)	(3.057)
T+1	3.521	0.528
	(3.061)	(3.243)
T+2	-1.787	-4.200
	(3.544)	(3.594)
T+3	-0.691	-3.510
	(3.574)	(3.789)
T+4	-4.327	-5.894
	(3.842)	(3.977)
T+5	-11.68**	-11.39**
	(4.976)	(4.860)
T+6	-13.49**	-13.46**
	(5.711)	(5.302)
T-1	11.16**	
	(4.935)	
T-2	11.11**	4.454*
	(4.612)	(2.421)
T-3	8.506**	2.591
	(4.214)	(2.237)
T-4	4.139	-1.290
	(3.512)	(1.857)
T-5	2.578	-2.545
	(3.011)	(1.949)
T-6	3.202	-0.882
	(2.366)	(2.218)
N	5773	6052
Joint Pretrends Tests	0.055	-
Cummulative Effect	-24.29067	-35.45193
	(21.95437)	(23.24138)
Likelihood Ratio Test	-	0.001
Bayes Test	-	0.246

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	(3) OLS ThwDnrLvBirths
T+0	-0.186	-0.163
	(0.305)	(0.280)
T+1	-0.00180	-0.0263
	(0.281)	(0.279)
T+2	-0.0415	0.142
	(0.529)	(0.412)
T+3	0.0266	0.0827
	(0.569)	(0.472)
T+4	-0.134	0.110
	(0.648)	(0.480)
T+5	-0.482	0.0537
	(0.994)	(0.729)
T+6	-0.931	-0.168
	(1.129)	(0.775)
T-1	-0.560	
	(0.445)	
T-2	-0.775**	-0.359
	(0.367)	(0.228)
T-3	-0.235	0.0736
	(0.365)	(0.248)
T-4	-0.0274	0.269
	(0.324)	(0.267)
T-5	-0.690**	-0.423*
	(0.270)	(0.238)
T-6	-0.135	0.0313
	(0.276)	(0.298)
Transfers	0.468***	0.431***
	(0.0395)	(0.0176)
N	5773	6052
Joint Pretrends Tests	0.0196	-
Cummulative Effect	-1.749	0.031
	(3.753)	(2.659)
Likelihood Ratio Test	-	4.753
Bayes Test	-	0.249

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	(3) OLS ThwNDLvBirths
T+0	-0.489	-0.386
	(0.796)	(0.712)
T+1	-1.045	-0.715
	(1.233)	(1.026)
T+2	0.606	0.430
	(1.482)	(1.221)
T+3	0.452	0.421
	(1.663)	(1.416)
T+4	-1.289	-0.574
	(2.256)	(1.703)
T+5	-2.415	-1.477
	(2.918)	(1.934)
T+6	-0.606	0.00731
	(3.552)	(2.229)
T-1	-2.279*	
	(1.177)	
T-2	-2.876**	-1.237*
	(1.126)	(0.716)
T-3	-1.945*	-0.545
	(1.000)	(0.772)
T-4	-1.467	-0.164
	(0.961)	(0.820)
T-5	-1.418	-0.197
	(0.879)	(0.858)
T-6	-0.640	0.374
	(0.664)	(0.828)
Transfers	0.484***	0.476***
	(0.0326)	(0.0175)
N	5773	6052
Joint Pretrends Tests	0.2878	-
Cummulative Effect	-4.786	-2.293
	(11.974)	(8.344)
Likelihood Ratio Test	-	2.415
Bayes Test	-	0.241

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 FshDnrBirths	(3) OLS FshDnrBirths
T+0	0.536*	0.597*
	(0.320)	(0.332)
T+1	0.283	0.327
	(0.332)	(0.313)
T+2	0.437	0.603
	(0.414)	(0.372)
T+3	0.0890	0.296
	(0.454)	(0.419)
T+4	0.524	0.519
	(0.449)	(0.447)
T+5	0.330	0.209
	(0.480)	(0.445)
T+6	-0.0115	0.00589
	(0.471)	(0.448)
T-1	0.0284	
	(0.574)	
T-2	0.00907	0.0827
	(0.552)	(0.358)
T-3	0.143	0.126
	(0.546)	(0.359)
T-4	0.303	0.307
	(0.513)	(0.348)
T-5	-0.00640	0.0207
	(0.434)	(0.398)
T-6	-0.522	-0.528
	(0.375)	(0.385)
Transfers	0.547***	0.506***
	(0.0246)	(0.0182)
N	5773	6052
Joint Pretrends Tests	0.530	-
Cummulative Effect	2.187	2.555
	(2.151)	(2.107)
Likelihood Ratio Test	-	0.006
Bayes Test	-	0.249

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	(3) OLS
	ThwDnrTrans	ThwDnrTrans
T+0	0.983	1.634
	(1.244)	(1.460)
T+1	2.398	3.635*
	(1.615)	(1.972)
T+2	5.342**	6.016**
	(2.487)	(2.771)
T+3	4.796	5.826*
	(3.188)	(3.419)
T+4	7.357**	7.711**
	(3.704)	(3.853)
T+5	9.888**	9.581**
	(4.318)	(4.351)
T+6	13.90**	12.67**
	(6.473)	(6.033)
T-1	2.310	
	(1.725)	
T-2	2.737*	1.966**
	(1.547)	(0.869)
T-3	1.743	0.726
	(1.561)	(0.928)
T-4	1.935	0.669
	(1.446)	(1.108)
T-5	1.641	0.504
	(1.006)	(0.925)
T-6	-0.215	-1.543
	(0.834)	(1.042)
N	5773	6052
Joint Pretrends Tests	0.265	-
Cummulative Effect	44.664**	47.069**
	(20.956)	(22.223)
Likelihood Ratio Test	0	0.000
Bayes Test	0	0.243

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	(3) OLS
	ThwNDTransfers	ThwNDTransfers
T+0	9.957***	9.405**
	(3.657)	(4.182)
T+1	12.76**	11.71*
	(5.570)	(6.396)
T+2	19.98**	21.19**
	(8.438)	(9.111)
T+3	22.35**	22.51**
	(9.732)	(10.86)
T+4	35.20***	34.43**
	(13.17)	(13.49)
T+5	56.98***	51.81***
	(17.63)	(16.99)
T+6	69.45***	62.59***
	(23.16)	(21.46)
T-1	13.29**	
	(6.131)	
T-2	6.673	1.195
	(4.917)	(3.324)
T-3	5.778	-0.908
	(4.104)	(3.514)
T-4	4.378	-3.266
	(3.539)	(3.713)
T-5	1.246	-6.757
	(2.880)	(4.150)
T-6	0.584	-7.925
	(2.080)	(4.816)
N	5773	6052
Joint Pretrends Tests	0.189	-
Cummulative Effect	226.673***	213.653***
	(76.064)	(77.828)
Likelihood Ratio Test	0	0.002
Bayes Test	0	0.232

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	(3) OLS
	FshDnrTransfers	FshDnrTransfers
T+0	2.232	2.176
	(1.665)	(1.900)
T+1	2.683	2.343
	(2.319)	(2.603)
T+2	5.024	3.929
	(3.290)	(3.429)
T+3	5.106	4.100
	(3.157)	(3.326)
T+4	2.563	1.802
	(2.879)	(3.047)
T+5	-0.548	-0.375
	(2.963)	(3.091)
T+6	-2.609	-1.802
	(3.101)	(3.094)
T-1	3.968	
	(2.518)	
T-2	3.825	1.606
	(2.627)	(1.485)
T-3	2.449	0.343
	(1.874)	(1.085)
T-4	2.448	0.434
	(1.769)	(1.052)
T-5	2.208	0.517
	(1.586)	(0.988)
T-6	1.346	-0.00902
	(1.177)	(1.175)
N	5773	6052
Joint Pretrends Tests	0.881	-
Cummulative Effect	14.452	12.173
	(16.662)	(18.435)
Likelihood Ratio Test	0	0.005
Bayes Test	0	0.245

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	(3) OLS
	FshNDCycle	FshNDCycle
T+0	11.86	6.561
	(9.875)	(9.736)
T+1	10.17	0.938
	(12.16)	(11.83)
T+2	-6.066	-12.97
	(13.57)	(12.73)
T+3	-4.310	-14.72
	(13.30)	(13.19)
T+4	-4.847	-13.40
	(13.99)	(13.90)
T+5	-16.58	-19.00
	(13.78)	(13.56)
T+6	-23.93	-23.94
	(16.07)	(15.14)
T-1	39.23**	
	(16.61)	
T-2	35.84**	13.67
	(16.39)	(8.519)
T-3	30.63*	11.06
	(16.87)	(9.925)
T-4	9.588	-8.462
	(10.85)	(6.349)
T-5	8.386	-8.444
	(7.970)	(6.547)
T-6	11.80**	-1.902
	(5.897)	(8.889)
N	5773	6052
Joint Pretrends Tests	0.017	-
Cummulative Effect	-33.693	-76.531
	(79.424)	(79.494)
Likelihood Ratio Test	0	0.001
Bayes Test	0	0.241

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	1.600**	0.644	0.945
	(0.695)	(0.402)	(0.589)
T+1	4.279***	2.833***	3.531***
	(1.359)	(0.922)	(1.262)
T+2	3.065**	2.569*	2.391
	(1.426)	(1.506)	(1.451)
T+3	1.393	0.837	0.923
	(1.110)	(1.493)	(1.187)
T-1	1.728		
	(1.079)		
T-2	0.638	-0.560	-0.528**
	(0.638)	(0.372)	(0.220)
T-3	0.0498	-1.249**	-0.533**
	(0.304)	(0.566)	(0.231)
N	5062		5129
Joint Pretrends Tests	0.1491	0.8230	-
Cummulative Effect	10.337***	6.882**	7.790**
	(3.296)	(3.433)	(3.473)
Likelihood Ratio Test	0	0	13.853
Bayes Test	0	0	0.220

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	3.829	0.546	-0.662
	(2.536)	(1.206)	(2.495)
T+1	8.389*	4.598	4.170
	(4.351)	(2.802)	(4.488)
T+2	10.55**	7.257	5.405
	(4.387)	(5.026)	(5.876)
T+3	13.37**	10.26	6.138
	(5.193)	(7.829)	(8.250)
T-1	10.01**		
	(4.072)		
T-2	5.061**	-2.257	-2.066*
	(2.117)	(1.556)	(1.115)
T-3	1.972**	-3.792	-2.039**
	(0.957)	(2.516)	(1.035)
N	5062		5129
Joint Pretrends Tests	0.1796	0.0780	-
Cummulative Effect	36.141***	22.664	15.051
	(12.574)	(14.827)	(18.243)
Likelihood Ratio Test	0	0	1.535
Bayes Test	0	0	.218

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 FshDnrBirths	(2) CS FshDnrBirths	(3) OLS FshDnrBirths
T+0	0.234	-1.041*	0.488
	(0.669)	(0.561)	(0.615)
T+1	-0.760	-3.392**	-0.499
	(1.095)	(1.521)	(1.138)
T+2	-1.100	-1.835	-0.662
	(1.797)	(2.636)	(1.824)
T+3	-1.097	-1.905	-0.921
	(1.177)	(1.352)	(0.946)
T-1	2.624		
	(1.747)		
T-2	1.201	-0.675	-0.0259
	(1.000)	(0.561)	(0.391)
T-3	0.483	-1.147	-0.252
	(0.540)	(0.748)	(0.361)
N	5062		5129
Joint Pretrends Tests	0.5437	0.0058	-
Cummulative Effect	-2.722	-8.173*	-1.594
	(3.430)	(4.730)	(3.556)
Likelihood Ratio Test	0	0	0.026
Bayes Test	0	0	0.218

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	-0.101	0.609	1.867
	(1.843)	(1.261)	(1.812)
T+1	-2.427	-2.784	-1.172
	(2.550)	(2.828)	(2.462)
T+2	1.331	-2.850	0.00410
	(4.480)	(5.836)	(4.281)
T+3	-2.006	-6.072	-1.328
	(6.974)	(9.924)	(6.403)
T-1	1.539		
	(4.403)		
T-2	2.837	1.485	1.382
	(2.970)	(1.396)	(1.089)
T-3	2.824	2.771	1.540
	(1.958)	(2.016)	(1.083)
N	5062		5129
Joint Pretrends Tests	0.1373	0.2354	-
Cummulative Effect	-3.203	-11.098	-0.628
	(13.506)	(17.678)	(12.192)
Likelihood Ratio Test	0	0	0.001
Bayes Test	0	0	0.218

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	0.652***	0.284	0.307
	(0.227)	(0.503)	(0.204)
T+1	1.274**	1.435	0.811*
	(0.496)	(1.011)	(0.429)
T+2	0.336	1.774	0.117
	(0.662)	(1.180)	(0.713)
T+3	-0.205	-0.680	-0.315
	(0.660)	(1.269)	(0.623)
T-1	0.203		
	(0.295)		
T-2	-0.104	-0.353	-0.188
	(0.223)	(0.374)	(0.122)
T-3	-0.207	-0.792	-0.139
	(0.181)	(0.546)	(0.154)
Transfers	0.380***		0.397***
	(0.0102)		(0.0141)
N	5062		5129
Joint Pretrends Tests	0.227	0.827	-
Cummulative Effect	2.057	2.813	0.920
	1.718	3.057	1.672
Likelihood Ratio Test	0	0	1.908
Bayes Test	0	0	0.221

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	1.291*	-1.298	0.0682
	(0.766)	(1.347)	(1.112)
T+1	0.0779	-1.076	-0.781
	(1.365)	(2.849)	(1.166)
T+2	-2.847	-1.366	-2.154
	(2.286)	(4.185)	(1.796)
T+3	-5.636*	-3.453	-5.054**
	(2.892)	(7.901)	(2.130)
T-1	0.249		
	(1.471)		
T-2	-0.841	-0.390	-0.190
	(1.105)	(1.531)	(0.525)
T-3	-0.923	-0.923	-0.188
	(0.738)	(2.533)	(0.456)
Transfers	0.457***		0.441***
	(0.0353)		(0.0338)
N	5062		5129
Joint Pretrends Tests	0.0705	0.0787	-
Cummulative Effect	-7.113	-7.193	-7.921
	(6.337)	(14.393)	(4.910)
Likelihood Ratio Test	0	0	0.050
Bayes Test	0	0	0.218

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	0.289	0.264	0.00696
	(0.219)	(0.668)	(0.213)
T+1	-0.00590	-1.388	-0.506
	(0.408)	(1.364)	(0.381)
T+2	-0.473	0.636	-0.801
	(0.805)	(2.105)	(0.857)
T+3	0.909	0.110	0.00377
	(0.680)	(1.637)	(0.674)
T-1	0.490		
	(0.424)		
T-2	0.306	-1.096	0.0762
	(0.347)	(0.729)	(0.172)
T-3	0.139	-1.740**	0.0176
	(0.254)	(0.805)	(0.169)
Transfers	0.507***		0.499***
	(0.0164)		(0.0189)
N	5062		5129
Joint Pretrends Tests	0.839	0.030	-
Cummulative Effect	0.719	-0.379	-1.296
	(1.777)	(4.079)	(1.783)
Likelihood Ratio Test	0	0	0.005
Bayes Test	0	0	0.219

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	(2) CS	(3) OLS
	ThwDnrTrans	ThwDnrTrans	ThwDnrTrans
T+0	2.493	0.955	1.609
	(1.622)	(0.862)	(1.332)
T+1	7.900**	4.558**	6.853**
	(3.158)	(2.064)	(2.966)
T+2	7.175**	5.631*	5.731*
	(3.587)	(3.346)	(3.433)
T+3	4.201	2.353	3.118
	(3.043)	(3.335)	(3.026)
T-1	4.013		
	(2.551)		
T-2	1.953	-0.838	-0.857*
	(1.499)	(0.694)	(0.483)
T-3	0.675	-1.972	-0.993*
	(0.663)	(1.207)	(0.529)
N	5062		5129
Joint Pretrends Tests	0.3910	0.0157	-
Cummulative Effect	21.769**	13.497*	17.311**
	(8.482)	(7.492)	(8.349)
Likelihood Ratio Test	0	0	0.595
Bayes Test	0	0	0.218

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	5.548	0.432	-1.655
	(5.104)	(2.868)	(5.959)
T+1	18.17**	10.35*	11.23
	(9.015)	(6.122)	(10.18)
T+2	29.30***	17.75	17.14
	(10.07)	(11.14)	(14.48)
T+3	41.55***	30.06*	25.37
	(12.24)	(17.06)	(21.12)
T-1	21.35**		
	(8.548)		
T-2	12.91**	-2.904	-4.252*
	(5.621)	(2.917)	(2.436)
T-3	6.330**	-4.764	-4.197*
	(2.993)	(4.529)	(2.163)
N	5062		5129
Joint Pretrends Tests	0.2129	0.4774	-
Cummulative Effect	94.568***	58.591*	52.084
	(28.674)	(33.444)	(47.250)
Likelihood Ratio Test	0	0	1.963
Bayes Test	0	0	0.219

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	-0.108	-2.202**	0.963
	(1.404)	(0.911)	(1.360)
T+1	-1.486	-5.813**	0.0145
	(1.992)	(2.660)	(2.148)
T+2	-1.236	-3.099	0.280
	(3.490)	(4.583)	(3.600)
T+3	-3.953	-5.884*	-1.854
	(2.660)	(3.216)	(2.557)
T-1	4.210		
	(3.497)		
T-2	1.765	-1.482*	-0.204
	(1.971)	(0.900)	(0.624)
T-3	0.677	-2.246	-0.540
	(0.938)	(1.401)	(0.628)
N	5062		5129
Joint Pretrends Tests	0.575	0.329	-
Cummulative Effect	-6.784	-16.998**	-0.597
	(7.262)	(9.051)	(8.110)
Likelihood Ratio Test	0	0	0.023
Bayes Test	0	0	0.218

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 FshNDCycle	(2) CS FshNDCycle	(3) OLS FshNDCycle
T+0	-0.474	2.342	7.490
	(5.987)	(3.778)	(6.953)
T+1	-6.111	-10.28	2.488
	(8.875)	(7.126)	(9.735)
T+2	16.85	-10.25	14.17
	(18.10)	(16.98)	(14.55)
T+3	21.14	-7.088	23.94
	(19.94)	(21.35)	(18.09)
T-1	15.49		
	(18.88)		
T-2	20.21	10.21***	5.625
	(13.78)	(3.769)	(4.107)
T-3	13.27	7.928	0.762
	(9.054)	(5.524)	(4.110)
N	5062		5129
Joint Pretrends Tests	0.014	0.000	
Cummulative Effect	31.405	-25.274	48.091
	44.355	38.014	37.525
Likelihood Ratio Test	0	0	0
Bayes Test	0	0	0.216

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 ThwDnrLvBirths	(2) CS ThwDnrLvBirths	(3) OLS ThwDnrLvBirths
T+0	2.193**	1.023*	1.070
	(1.014)	(0.580)	(0.805)
T+1	3.961***	2.878***	2.975**
	(1.526)	(1.030)	(1.264)
T+2	2.833**	2.512*	1.897*
	(1.194)	(1.447)	(0.983)
T+3	1.221	0.716	0.348
	(1.442)	(1.891)	(1.266)
T-1	1.680		
	(1.080)		
T-2	0.263	-0.901**	-0.842***
	(0.651)	(0.430)	(0.319)
T-3	0.343	-1.215	-0.370
	(0.360)	(0.759)	(0.299)
N	2608		2688
Joint Pretrends Tests	0.192	0.735	-
Cummulative Effect	10.208***	7.129*	6.290**
	(3.814)	(3.936)	(3.148)
Likelihood Ratio Test	0	0	32.154
Bayes Test	0	0	0.221

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 ThwNDLvBirths	(2) CS ThwNDLvBirths	(3) OLS ThwNDLvBirths
T+0	2.525	0.793	-2.942
	(3.964)	(1.835)	(3.714)
T+1	3.760	2.242	-0.424
	(6.222)	(4.194)	(5.446)
T+2	10.19**	8.542	3.241
	(5.046)	(5.971)	(6.408)
T+3	10.05	5.912	2.078
	(7.364)	(10.29)	(8.940)
T-1	9.029**		
	(4.577)		
T-2	5.903**	-1.199	-1.376
	(2.588)	(2.710)	(2.102)
T-3	3.264***	-1.421	-1.086
	(1.259)	(0.914)	(1.407)
N	2608		2688
Joint Pretrends Tests	0.300	0.009	-
Cummulative Effect	26.524	17.490	1.953
	(19.396)	(20.656)	(21.916)
Likelihood Ratio Test	0	0	0.189
Bayes Test	0	0	0.219

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	0.430	-1.490*	0.827
	(0.974)	(0.856)	(0.884)
T+1	-0.588	-2.928*	-0.0181
	(1.071)	(1.671)	(1.264)
T+2	0.453	0.516	0.988
	(1.512)	(1.835)	(1.457)
T+3	-2.123	-1.767	-0.962
	(1.449)	(1.491)	(1.220)
T-1	2.157		
	(1.812)		
T-2	0.552	-1.421	0.0725
	(1.064)	(0.914)	(0.707)
T-3	0.282	-1.990*	-0.265
	(0.701)	(1.186)	(0.549)
N	2608		2688
Joint Pretrends Tests	0.5098	0.2653	-
Cummulative Effect	-1.829	-5.669	0.836
	(3.573)	(4.638)	(3.833)
Likelihood Ratio Test	0	0	0.020
Bayes Test	0	0	0.219

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	2.055	0.952	2.386
	(2.832)	(2.181)	(2.739)
T+1	0.130	0.228	0.381
	(3.352)	(3.737)	(3.004)
T+2	3.369	1.033	0.692
	(6.254)	(7.975)	(5.680)
T+3	-1.263	-2.187	-0.966
	(8.308)	(10.87)	(6.915)
T-1	0.493		
	(5.423)		
T-2	1.307	1.731	0.736
	(3.914)	(2.225)	(1.916)
T-3	0.277	0.625	-0.258
	(2.866)	(3.175)	(1.720)
N	2608		2688
Joint Pretrends Tests	0.7525	0.1378	-
Cummulative Effect	4.291	0.026	2.492
	(17.881)	(22.172)	(15.014)
Likelihood Ratio Test	0	0	0.008
Bayes Test	0	0	0.219

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 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.

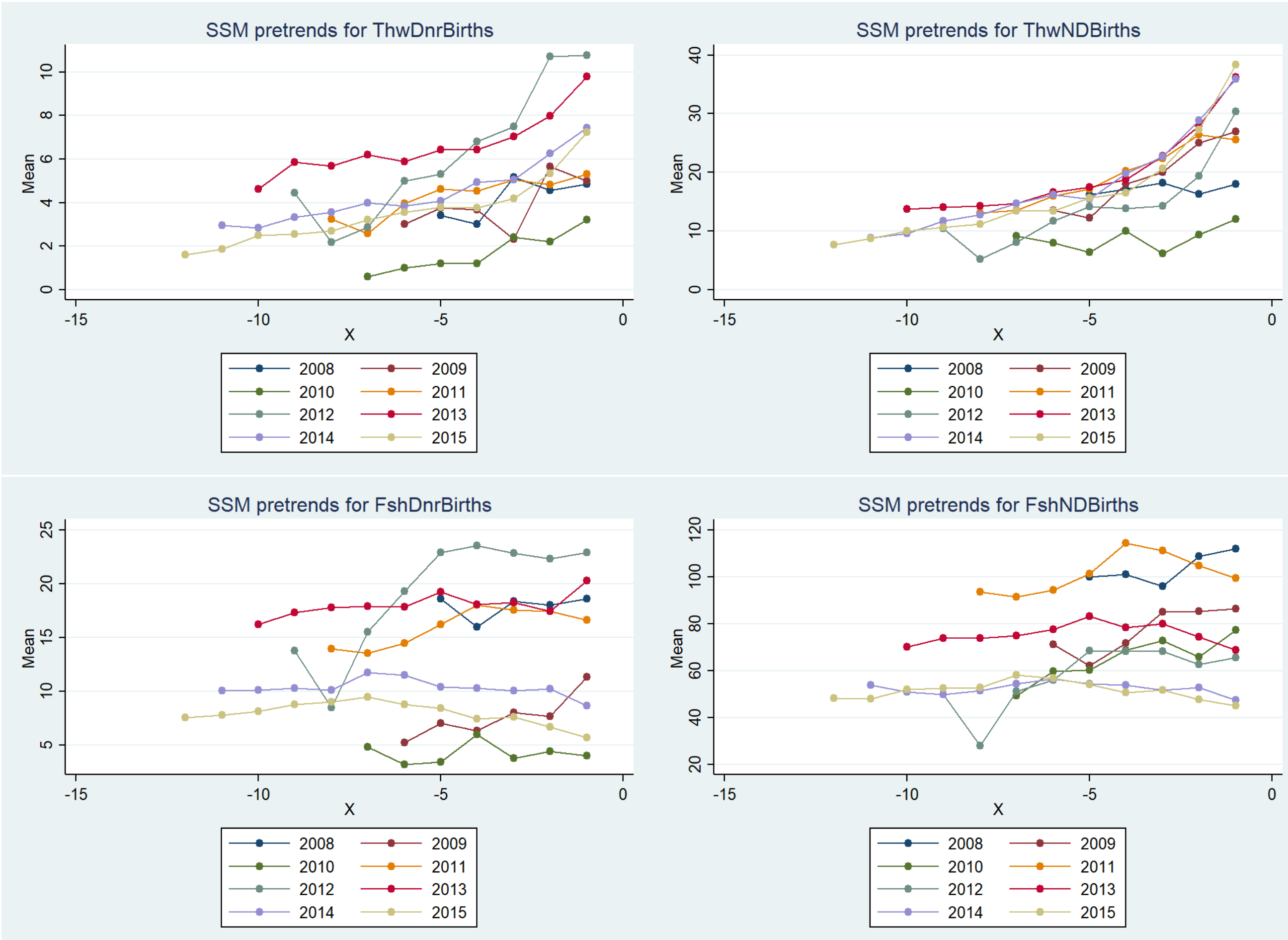
Table 33: Results for Number of Clinics in a City after SSM Legalization

	(1) BJS	(2) OLS
	howmanycity	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
* $p < .10$, ** $p < .05$, *** $p < .01$

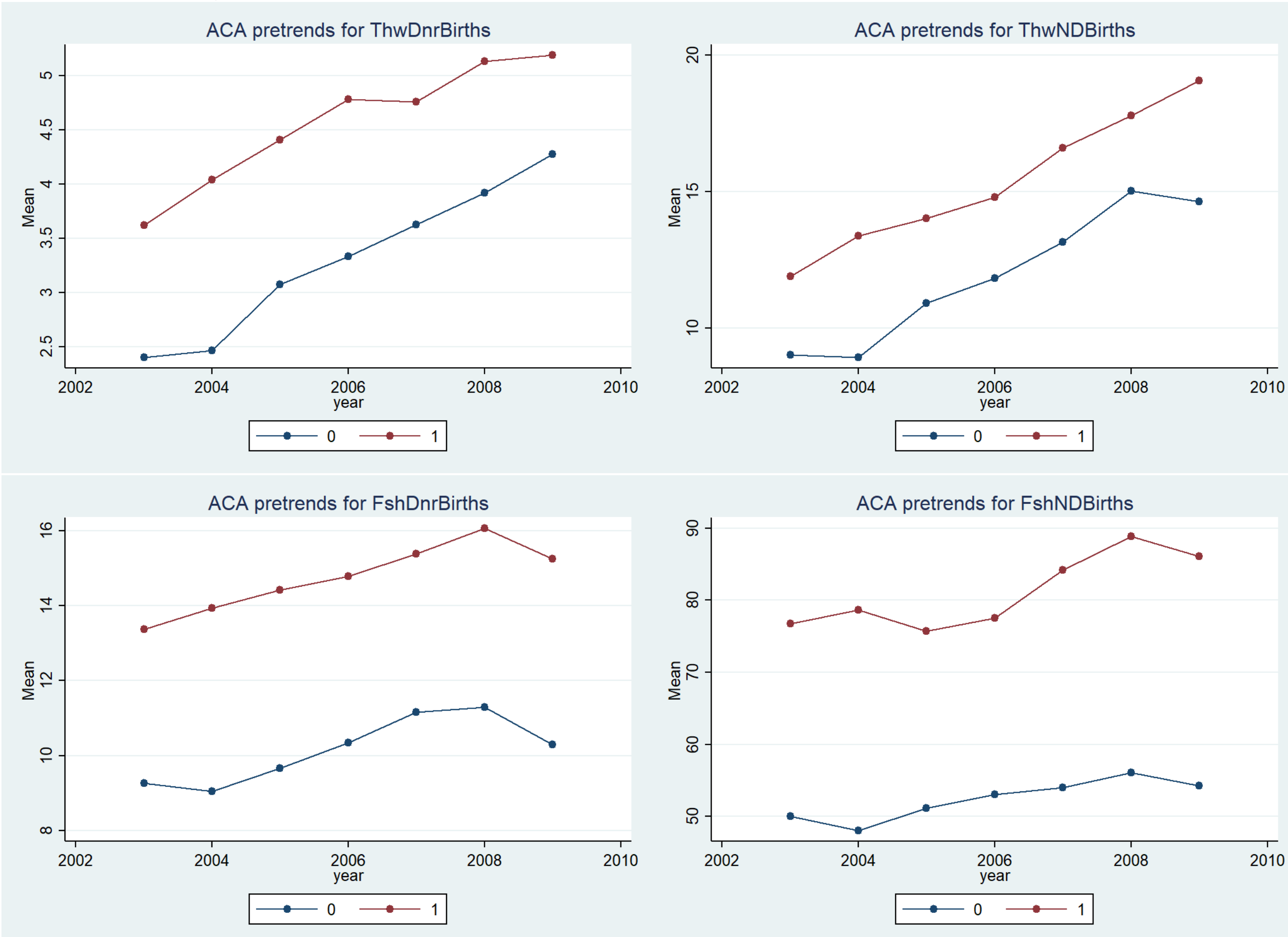
Note: These results display the results from equation 3 for SSM legalization.

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.