# ISyE 6740 - Summer 2025
# Final Project

**Group 158**

**Team Member Names:** Miranda Lamb

**Project Title:** The Effects of Abortion Restrictions on Women's Incomes in the U.S.

### Problem Statement

It is well studied that the decision a woman makes about whether or not to have children has significant consequence to her career. According to one study, it is estimated that having a child causes the "average high skilled woman $230,000 lost in lifetime wages compared to women who never gave birth" [1]. There is an undeniable link between a woman's childbearing decisions and her income: thus there is an undeniable link between her reproductive freedoms and her income. One study found that around one third of all wage increases for women since the 1960's can be attributed to the accessibility of birth control [2]. Similarly, the percent of women aged 25-54 in the workforce has increased from 51% in 1972, before Roe v. Wade, to 78% in 2024 [3]. This relationship, between a woman's reproductive freedoms and her income, has become especially prevalent in recent years when Dobbs v. Jackson Women's Health Organization overturned Roe v. Wade in 2022, eliminating the federal protection for abortion. Since then, research is beginning to emerge investigating how this change affected women's financial outcomes, and economic outcomes as a whole. For example, one study found that states with abortion bans have, on average, lower minimum wages, lower unionization levels, and a 1.5 times higher incarceration rates [4].

Although there is a body of research around abortion access and women's economic outcomes, there is less research attempting to identify the dollar difference in women's income caused by the Dobbs decision. In this paper, I plan to explore women's incomes in the US, and how they have been affected by the overturning of Roe v. Wade and the subsequent abortion bans that went into effect. The analysis is based on CPS data from 2019-2024, ultimately answering the question: how did the Dobbs ruling and its subsequent abortion restrictions affect women's income?

### Data Source

To conduct this analysis, I used IPUMS CPS data. In particular, my dataset contained the following CPS variables from 2019-2024:

- YEAR (survey year)
- STATEFIP (State Fips Code)
- AGE

– SEX
– RACE
– EDUC (highest year of school or degree completed)
– INCWAGE (Wage and salary income)

After downloading this dataset, I performed data cleaning to ready the dataset for analysis and to narrow down to the relevant observations. I kept only female observations with an age of 15-80, to focus on a generous range of working age women. I recoded the education variable into bins corresponding to their highest education level: non-high school grads, high school grads, some college, Bachelor's degree, and higher than a Bachelor's degree. I also dropped observations with missing or NIU values for each of my variables. After this cleaning, the final dataset had 361,127 observations

This data can be found at: https://cps.ipums.org/cps/index.shtml

For this model, the data will be differentiated between states that did implement a total/near total ban of abortion, and states that did not, as specified by CNN [5]. The states that are a part of the "ban" group are: Alabama, Arkansas, Idaho, Indiana, Kentucky, Louisiana, Missouri, Mississippi, Oklahoma, South Dakota, and Tennessee.

**Methodology**

The main methodology that I used to conduct this analysis is a difference-in difference regression. A DiD model in this setting is a linear regression model that operates on two key distinctions of time series data. The first is that there is some sort of treatment (in this case, the Dobbs decision and its subsequent state abortion bans) that was applied one group, and not another. The second is that the treatment went into effect at one time (in this case, June 2022) for all groups that did receive the treatment.

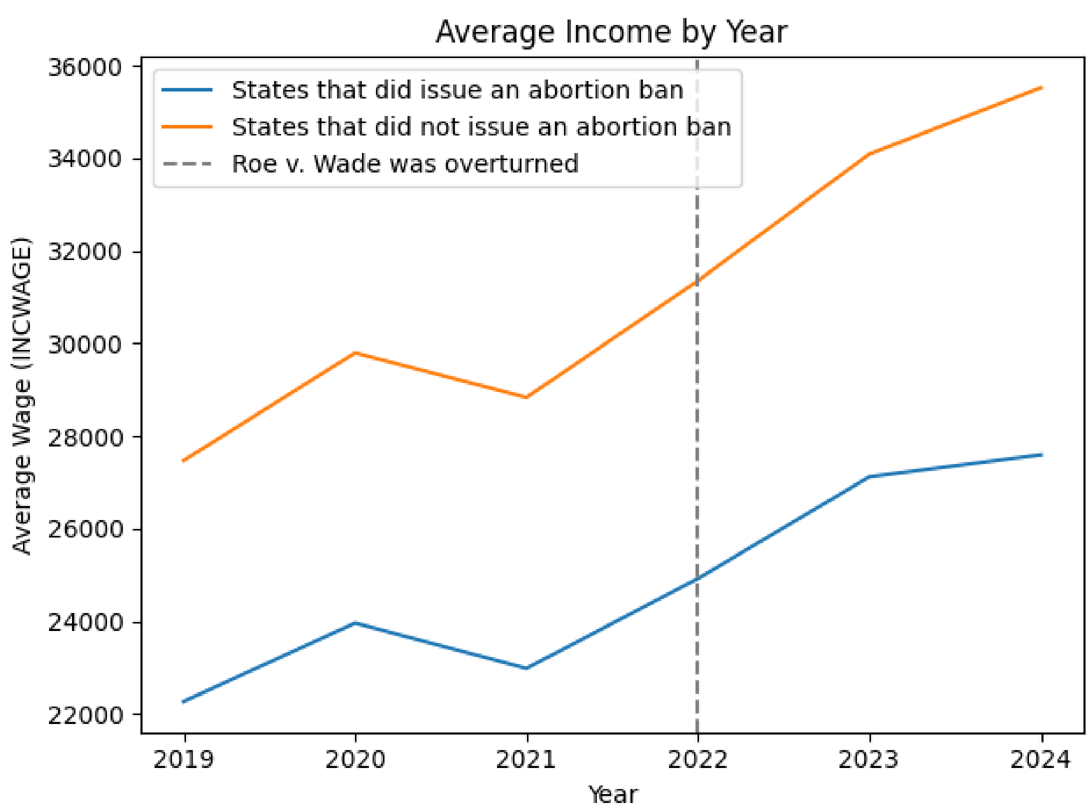
The intuition (and assumption) of this model is that for the two groups (states that did enact an abortion ban in 2022 and those that didn't), the outcome variable (women's income) might fluctuate over time, but those fluctuations are parallel. If women's income in these two groups did move in parallel before the treatment went into effect, we can assume that in the time period after the treatment went into effect, if it weren't for the treatment, they would continue to move in parallel. We would assume that without a treatment, women's income for both groups might have differences from year to year, but those differences would be consistent with each other. So, based on this assumption, if after the treatment went into place, the differences in women's income over time for each group are not consistent with each other, that discrepancy (the difference (between groups) in the difference (over time)) can be considered the effect of the treatment.

In practice, this model is implemented as a linear regression where the women's income is regressed on an indicator variable for if the observation was before or after the the Dobbs decision (post), an indicator variable for if the observation came from a state that enacted an abortion ban (banned), and an interaction term between the two (postxbanned). We will also include a set of indicator variables for each state (minus one) and for each year (minus one) to control for state and year fixed effects: things that might cause bias between years (economic changes, political economy, etc) and between states (political party, state demographics), to isolate the relationship of interest. Additionally, I included the education bins I created to control for differences in education levels among people in each state. The equation for this analysis is:

$$WomensIncome_i = \alpha + \beta_1 \text{post}_i + \beta_2 \text{banned}_i + \beta_3 \text{postxbanned}_i + \beta_4 \text{educGroup}_i + \beta_{SE}(\text{StateEffects})_i + \beta_{TE} \text{TimeEffects}_i$$

In this model, the coefficient on the postxbanned interaction term will serve as the effect of the treatment: the result to the question that we are trying to answer. $\beta_1$ tells us the expected difference in income for observations after 2022 relative to before 2022. $\beta_2$ tells us the expected difference in income for observations belonging to states that did enact a ban relative to states that did not. $\beta_3$ gives us the difference in those differences: the expected difference in income resulting from the abortion bans, relative to states that did not enact abortion bans.

As mentioned above, the difference-in-difference model hinges on the assumption that the two groups would move parallel to each other, had the abortion bans not gone into place. We of course cannot observe what would have happened after 2022, however to gather evidence to support this assumption, we can look at the trends of the two groups before the treatment. The below chart shows the average income for each group (states that did enact a ban, and states that didn't) across each year in the data, with 2022 (the year that Roe v. Wade was overturned and the abortion bans went into effect) marked. Although it is difficult to tell the exact relationship from this chart, the income trends before 2022 when the "treatment" went into effect do appear to be parallel. Thus, we will proceed with the assumption that trends would have continued to be parallel after 2022 had there been no treatment.



**Evaluation and Final Results**

The coefficients of the model are shown in the below table.

| Variable | Coefficient | P> t | [0.025 | 0.975] |
|---|---|---|---|---|
| Intercept | 17,130 | 0.000 | 16,800 | 17,500 |
| Non-high School Grad | -11,600 | 0.000 | -13,900 | -300 |
| High School Grad | -1,058 | 0.000 | -1,487 | -628 |
| Bachelor's Degree | 25,260 | 0.000 | 24,800 | 25,700 |
| More than a Bachelor's Degree | 47,750 | 0.000 | 47,200 | 48,300 |
| Post | 4,285 | 0.000 | 3,911 | 4,658 |
| Banned | -3,153 | 0.000 | -3,756 | -2,550 |
| PostXbanned | -1,178 | 0.000 | -2,057 | -300 |

The control group of this model is an observation before 2022, belonging to a state that did not enact an abortion ban, who's highest education level was "some college". All coefficients are relative to that group. We can see that our coefficient of interest, PostXBanned, has a value of $-1,178. For the control group of those with "some college", the expected income for a woman living in a state that did not enact a ban was $17,130 before 2022, and $21,415 after. For those living in a state that did enact a ban, their expected income before the ban was $13,977, and $17,084 after the ban. So, over the two time periods, both saw an increase in salary: $4,285 for states without a ban, and $3,107 for those with a ban. However, because the difference in income for the non-ban states was larger than the difference in the ban states, this models suggests that this difference (in difference) is the causal effect of $1,178. Meaning, the overturning of Roe v. Wade and its subsequent abortion bans caused $1,178 of lost women's income.

We can see that for this model, all coefficients had a P-value of less than .05, meaning they are all statistically significant at the 95% level. However, it is important to note that there were 361,127 data points used for this model. Having such a high n can make all coefficients look statistically significant, regardless of their actual impact on the outcome. We can also look at the confidence intervals and see that none of them contain zero, suggesting again that these variables are statistically significant, but again this could be distorted by the high number of data points. To help get a better idea of true statistical significance, we can look at the size of the confidence intervals. For example, the "More than a Bachelor's Degree" variable has confidence interval range of 1,100 which is somewhat narrow relative to its magnitude, suggesting that whether or not a woman has an education beyond a Bachelor's degree likely has a statistically significant relationship with her income. The range for the PostXBanned variable is 1757, which is relatively large, and the lower range of the interval of -300 is close to zero in the context of income changes. So, although this model did predict a decrease in women's income as a result of the Dobbs decision (relative to states without abortion bans), the evidence for a causal relationship is suggestive but not conclusive. Also, it is important to note that there could be other unknown confounding variables that cause bias in the outcomes of this model.

To help evaluate the model's fit, below is a table of the model's R-squared and adjusted R-squared values. These tell us the proportion of the variance in women's incomes that can be explained by the model (R-squared), and the same but with a penalty for model complexity (adjusted R-squared). Here, we can see that roughly 10% of the variation in income can be explained by our model. However, CPS data is individual-level, which causes it to be very noisy. In this context, is is expected to have a somewhat low R-squared value, and it does not necessarily mean that this model is not a good fit for the data.

| R-squared | adj. R-squared |
|---|---|
| 0.106 | 0.106 |

**Conclusion and Future Research Areas**

This paper explored a difference-in-difference regression model with 2019-2024 CPS data to estimate the effect of the 2022 Dobbs decision on women's incomes. The model suggests that the Dobbs decision and its subsequent abortion bans caused a $-1,178 decrease in women's incomes, relative to the incomes of women in states that did not implement abortion bans. However, due to the size of the data and the relatively small magnitude of the coefficient in question, it is not clear whether these results can be deemed statistically significant.

As established, there is a clear link between a woman's choice to have children, and her income, and thus between reproductive freedoms and income. The 2022 Dobbs decision eliminated federal protection of these reproductive freedoms. This paper began to explore the impact of this decision, however it did not explore more detailed questions such as how the bans might be affecting the incomes of women of difference races, education levels, marital status, and many other demographic factors. Exploring the impact of the Dobbs decision on women's income, or other outcomes for women, and how those impacts vary across different intersectional groups could help us understand who and how the bans are affecting the most. Research is beginning to emerge surrounding the socioeconomic impacts of this decision and the abortion bans, however more research is needed to determine if and how the decision is affecting women's incomes.

References

1 How childbearing affects women's wages. NBER. (n.d.). https://www.nber.org/digest/apr11/how-childbearing-affects-womens-wages

2 The-economic-benefits-of-birth-control-and-access-to-family ... Joint Economic Committee. (n.d.). https://www.jec.senate.gov/public/cache/files/bb400414-8dee-4e39-abd3-c2460fd30e7d/the-economic-benefits-of-birth-control-and-access-to-family-planning.pdf

3 Simmons-Duffin, S., Horsley, S. (2024, September 3). Abortion has huge financial consequences in a woman's life - and in the economy. NPR. https://www.npr.org/2024/08/27/nx-s1-4998884/the-financial-side-of-abortion-access

4 Banerjee, A. (n.d.). Abortion bans, low wages, and public underinvestment are ... Economic Policy Institute. https://www.epi.org/publication/economics-of-abortion-bans/

5 Choi, A., Cole, D. (2025, June 26). Abortion law state map: See where abortions are legal or banned. CNN. https://www.cnn.com/us/abortion-access-restrictions-bans-us-dg