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How Marriage Policy Affects Women's LFP

Bohan Bai[1,a,*]

[1]*College of Letters and Science, University of California, Berkeley, 94704, U.S.*
a. bbai02@berkeley.edu
**corresponding author*

Abstract: With technological advancement coupled with the recent pandemic, perceptions of women's societal roles have undoubtedly evolved over the recent decades. Often, their social role is measured through their employment status, with rising labor force participation indicating an elevated social standing. While most of the previous research tends to link women's labor force participation with factors including wage rates, childbirth, and education, the correlation between their labor force participation and marriage has remained underexplored. Given the profound impact marriage can have on women's employment, it is crucial to adopt innovative research approaches that reflect modern shifts in women's social roles. This paper seeks to unravel the link between marriage and women's labor force participation in the U.S., focusing specifically on the influence of legal marriage age via a difference-in-difference design. The goal is to inform the government of better policy decisions, such as pushing for enhanced economic and marriage policies that could further facilitate women's role in the professional realm.

Keywords: marriage policy, labor force participation, women, gender inequality, employment

1. Introduction

Women's labor force participation (LFP) has been one of the main focuses in the field of labor economics. As the world progresses, increasingly educational resources are available for women, enabling their LFP to increase rapidly in the 20th century. However, statistics have shown that married women are less likely to participate in the labor force (only 36.5%) than never-married women as well as their male counterparts [1]. It is crucial to delve into both the psychological and sociological factors influencing how heterosexual marriage impacts women's LFP rates in the U.S.

The difference in difference design (DID) is a suitable research approach to examine the causal relationship between the two. To begin, the null hypothesis for this design posits that changes in the legal age of marriage have no impact on women's LFP. The DID design incorporates the treatment, "post", post-treatment, and control variables, resulting in the following linear model:

$$Y = logit\,(\alpha_1 intercept + \alpha_2 Post_t + \alpha_3 Treat_i + \alpha_4 Post_t * Treat_i + \epsilon_i)^{-1} \tag{1}$$

One of the primary motivations for exploring this topic is its limited coverage in labor economics. Society can better understand women's societal roles by thoroughly examining the relationship between marriage and women's LFP. This knowledge can guide the creation of effective economic or marriage policies that support women in the workforce and enhance their overall social status.

To begin with, whether there is a change in women's LFP after marriage is mainly discussed by Jacob Mincer, who uses cross-sectional analysis of census data between 1960 - 1970 from the U.S. to show that married women's chance of remaining in the labor force increases with their husband's income and education levels [2]. In addition, women who gave birth decreased their LFP [3], but such an effect was reduced as the child grew older. Mincer concludes that women's LFP increased over time due to changing social norms and economic factors. Especially beginning with the baby boom generatio, women become less likely to enter the labor force after marriage and giving birth [4].

Moreover, in terms of household labor allocation, women continue to perform a disproportionate share of household labor even though there is an increase in their participation in paid work [5]. Wives' traits valued in the marriage market are expected to be associated with lower LFP [6]. All these papers present relevant evidence of the changes in women's LFP before and after marriage.

2. Methodology

The previously reviewed academic papers ranging from 1962 to 2016 have no subsequent findings on the topic. This range may not adequately reflect the contemporary factors influencing married women's LFP, especially post-pandemic. To address these challenges and provide a comprehensive insight, a difference-in-difference design is adopted, focusing on marriage policy, such as the legal age of marriage, and accounts for any policy changes and their subsequent effects during a designated period.

In addition, the model should account for potential biases created by single women's LFP rate who are under cohabitation. There were approximately 18 million unmarried partner households in the U.S. Out of these, 12.5 were cohabiting partners, and 41% of them had at least one child under the age of 18 in 2020 [1]. The statistics imply that cohabiting has become a growing trend today, corresponding to the literature reviews that having children can significantly impact women's LFP. In this case, including the number of childbirths as a control for the regression model is necessary for more accurate results.

3. Elaboration of Research Design

To reiterate, the following DID regression model is used to analyze the effect of marriage policy on women's LFP:

$$Y = logit\,(\alpha_1 intercept + \alpha_2 Post_t + \alpha_3 Treat_i + a_4 Post_t * Treat_i + \epsilon_i)^{-1} \quad (2)$$

Given the binary dependent variable, women's LFP (either 0 or 1), this analysis employs logistic regression. The intercept represents the log odds of labor force participatin for the control group ($Treat_i = 0$) before the intervention ($Post_t = 0$). The term "odds" refers to the ratio of success probability to failure probability, while log odds represent its logarithm [7]. The model has three independent variables: Treat_i (binary treatment for legal marriage; 0 for policy change, 1 otherwise), Post_(t) (time dummy; 0 before, 1 after intervention), and Post_t X Treat_i (interaction of group and time variables capturing treatment and control group divergence).

The main coefficient (a_4) on the interaction term captures the differential change in the outcome for the treatment group compared to the control group, from pre- to post-intervention periods. It signifies the causal effect of the intervention, based on the assumption of parallel trends without the intervention. To elaborate, a positive α_4 value indicates a greater likelihood for women to enter the labor force after a change in the legal age of marriage.

Relevant control variables, such as women's LFP, age, and education are included. They can mitigate potential biases and errors from regression results (e.g., assignment biases, SUTVA violation, time-varying confounding, etc.). Suppose the coefficient of the childbirth variable is negative, then it implies the different numbers of childbirths have an overall negative correlation on women's LFP.

For a DID design, the parallel assumption ensures both treatment and control groups follow similar trends until the treatment's introduction, which is crucial for accurate results. To support parallel trends, assigning geographically close states as treatment and controls is beneficial due to the likelihood of shared lifestyles, demographics, and policy impacts. After researching, five states - Wisconsin, Montana, Nebraska, South Dakota, and Wyoming - were chosen as control states due to their unchanged legal age of marriage from 2001 to 2019. Fortunately, all these states are clustered in the same region, indicating a high chance of maintaining parallel trends. Missouri was selected as the treatment state due to its geographical proximity to the five control states that altered the legal age of marriage in 2018.

4. Overview of Data and Initial Results

Before conducting the regression, the PSID [8] dataset's summary statistics provide an overview, ensuring no major imbalance, like the overrepresentation of certain columns, that might bias later analyses. Overall, out of the 3739 observations, 83% of women are not married and 22% of them are employed (as shown in Figure 1). According to Table 1, the average age of the women is 14.98, with 0.67 children each, and 5.59 years of schooling, roughly 5th - 6th grade. Location-wise, between 2001 and 2019, 37% of women resided in Wisconsin, 29% in Nebraska, 18% in Missouri (treatment), 9% in Montana, 4% in Wyoming, and 3% in South Dakota, with the majority from Wisconsin, Nebraska, and Wyoming.

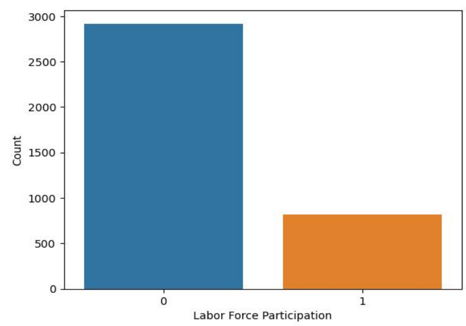

Figure 1: Distribution of women's labor force participation.

Table 1: Summary statistics for non-categorial data.

Stats	Child BIRTHS ALL YEAR	AGE	EDUC LEVEL
count	3739.00	3739.00	3739.00
mean	0.67	14.98	5.59
std	1.10	6.22	6.20
min	0.00	0.00	0.00
25%	0.00	11.00	0.00
50%	0.00	16.00	0.00
75%	1.00	20.00	12.00
max	8.00	25.00	17.00

Furthermore, Missouri, the sole state in the treatment group adjusted the legal marriage age to 16 with parental consent, it is probable that those in their early to mid-twenties, who are more inclined

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to marry, will be impacted by this change. Thus, the age limit of this model is set to 25 (As shown in Table 1).

To verify the parallel trends assumption, one efficient way is to ensure that a consistent time series exists between the treatment and control groups. This is demonstrated by graphing women's average LFP in control states (e.g., Nebraska, South Dakota, Wisconsin, etc.) and comparing it to the average in the treatment state (Missouri) over the period from 2001 to 2019 (about 10 years).There is no standard error for the treatment group since only one observation exists. The resulting plot (Figure 2) suggests that the parallel trend assumption holds for both the treatment and control states since the lines were relatively parallel until the treatment came into effect in 2018 (the red vertical dashed line).

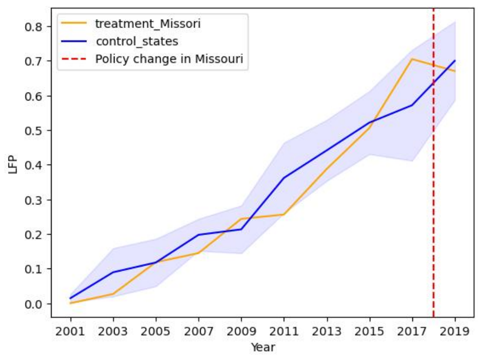

Figure 2: Time series of average LFP parallel trends by treatment and control states.

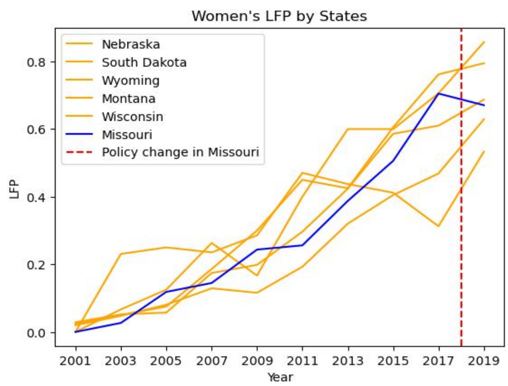

Figure 3: Time series of LFP parallel trends by States.

However, only comparing the average LFP of the treatment and control groups might not conclusively confirm parallel trends, as averaging might diminish the effect of outliers in the data, potentially skewing the trends. Thus, the time series of women's LFP for each of the treatment and control states is illustrated in Figure 3. The plot indicates that all the control states (orange lines) are relevantly parallel to the treatment state (blue line) until the treatment year. Correspondingly, parallel trends of women's LFP are constructed for the age sample restricted to 15-19 (Figure 4-5). Due to Missouri's policy change to a legal age of 16 with parental consent, this sub-population is more likely to be impacted by the change. The graph shows noticeable fluctuations in the slopes of the treatment and control states, compared to Figure 2 - 3, attributable to a reduced sample size and age control. Despite this, the overall parallel trends still hold, as the control group's slope trends mirror the treatment state's.

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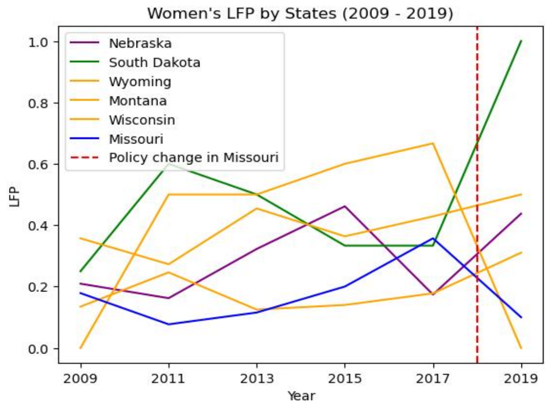

Figure 4: Time series of women's LFP (age 15 – 19) parallel trends by state.

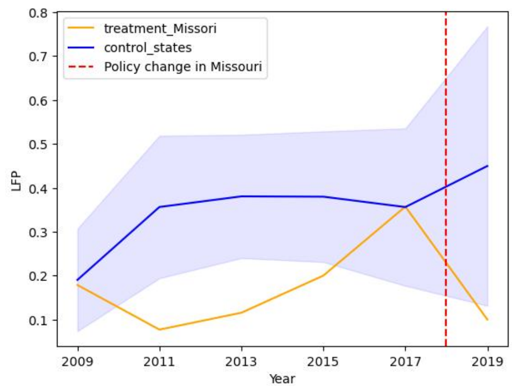

Figure 5: Time series of LFP parallel trends average age (15 – 19) by treatment and control.

Nonetheless, as demonstrated in Figures 2 and 5, a change in the slope of women's LFP appeared in 2017 for both groups right before the year of the treatment introduction. Such a change could be caused by numerous factors and can be difficult to determine but are potentially tied to economic events in 2017. First, the slight slope increase in the control groups for both populations (the blue line) could possibly result from economic policies under the Trump administration. Trump's policy emphasized individual and corporative tax cuts and aims to stimulate economic growth and create jobs, which can potentially encourage women's LFP [9]. Additionally, there is a 3.45% increase in average wage reported in 2017, another factor that might contribute to the slight increase in women's LFP [10].

By contrast, the LFP in the treatment state (Missouri) experienced a significant decrease right before the policy change. This decrease might be attributed to the state's repeal of the prevailing wage law through Senate Bill NO.19. The prevailing wage law sets the minimum wage rates for construction projects that receive public funding. Additionally, given Missouri's policy shift raising the marriage age to sixteen, those wishing to marry earlier might do so before the change. Considering the young sample population, this could account for the notable drop in Missouri's LFP in 2017, as early marriage might deter women from joining the labor force.

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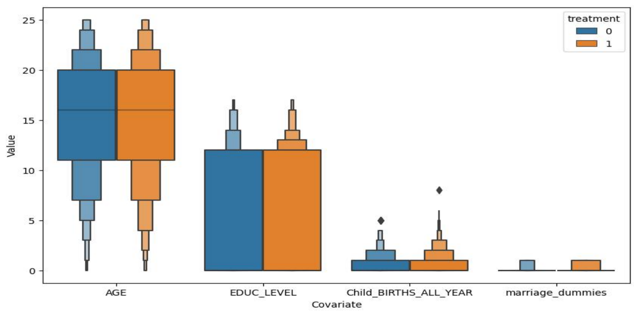

Figure 6: Balance plot showing the balance of covariates across treatment groups.

Based on the analysis above, both the treatment and control groups likely follow parallel trends. A covariate balance plot (Figure 6) displays the pre-treatment similarity in control variable distributions for both groups, further validating the parallel trend assumption.

With the key assumption of the DID model met, the next step is to conduct the logit regression analysis. This entails comparing the LFP of individual women in both treatment and control groups and evaluating the outcome differences. To reiterate, my DID mode is:

$$Y = logit\,(\alpha_1 intercept + \alpha_2 Post_t + \alpha_3 Treat_i + a_4 Post_t * Treat_i + \epsilon_i)^{-1} \quad (3)$$

Table 2: Regression result of women's age, education level, and childbirth.

	DID With Controls women_LFP		DID without Controls women_LFP
const	-7.7620***	const	-1.3548***
	(0.3996)		(0.0988)
post	-0.2391	post	1.1923***
	(0.3919)		(0.3443)
treatment	0.0145	treatment	-0.0324
	(0.1460)		(0.1091)
post_treatment	0.5222	post_treatment	0.5080
	(0.4358)		(0.3823)
AGE	0.2052***		
	(0.0221)		
Education level	0.3003***		
	(0.0220)		
Childbirth all year	-0.2232***		
	(0.0498)		
Marriage_dummies	0.2741**		
	(0.1383)		

The logit regression was conducted twice: one with control variables and one without. Importantly, the regression coefficients signify that a unit increase in the variable results in a corresponding increase in the log odds ($logit(p)$) by the coefficient's magnitude. For clarity, the exponential of these coefficients will be used to determine the odds ratio, illustrating the percentage rise in odds for that variable [7].

To begin, the first regression result controls for women's age, education level, and childbirth (Table 2). The main coefficient on the interaction term (α_4) is positive with a magnitude of 0.5222, or odds ratio of

$$e^{0.5222} = 1.69 \tag{4}$$

This term captures the DID estimate of how marriage policy impacts women's LFP in the treatment state relative to the control state. The magnitude of 1.69 suggests that after the policy change, the odds of women's LFP in the treatment state increased by 69% compared to the control states, assuming all other variables are constant. In comparison, the magnitude of α_4 without controls is 0.5080

$$(e^{0.5080} = 1.66) \tag{5}$$

Which is slightly lower than the result with controls. However, both values of α_4 are not statistically significant at any conventional significance level.

To discern the variations between the two regression attempts, observe the coefficient shifts in the control variables. Before adding controls, "α_2" and "α_3" significantly exceed their respective standard errors (e.g., "α_2" is 1.1923 with a standard error of 0.344), with "α_3" being negative. Upon incorporating controls, the standard errors of each coefficient are smaller, and the coefficients of all variables more closely align with their respective standard errors (for instance, the magnitude of "α_2" is now -0.2391 with a standard error of 0.392), indicating increased precision. The changes in coefficients suggest that integrating control variables compensates for variations in the dependent variable previously attributed to the primary independent variables ("post" and "treatment").

Table 3: DID controlled for age 15-19 and DID without NE and SD.

	women_LFP		women_LFP
const	-7.4200***	const	-7.8736***
	(1.6813)		(2.0416)
post	-1.1939	post	-1.1474
	(1.0941)		(1.0947)
treatment	0.4108	treatment	0.3720
	(0.2884)		(0.3013)
post_treatment	1.3119	post_treatment	1.0799
	(1.1395)		(1.1660)
AGE	0.1441	AGE	0.1937
	(0.1152)		(0.1359)
Education level	0.3297***	EDUC_LEVEL	0.2886***
	(0.0772)		(0.0818)
Childbirth all year	-0.3913***	Child_BIRTHS_ALL_YEAR	-0.3071*
	(0.1322)		(0.1622)
marriage_dummies	0.4290	marriage_dummies	0.3248
	(0.3155)		(0.4055)

To gain insights on the effect of marriage policy on women's LFP, regression is conducted on the restricted population (15-19). As displayed in the left half of Table 3, α_4 is 1.3119 ($e^{1.3119} = 3.71$), indicating the odds of women's LFP in the treatment state increased by 271% compared to the control states after the policy change, assuming all other variables are constant. This is unusually large, which can be caused by a smaller sample size due to the restriction of age.

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However, the magnitude of the main coefficient is not statistically significant at any conventional significance level.

In addition, Figure 4 reveals fluctuating slopes for Nebraska (purple) and South Dakota (green) prior to the treatment introduction. Consequently, a regression model dropping Nebraska and South Dakota is conducted. As displayed in the right half of Table 10, α_4 is 1.0799 ($e^{1.0799} = 2.94$), indicating the odds of women's LFP in the treatment state increased by 194% compared to the control states after the policy change, assuming all other variables are constant. Still, the magnitude of the main coefficient is not statistically significant at any conventional significance level. Regarding the model's accuracy, high standard deviations for both post and post-treatment in the regressions indicate significant uncertainty in estimating this effect.

5. Conclusion

Ultimately, based on the preliminary findings, the null hypothesis asserting that marriage policies concerning the legal age of marriage have no impact on women's Labor Force Participation (LFP) in the U.S. cannot be rejected. Patterns and coefficients indicate a certain trend, but some irregularities are hard to explain. For example, temporal confounders can reduce result accuracy. Identifying them in a short period is challenging, making it hard to differentiate between treatment effects and concurrent events. The complexity is further compounded by the outbreak of the COVID-19 pandemic in late 2019 and early 2020. Furthermore, the regression outcome may be influenced by economic events preceding the 2017 policy change, possibly inflating the result estimates. High standard errors in the restricted population regression hint at variability in outcomes or predictor variables and suggest omitted variable bias. Some future steps to take on this research could be finding datasets with sufficient data on women's LFP, long enough for a DID model.

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