Paid Maternity Leave and Women's Human Capital: Evidence from California*

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Abstract

Does mandatory paid maternity leave affect women's human capital investment decisions? I test whether the implementation of the California Paid Family Leave Act increased young women's human capital investment, specifically college enrollment. Using a synthetic control approach, I estimate that the policy increased the probability that women enroll in college by about 2 percentage points. I present a simple human capital model of women's schooling choices that rationalizes these results as the effect of an expected decrease in the effects of motherhood on labor supply. Finally, I present evidence from survey data and Internet searches that provides support to the hypothesized mechanism.

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Introduction

Women face important tradeoffs between work and family. Despite female labor supply increasing in the last century, women still encounter several barriers. These include lower salaries, barriers to promotion, and job loss due to pregnancy. Maternity leave policies were originally established to provide some protection from gender discrimination in the workplace: so women could have some time to bond with their children and recover from childbirth without risking their jobs. These policies have been promoted as a way to ease the tradeoffs between work and family that women face, especially given the cultural expectation that they take the role of primary caregivers of their children.

Economists and other social scientists have studied the implications of maternity leave policies on several spheres. Particular attention has been paid to effects on the labor market. Studied effects include those on female labor supply, female labor earnings, and the gender gap in employment outcomes. Despite considerable interest on the effects of these policies on women's labor-market outcomes, effects on women's own human capital investment decisions have not yet been studied. If policies have an expected impact on women's labor-market outcomes, investments decisions should respond.

I study the question of whether paid maternity leave changes women's human capital investment decisions. I address the fact that women make investment decisions based on their expectations of the returns to those investments. Do women expect maternity leave to ease the work-family tradeoffs that they face? Are women's educational choices constrained by these tradeoffs?

I use the introduction of the California Paid Family Leave Act (CPFLA), which was the first of its kind in the US, to estimate the relationship between paid maternity leave and women's human capital investment decisions. I take the synthetic control approach of Abadie and Gardeazabal (2003), comparing women in California who were likely to make their college enrollment decisions before and after the policy went into effect, to the equivalent groups of women in the synthetic control. I estimate that the policy increased female college enrollment by about two percentage points. This effect is statistically significant and persists for at least several years.

Beyond the rationale against discrimination in the workplace, promoters of maternity leave argue that these policies are welfare increasing for mothers and children. There is evidence of improvements in child health outcomes, including increases in birth weight and a reduction in infant mortality among children of highly educated, married women (Rossin (2011)), as well as long-term benefits for children, such as higher wages and lower high-school dropout rates (Carneiro et al. (2015b)).

One literature has focused on the effects of maternity leave policies on women's labor market outcomes and the gender gap. Researchers have found that mothers tend to extend their leave when the leave is paid (Baum and Ruhm (2013)), and that paid leave increases hours worked and wages (Rossin-Slater et al. (2011)). Women are more likely to be employed 9 to 12 months after giving birth (Baum and Ruhm (2013)), and overall job retention after having a child increases (Waldfogel (1998), Rossin-Slater et al. (2011)). However, Bailey et al. (2019) provide evidence that, over the long term, the CPFLA has not decreased the gender gap in labor force participation, and may have widened it for some groups. The lack of apparent consensus in the literature regarding the effects of maternity leave policies on women's labor-market outcomes stems in part from the fact that different features of maternity leave policies may have different impacts. For example, job-protection and wage replacement may act in different directions (Rossin-Slater (2017), Stearns (2015)).

Despite all the interest in the effects of maternity leave policies on women's labor supply, little attention has been paid to the effects of these policies on women's human capital investment decisions. Expected effects of maternity leave policies on labor market outcomes may provide incentives for women to increase investments in human capital. Women may interpret mandated paid maternity leave policies as a signal of more parent-friendly work environments, or more generally, as a decrease in the cost of motherhood on their labor supply. Women can then expect an increase in their labor supply, either in the intensive or the extensive margins, relative to the counterfactual scenario with no policy. Under those conditions, each additional unit of human capital becomes more profitable, as it would yield benefits over a longer period of time. Namely, if women expect to work more as a result of this policy, investing in human capital is more profitable.

These effects can arise regardless of whether women actually remain in the labor-force after motherhood. The expectation that they are more likely to remain in the labor-force after having a child is enough to drive an increase in investment, in this case college enrollment. In other words, beyond what happens to labor supply ex-post, women make investment decisions using their ex-ante expectations of what will happen to their labor supply. In this sense, my results are not susceptible to the apparent lack of consensus in the literature about the labor-market effects of maternity leave, because the mechanism does not depend on the realized effects of the policy, but the ex-ante expectation that women have.

My contribution is twofold. First, I show that maternity leave policies can influence women's schooling decisions, and thus show that women's schooling decisions are constrained by the work-family tradeoffs that they face. Second, this paper brings attention to the fact that women expect these policies to ease such tradeoffs.

I present a human capital accumulation model, modified from Kuziemko et al. (2018), that rationalizes the mechanisms depicted above. The model describes women's schooling decisions in the face of motherhood effects on their labor supply. Working with this model, I rationalize my empirical results as women internalizing this policy as a sign of lower expected cost of motherhood on future labor supply. To further motivate my hypothesized mechanism, I present evidence from survey data that supports the presented model. Additionally, I present Google Trends data showing that interest in paid maternity leave increased in California (more than elsewhere) around the time of policy implementation, which provides support to the hypothesized mechanism.

The rest of the paper is structured as follows: in Section 2 I discuss the literature on the effects of maternity leave policies, and briefly describe the CPFLA. In Section 3 I describe the data and my empirical strategy. Section 4 presents the results of the synthetic control exercises. Section 5 contains the model, Section 6 contains additional evidence of my hypothesized mechanism. Section 7 concludes.

1 Background

1.1 Maternity Leave

Maternity leave policies have the purpose of providing protection against workplace discrimination, and allow time for mothers to recover from childbirth, care for, and bond with a new child. These policies have received much interest from the research community and policy makers. Effects of maternity leave on a variety of outcomes have been studied. For example, there is substantial evidence that takeup increases when leave is paid or expanded (Han et al. (2009), Baum and Ruhm (2016), Bartel et al. (2018)).

There is also evidence of positive effects on outcomes for children. Increases in leave entitlement leads to a decline in high school dropout rates for children (Carneiro et al. (2015a)). Paid leave increases the likelihood and duration of breastfeeding (Pac et al. (2019)), and improves birth and health outcomes (Rossin (2011), Stearns (2015)). Bailey et al. (2019) find evidence that the CPFLA increased the time that mothers spend with their children.

Given labor market disparities between men and women, and gender disparities in time allocated to child rearing, there is an extensive literature that has focused on labor market effects of maternity leave policies. Theoretical effects of maternity leave on post-leave employment outcomes are ambiguous

(Klerman and Leibowitz (1998)), and there is an apparent lack of consensus of the empirical evidence.

On one hand, several studies have found that maternity leave is associated with an increase in employment after birth (Baum and Ruhm (2016), Kluve and Tamm (2013)), job attachment (Baum and Ruhm (2016), Byker (2016)), and hours and weeks worked (Rossin-Slater et al. (2013)). It is important to note that these effects are measured at different times. For example, effects may differ three years after birth vs. in the period directly before and after childbirth. The effects of these policies are plausibly different in different moments of the child's life, and for different parities.

However, Bailey et al. (2019) use a large administrative data set to evaluate long term effects of the CPFLA. They find no evidence that the policy has closed the gender gap in labor-market outcomes such as employment, wage earnings or job attachment. In fact, they find a reduction in annual wages for new mothers who take leave via CPFLA.

The apparent lack of consensus on the effects of maternity leave policies on women's future labor market outcomes likely partially stems from the variation that exists in maternity leave policies and how these interact with the context (see Rossin-Slater (2017) for a comprehensive review of the literature on maternity leave policies). Different features of leave policies may have different effects. For example, FMLA offers job protection but no wage replacement, while CPFLA offers partial wage replacement but no job protection. These two features may impact have different effects across groups of women (Stearns (2015)). There is evidence of large heterogeneity in the effects across income groups (Bailey et al. (2019), Bedard and Rossin-Slater (2016)), and the effects may be very different depending on the length of the leave (Lequien (2012)).

The lack of conclusive evidence notwithstanding, to study the effects of women's schooling decisions, what matters is what women expect to happen, ex-ante. In particular, what they expect at the time when they make their investment decisions. In the case of the CPFLA, women had little evidence on what wold happen to their labor supply post motherhood, since this was the first mandated paid maternity leave policy implemented in the US.

In Kuziemko et al. (2018), it is shown that in the US and the UK, women have increased their schooling in the last few decades despite the fact that women are not working outside the home much more than before. The authors frame these two facts as women systematically underestimating the cost of motherhood on their labor supply. Women make schooling decisions expecting they will work after motherhood, but when they become mothers they receive an information shock and realize it is too costly to do both, so they end up with inefficiently high levels of human capital for the labor they end up supplying.

Kuziemko et al. (2018) argue that the reason for this systematic underestimation is that the cost of motherhood on labor supply has increased across cohorts, but women make decisions as if it had remained constant. The authors suggest that this increase is not driven by the work side of the work-family tradeoff, but by the family side, perhaps via increased requirements on childbearing (such as the promotion of breast feeding) or decreased support from networks. In this paper I argue that, additionally, women may have taken the implementation of maternity leave policies as a sign of a decrease in the work side of the tradeoff, perhaps inferring from the implementation of maternity leave policies that workplaces were becoming more family friendly, or that society was more accomodating to women's dual role as childrearers and workers.

Regardless of the evidence we currently hold about labor market effects on women's labor supply, if, at the time they were making their schooling decisions, women expected that the CPFLA would increase their probability of returning to the work place after having a child, that would be enough to drive the effect on college enrollment I find in this paper.

1.2 The California Paid Family Leave Act

Since 1993 and before the CPFLA passed, in 2004, some working women in the US were entitled to 12 weeks of job-protected leave per child (born to them or that they adopted) via the Family and Medical Leave Act (FMLA). This policy also provides job-protected leave for other reasons, such as caring for a sick family member, and it also grants paternity leave to eligible fathers. Parents are eligible for 12 weeks of job protection through FMLA if they had worked for an eligible employer at least 1,250 hours in the 12 months before taking the leave. Eligible employers include those with over 50 employees that lived within 75 miles. Fathers and mothers are entitled to the same benefits via FMLA.

The California Paid Family Leave Act introduced partial pay benefits for eligible employees living and working in the state of California, that had a new child entering the family, or were taking care of a sick family member. Eligibility requirements include that workers have earned $300 in wages that were subject to the State Disability Insurance deductions. The CPFLA does not provide job protection.

Those who are eligible for both FMLA and CPFLA can take both simultaneously, thus enjoying job protection via FMLA for up to twelve weeks, and (partial) wage replacement via CPFLA for up to 6 weeks. Even though CPFLA has fewer eligibility restrictions than FMLA, those women who are not eligible for FMLA may find it difficult to claim wage replacements via CPFLA if they are not covered by job-protection policies. It is also important to note that some women, especially those earning higher wages, may have already enjoyed paid maternity leave provided by their employers as part of a private benefit package.

2 Data and Empirical Strategy

2.1 Data and Descriptive Statistics

I use pooled Current Population Survey (CPS) data from all monthly CPS surveys from 2011 to 2017, through IPUMS-CPS.[1] The monthly CPS is a rotating panel, so from the pooled data I take the latest observation available for each woman. I drop from the sample women who were younger than 22 when they were last interviewed, to keep only women who have plausibly already finalized their decision of enrolling in college or not.

For privacy purposes, the CPS does not include information on participant's year of birth. To be able to perform aggregate analyses at the birth year-state level, I impute birth year by subtracting age at interview and year of interview. This can generate some noise in my imputed birth year variable, depending on month of birth and month of interview. However, this noise is not a major concern, since my imputation would not misclassify women by more than one calendar year, and the direction in which the misclassification occurs is not likely related to any relevant characteristics. As a robustness check, I perform the main analyses defining treatment for birth-year cohorts one and two years before and after treatment actually occurred, and results are qualitatively similar.

As my outcome variable of interest, I define the binary variable "college enrolled", which takes a value of one if the woman has a college degree or any college studies, and zero otherwise. This variable is constructed from different categories that women can select from in the CPS when reporting their educational attainment. Women who report having 1 year or college, some college but no degree, or anything beyond that count as college enrolled under this categorization. Other margins of human capital accumulation can be explored in a similar way, for example by using a binary variable for having attended graduate school as a dependent variable.

Other variables I use from the CPS include four race and ethnicity categories (Asian, Black, White, and Hispanic), high school graduation, and total household income. Using the described sample from

[1]IPUMS-CPS, Sarah Flood, Miriam King, Steven Ruggles, and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 5.0. [dataset]. Minneapolis: University of Minnesota, 2017. https://doi.org/10.18128/D030.V5.0.

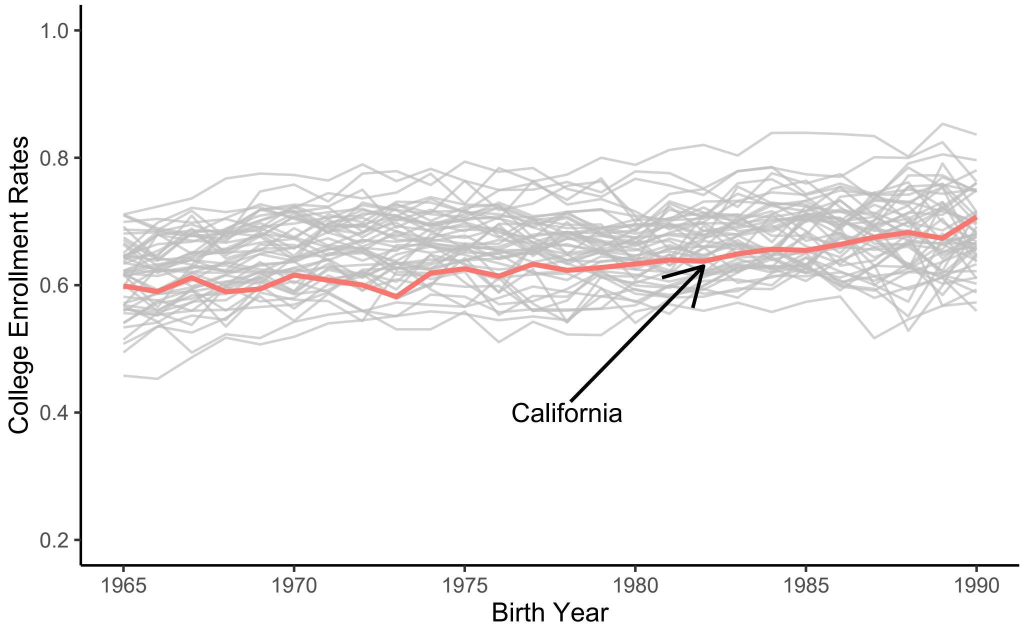

Figure 1: College Enrollment Trends in California and Other States

the pooled CPS data, I collapse by state and the imputed birth year to obtain a strongly balanced panel of state and birth year averages of the variables I use.

I abstract from fertility choices, by including women in my sample regardless of whether they have children or not. I do this in part because there is reason to believe that the timing of pregnancy or motherhood can be susceptible to the policy, and in part because selection into motherhood itself cannot be properly dealt with using this method. Additionally, if I wanted to ensure that women had plausibly completed their fertility decisions, I would have to restrict my sample further by age. Women who were 18 in 2004, when the policy went into effect, are only 34 years old now. I do not include this restriction in my analysis, so my results should be interpreted as an average treatment effect.

Figure 1 Shows a plot of college enrollment rates by birth year in the period of study for different states in the US, calculated using the CPS. California is highlighted in red and a thicker line, while the rest of the states are shown in gray. We can see that the overall trend of all states is positive, and California remains in the middle of the pack throughout. Women in California who belong to the 1987 cohort had a college enrollment rate of 0.675. Figure 2 shows the estimated college enrollment rates for the 1987 cohort in each state. We can see that the state with highest college enrollment rates is DC with 0.834, and the state with the lowest is Nevada with a rate of 0.517.

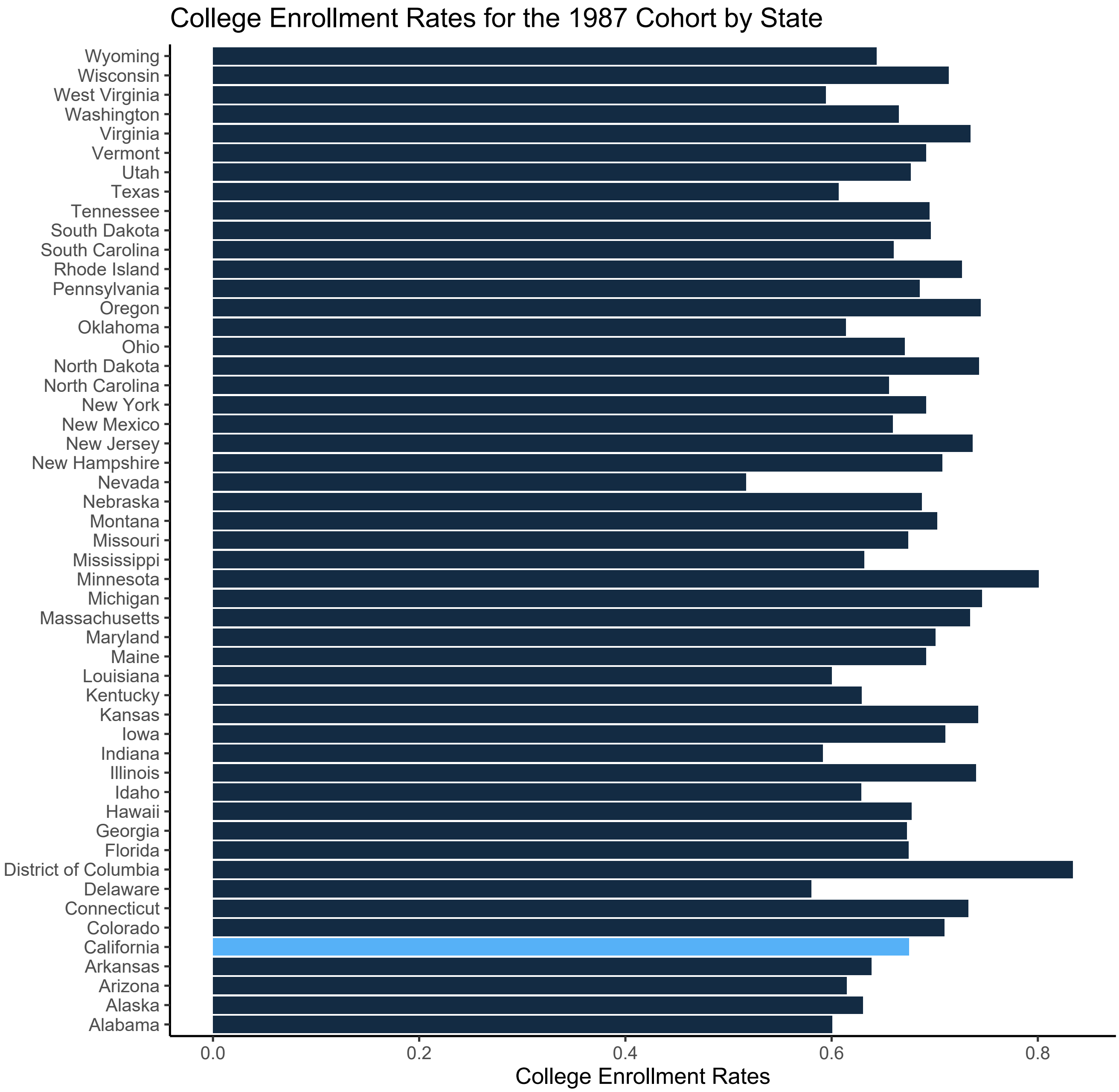

Figure 2: College Enrollment Rates in California and Other States for the 1987 Cohort

2.2 Empirical Strategy

The main challenge in evaluating the effects of a policy like this one is that it is hard to find a geographical group that could serve as a reasonable counterfactual to the state of California. The entire US may not be a good counterfactual since college enrollment in the country as a whole may face different dynamics as the same variable in California. As far as particular states, the choice is not clear: California's neighboring states could be a potential choice with the argument that they are subject to similar economic conditions, but these states are demographically and otherwise different from California. Moreover, using individuals who live close to the state border, between California and Nevada for example, is not a good fit for this research question. While these people may be very similar, endogenous mobility could bias our estimates, especially when one state offers a benefit that the other does not.

The synthetic control method of Abadie et al. (2010) is well suited for the evaluation of aggregated policies such as this. The idea behind this approach is to construct a synthetic California, as a linear combination of untreated states, which will be a good counter factual for an untreated California. Equation 1 expresses this idea, where $\hat{Y}^s$ is the value of the outcome variable for the synthetic California in time t, ω_i is the weight (between 0 and 1) chosen for each state i, and Y_{it} is the value of the outcome variable in state i, in time t. In this notation, states that are untreated include $i = 1, 2, ...N - 1$ and California is indexed by $i = N$.

$$\hat{Y_t}^s = \sum_{i}^{N-1} \hat{\omega}_i Y_{it} \approx Y_{Nt} \tag{1}$$

The method takes as inputs the values of some outcome predictor variables and the outcome variable itself for several periods before treatment, and uses them to calculate non-negative weights for every state in the country, such that the weighted average of all states approximates the pre-policy values of the state of California. This is represented in Equation 2, where $\hat{\omega}$ is the vector of all state weights $\hat{\omega}_i$.

$$\hat{\omega} = argmin \sum_{t=1}^{T-1} (\sum_{i=1}^{N-1} \hat{\omega}_i Y_{it} - Y_{Nt})^2 \tag{2}$$

Once the weights are chosen, a synthetic control is then calculated as the weighted average of all states, using the optimal weights. This synthetic control is also projected into the post-policy years, using the same weights. The treatment effect in each period is estimated as the discrepancy between the synthetic control and what actually occurred in California, allowing us to calculate dynamic treatment effects. Equation 3 specifies this.

$$\hat{\tau}_t = Y_{Nt} - \hat{Y}_t^s \tag{3}$$

I apply the synthetic control method to my prepared CPS data. I Take college enrollment rates from 1975 to 1985 as pre-treatment observations to fit the synthetic control to. As predictor variables, I use the share of women who report belonging to four racial and ethnic categories, as well as high school graduation rates, and total household income.

I define treated cohorts as those with imputed birth years after 1987. Those born in 1987 were about 17 years old in 2004, when the policy was implemented and thus more likely to still be in high school. College enrollment decisions were more likely to be affected for women who were still in high school at the time of policy implementation. Women who were older and had previously decided not to enroll in college would likely face higher costs if they were to return to school.

3 Results

3.1 Main Results

Table 1 shows the states for which positive weights were chosen for the synthetic control for college enrollment. In this case, only Arizona, Hawaii, New Jersey, New Mexico and Texas were chosen. As Abadie (2019) explains, an attractive property of this method is that it is transparent in how it builds a synthetic counterfactual. Part of this transparency is the fact that the number of states with positive weights is small.

Predictor variables are used to choose state-weights. The relative importance of each predictor variable can be assigned in several ways. In this case, they are chosen proportionally to their variance. These proportions are called v-weights, and they can be found in Table 2.

Table 3 shows the demographic characteristics of California and its synthetic control. Perhaps unsurprisingly, the hardest control to match is the rate of hispanic women in California. Table 2 shows that this predictor variable has a small role in choosing state-weights.

Figure 3 shows the trends of real and synthetic California for women with imputed birth years between 1975 and 1990. The dashed vertical line represents the cohort that was first treated. We can see that the synthetic California follows the trend of California quite closely before the policy. The divergence between the two Californias after the vertical dashed line represents the treatment effect.

Table 1: Synthetic Control Weights: College Enrollment

Weight	State
0.407	Arizona
0.116	Hawaii
0.283	New Jersey
0.059	New Mexico
0.153	Texas

Table 2: V Weights

Variable	Weight
Asian	0.021
Black	0.262
Hispanic	0.04
White	0.265
High School Diploma	0
Household Income	0.412

The two lines never cross after treatment, and the size of the gap remains quite constant for the cohorts shown.

The size of the effect may not seem large, but it represents a persistent treatment effect of about 2 percentage points. This is quite large considering the indirect nature of the hypothesized mechanism. After all, the CPFLA only offered about 6 weeks of 60% to 70% of women's wages, and it would have been difficult to claim for women who were not eligible for FMLA. This effect is also large considering that enrollment rates in California were quite high to begin with, at over 65%. Furthermore, this estimate is large if we consider it measures effects on human capital investment at the extensive margin. Intensive margin outcomes would likely show larger effects.

3.2 Inference

In order to asses significance, I perform a sequence of placebo tests, following Abadie et al. (2010). These placebos perform the same exercise described above, but assign treatment to each one of the untreated states.

The next step to assess statistical significance is to calculate the ratio of pre-treatment RMPSE to post treatment RMSPE for every state, and rank them, following Abadie et al. (2010). The RMSPE ratio is a way to normalize the estimated treatment effect by the pre-treatment fit. The larger the ratio, the less likely the true effect is zero. Ranking all RMSPE ratios allows us to calculate exact p-values.

Table 3: Synthetic Control Balance

	Treated	Synthetic	Sample Mean
Asian	0.136	0.086	0.043
Black	0.060	0.074	0.117
Hispanic	0.418	0.262	0.114
White	0.757	0.750	0.794
High School Diploma	0.856	0.882	0.913
Household Income	67,723.54	67,328.14	61,686.99

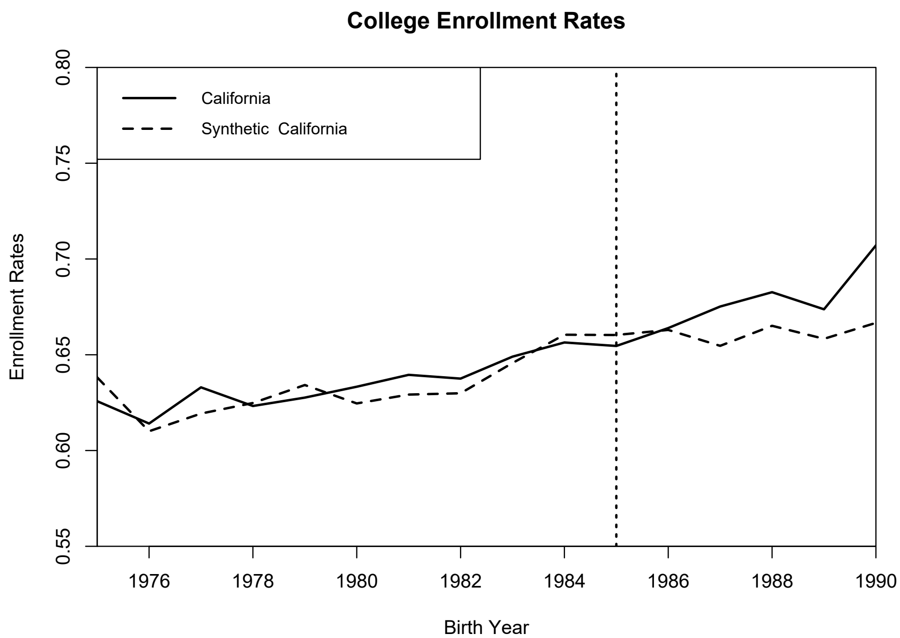

Figure 3: College Enrollment Rates for California and Synthetic California

Assessing inference based on these 50 placebo tests is a demanding test of statistical significance.

The histogram of RMSPE ratios is shown in Figure 4. As we can see, California's ratio is larger than all but one state, and it is quite removed from the rest of the ratios in the distribution. The p-value of the effect is calculated as the ranking divided by the number of placebos. In this case, this yields a value of 0.039, which makes my results significant at the 5% level.

A falsification test of sorts is checking for effects in other variables of interest where we would not expect an effect. Figure 5 shows the synthetic controls exercise for high school graduation rates. As discussed before, it might be costly for women to adjust some margins of decision on short notice, given previous investments. This is why I did not expect an effect on high school graduation rates,

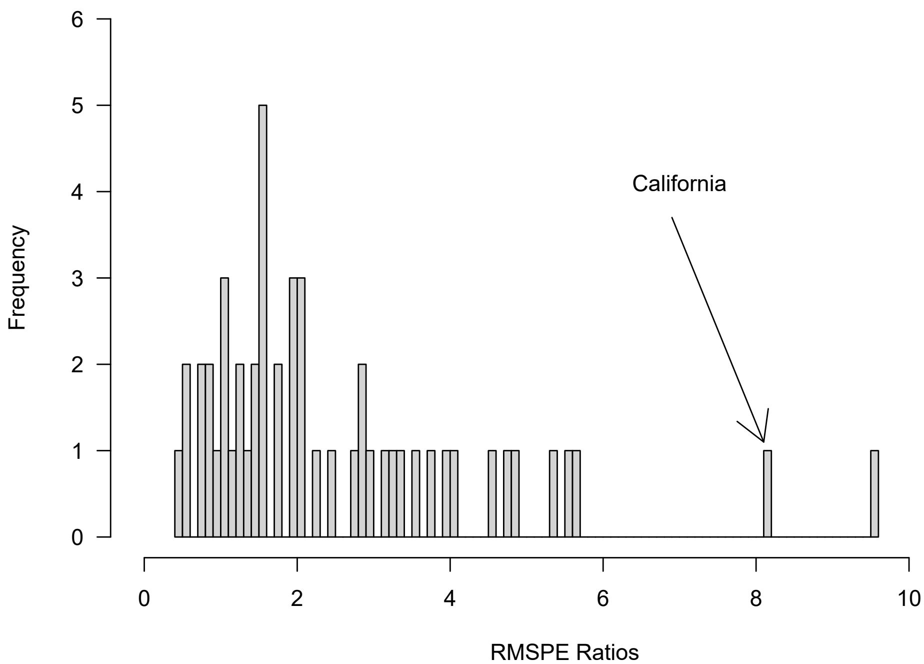

Figure 4: Histogram of RMSPE Ratios

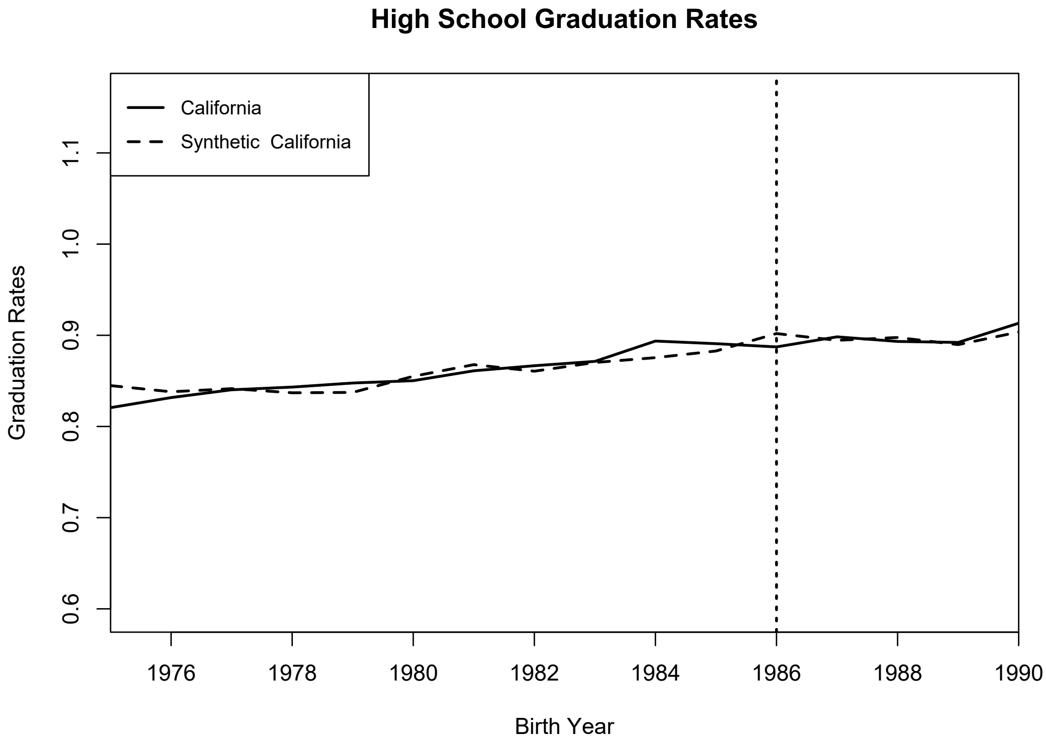

Figure 5: High School Graduation Rates for California and Synthetic California

and in fact this placebo test shows no effect. Figure 5 shows that the trends of California and its synthetic counterfactual follow each other closely, even after treatment. The high school placebo is also encouraging for the main results, since it provides evidence that the method is able to predict future trends quite well in the absence of treatment.

3.3 Heterogeneity by Race and Ethnicity

The average effect found in Figure 3 may contain substantial heterogeneity. Given the fact that higher-earning women are more likely to obtain this benefit from their employer, women who expect to be higher-earning are less likely to be affected by the policy. Thus, one can expect heterogeneous treatment effects by some characteristics, such as race and ethnicity, that are related to potential earnings. I therefore construct four strongly balanced panels from the CPS data that contain state-birthyear averages as before, but for each one of the following four categories: asian women, black women, hispanic women, and white women. Hispanic is not mutually exclusive with the other three categories, since hispanic origin is asked as a separate question from race. These categories don't

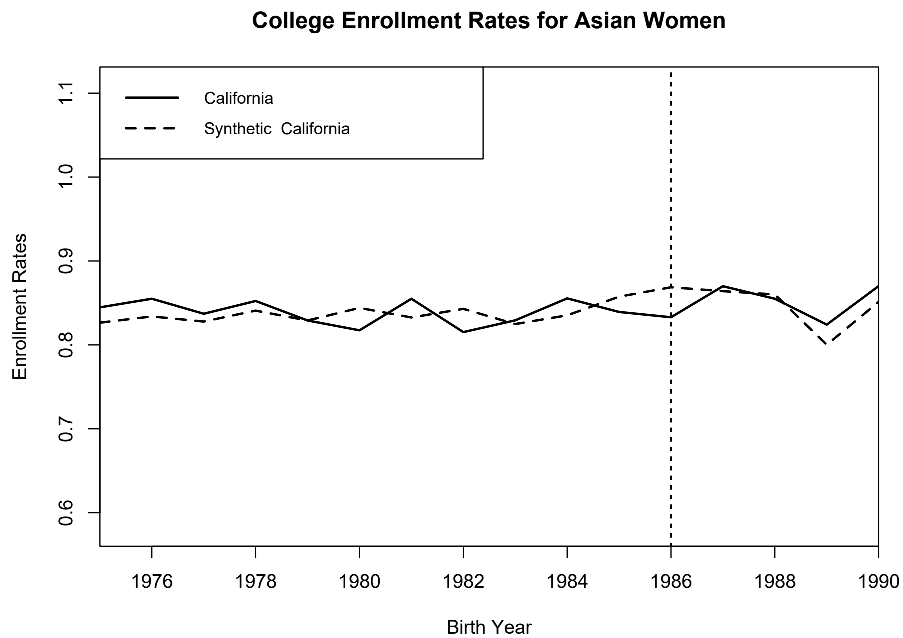

Figure 6: Synthetic Control: College Enrollment of Asian Women

include all women in the CPS, since respondents can select other categories such as Native American, and multi-racial combinations.

Figures 6 through 9 show the plots for each one of the ethnic and racial categories. Most of them have a reasonable pre-trend fit with the exception of college enrollment of black women, which seems to be very noisy, making it harder to fit by the synthetic control. The only category that seems to show an effect is that of hispanic women. This suggests that the average effect may be higher for hispanic women. However, it is important to note that breaking down the data by race and ethnicity may introduce more noise in the trend, especially in the case of hispanic women outside of California. This could explain why the synthetic control for this group, in Figure 8 is not able to match the smooth California trend even before treatment.

The synthetic control method has estimated a statistically significant effect of the introduction of CPFLA on women's college enrollment. The question remains of where this effect comes from. After all, CPFLA only offered six weeks of partial pay. Only for women at the very margin would this amount of money be enough to tip the balance in favor of a college education. I argue that it is likely that women internalized the implementation of this policy as a reduction in the cost of motherhood on their labor supply. Either because women expected that workplaces had become more parent-friendly

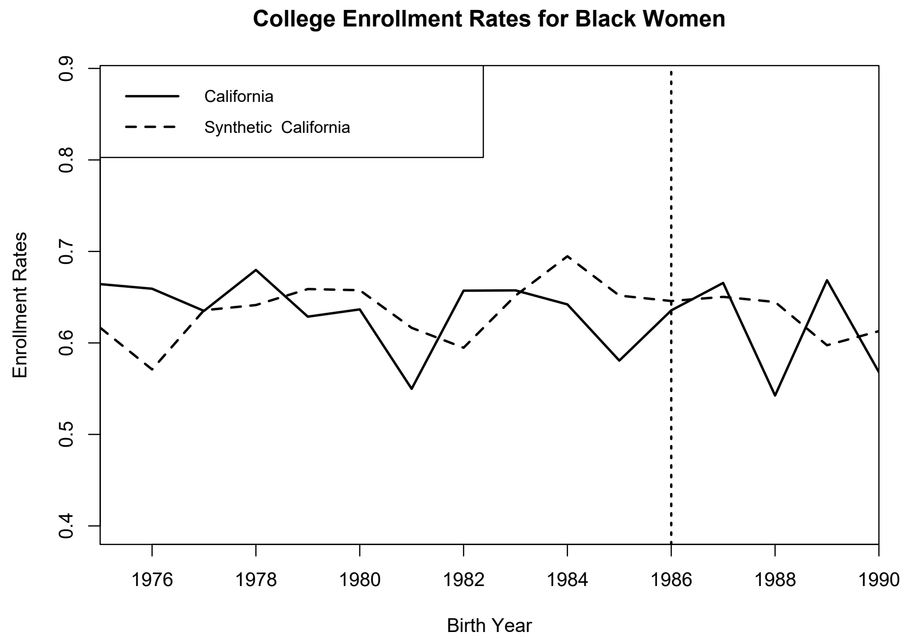

Figure 7: Synthetic Control: College Enrollment of Black Women

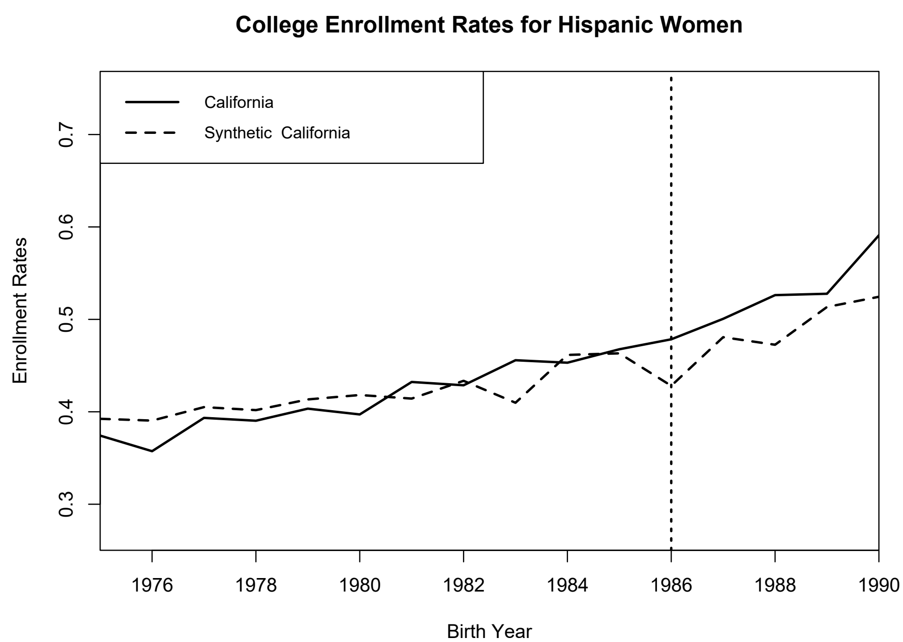

Figure 8: Synthetic Control: College Enrollment of Hispanic Women

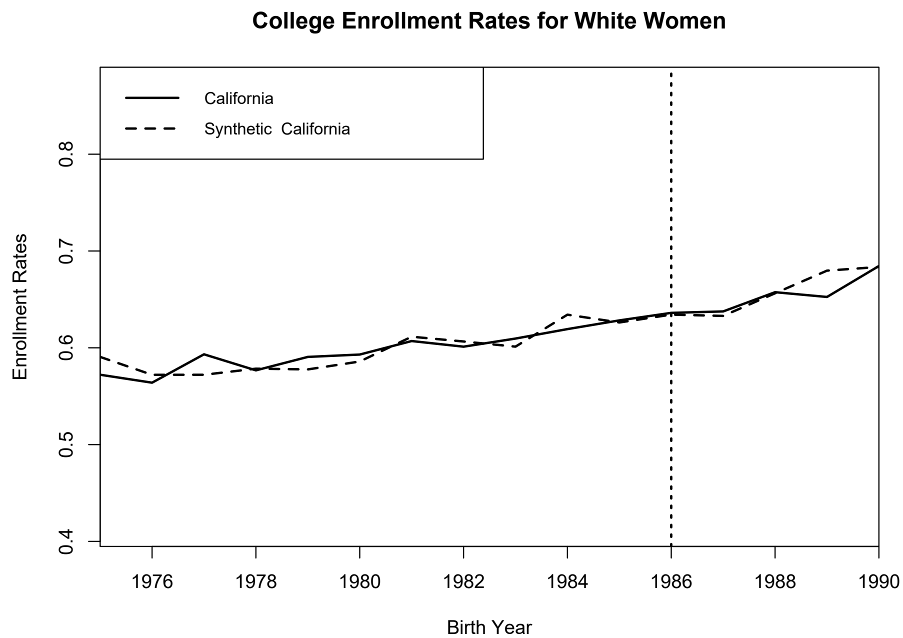

Figure 9: Synthetic Control: College Enrollment of White Women

or because society as a whole was more accommodating for women's dual role. To formalize the framework for this mechanism, in the following section I present a simple human capital model.

4 Model

Modifying the model from Kuziemko et al. (2018), I characterize women's optimization problem as follows. Women live two periods, in which they enjoy consumption and leisure, and earn a competitive wage (w) for the labor they sell on the market. They must choose how much to work on each period, and whether to invest in human capital (schooling) in the first period. If they choose to do so, they will pay tuition (α) on the first period and earn a wage premium (δ, per hour worked) in the second period.

For every hour women choose to work in the second period, they must pay m_i, motherhood costs. Following Kuziemko et al. (2018), I define motherhood costs broadly as any cost mothers have to incur if they work. An obvious example of this is childcare, but m can also include psychological costs, decreases in child quality, and others. The motherhood cost faced by an individual woman comes from an distribution with mean μ. Individual motherhood costs include idiosyncratic variation that represents the fact that although some costs are faced by all, women face different circumstances. Having a network that can provide childcare, living close to childcare facilities, or family members, etc, would be included in ρ_i.

The following is the woman's optimization problem:

$$\max_{c_t,h_t,e} \quad c_1 - \frac{h_1^{\gamma+1}}{\gamma+1} + \beta\left(c_2 - \frac{h_2^{\gamma+1}}{\gamma+1}\right) \tag{4}$$

$$\begin{aligned} \text{s.t.} \qquad & \mathrm{c}_1 = wh_1 - e\alpha \\ & \mathrm{c}_2 = \bar{c} + (\tilde{w} - m_i)h_2 \\ & \tilde{w} = w + \delta e \\ & \mathrm{m}_i = \mu + \rho_i \\ & \mathrm{e} \in \{0,1\} \\ & \rho_i \sim \mathrm{iid}(0,1) \end{aligned}$$

In this model, I assume that women know both components of their own motherhood costs. Because I am looking to rationalize increases in schooling as a result of paid maternity leave policies, and not changes in women's labor supply, I abstract from the issue of uncertainty of motherhood costs. In other words, I am interested in the problem that women are solving when they have to make their schooling decisions, not in the labor outcomes ex-post.

Women can choose not to work, in which case they would not have to pay motherhood costs in the second period, but they would also earn no wages. I incorporate non-labor income in the second period, to account for the income shared by a woman's partner, although this is not the situation faced by all mothers. In this model, mother's childcare labor is unpaid. The model abstracts from several potentially important aspects of motherhood. For example, I abstract from the endogeneity of fertility.

Given a level of education, women can compute the optimal number of hours they will supply on the second period. Hence, this problem is easily solved by backward induction. There are three possible solutions: 1) women decide not to invest in schooling and not work in the second period, 2) women decide not to invest in schooling and work in the second period, and 3) women decide to invest in schooling and work in the second period. Because there is no uncertainty about the returns to schooling or any other parameter in this model, there is no optimal case in which women decide to invest in schooling but do not work. Table 4 shows the value function in these three possible cases.

Even though his model does not include the possibility of the phenomenon documented in Kuziemko et al. (2018) and elsewhere, that women over-invest in education for their labor supply, my results are consistent with the mechanism argued for in Kuziemko et al. (2018): women may be taking cues from society (such as maternity leave policies) as a sign of decreased costs of motherhood, when in fact these costs have increased. In other words, policies like maternity leave could be exacerbating the systematical underestimation of motherhood costs.

Table 4: Value Functions

(1) No school, no work in t=2	$\frac{\gamma}{\gamma+1}w^{\frac{\gamma+1}{\gamma}}+\beta\bar{c}$
(2) No school, work in t=2	$\frac{\gamma}{\gamma+1}w^{\frac{\gamma+1}{\gamma}}+\beta[\bar{c}+(w-m_i)^{\frac{\gamma+1}{\gamma}}\frac{\gamma}{\gamma+1}]$
(3) School and work in t=2	$\frac{\gamma}{\gamma+1}w^{\frac{\gamma+1}{\gamma}}-\alpha+\beta[\bar{c}+(w+\delta-m_i)^{\frac{\gamma+1}{\gamma}}\frac{\gamma}{\gamma+1}]$

Given this optimization problem, the question that I ask is how does the choice of solution change with m? In particular, I am interested in how the schooling choice changes when women are faced with changes in m. Can an increase in the enrollment rate be the product of a decrease in μ? I begin with some definitions.

Definition 1: Let $\bar{m}_{a,b}$ be the smallest value of m_i that would make a woman indifferent between cases a and b.

We therefore have three different $\bar{m}$. The value of $\bar{m}_{1,2}$ is of course equal to w, while $\bar{m}_{1,3} = w+\delta-(\frac{\alpha}{\beta}\frac{\gamma+1}{\gamma})^{\frac{\gamma}{1+\gamma}}$. The value of $\bar{m}_{2,3}$ does not have an analytical solution. However, being able to order the magnitudes of these cutoffs is enough to characterize the way in which the schooling choice varies with m.

Proposition 1: Out of the eight plausible orderings of $\bar{m}_{1,2}$, $\bar{m}_{1,3}$, $\bar{m}_{2,3}$, only the following are feasible:

- A: $\bar{m}_{2,3} < \bar{m}_{1,3} < \bar{m}_{1,2}$
- B: $\bar{m}_{1,2} < \bar{m}_{1,3} < \bar{m}_{2,3}$
- C: $\bar{m}_{1,3} < \bar{m}_{1,2} < \bar{m}_{2,3}$

Proof: See Appendix.

Cases A, B, and C are shown in Figures 10 through 12. For a given value of m_i, women would choose to be in the case that has the highest value, so the value function is the upper contour of the three graphs presented. For our purposes, only cases A and B are relevant. Case C implies that there is no value of m_i for which schooling would be optimal. In case A, there are values of m_i that would make cases 1, 2, or 3 optimal. In this case, reductions in μ could move women from not working and not acquiring education to just working or to acquire education as well, depending on the magnitude of the change. Reductions in μ could also move some women from case 2 to case 3: women who would have optimized working anyway would now also acquire schooling. I will focus on case A, since it is more general, and because in reality we observe a non-negative share of women in all three cases.

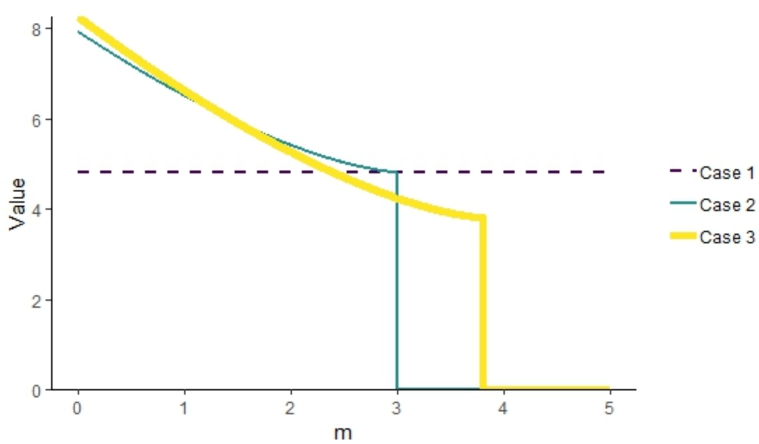

Figure 10: Case A

Figure 13 shows two distributions of motherhood costs under the case A graph of value functions. Depending on their individual value of ρ_i, women would make different decisions, falling in cases 1 through 3, separated by vertical dashed lines, and labeled in grey. If the mean cost of motherhood decreased, the entire distribution will shift to the left, as illustrated in the bottom panel. This would

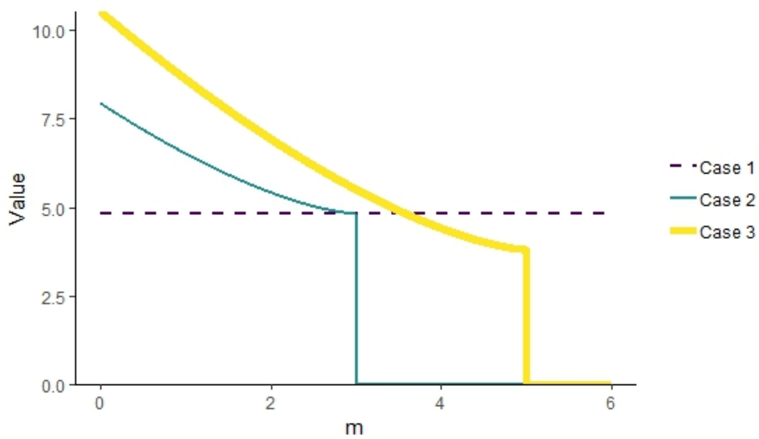

Figure 11: Case B

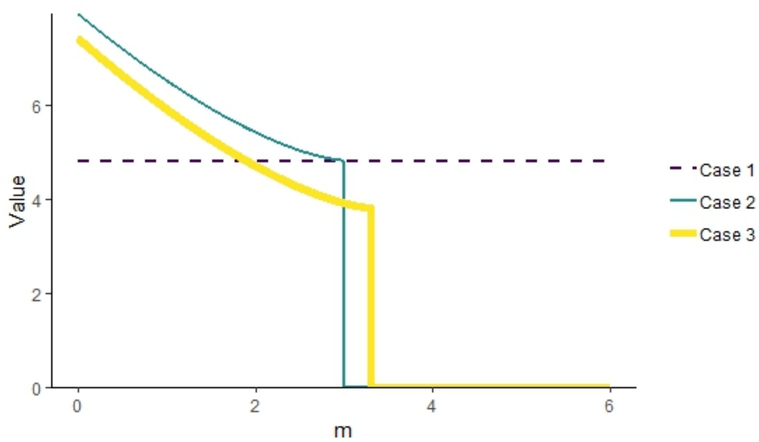

Figure 12: Case C

move some women from case 1 to case 2, and from case 2 to case 3. A larger decrease in mu could even move some women from case 1 to case 3. If we were in the broader case B, where it is never optimal to work without going to school, women would shift from case 3 to case 1. Therefore, a reduction in μ would increase the share of women in case 3, which is consistent with the increase in college enrollment documented in Section 3.

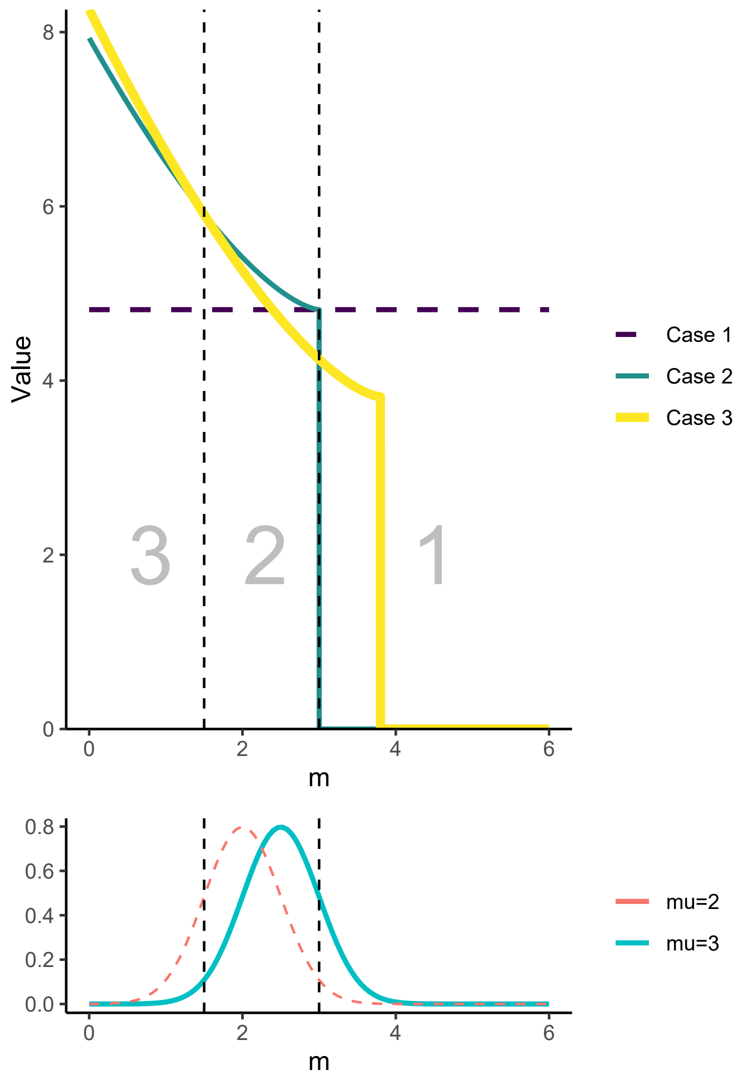

Figure 13: Case A With Distribution of Motherhood Costs

5 Other Evidence

5.1 Survey Data: General Social Survey

Section 3 estimates a positive effect of the implementation of CPFLA on women's college enrollment. In this section, I present evidence from the General Social Survey (GSS) that suggests the effect occurs through women internalizing the policy as an expected easing of the family-work tradeoffs they face.

The General Social Survey has been collected since 1972, currently on a biannual basis. It contains a large set of questions about opinions held by American adults on topics such as crime, institutions, gender, and others. Its purpose is to inform researchers and policymakers.

For privacy reasons, state markers are not publicly released. I use the regional marker of Pacific, which includes also other states: Washington, Oregon, Alaska and Hawaii. This grouping would mechanically reduce the estimated average effect of the policy with a difference-in-difference estimation. Guided by the heterogeneous effects found in Section 3, and because California has the largest hispanic population of all the states in the Pacific region of the GSS, I run a triple differences specification with the hispanic marker. The triple interaction is composed of: 1) being interviewed before or after the implementation of the policy (2004), 2) living in the Pacific region at the age or 16 or elsewhere in the US, and 3) identifying as hispanic. This triple interaction is more likely to identify the effects of the policy, since most hispanic women in the Pacific region are in the state of California, and results in Section 3 suggest hispanic women are more likely to be affected within California.

In this specification, treatment is not defined by the year of birth, but rather the year of interview. This is to identify young women's beliefs before and after the policy came to effect, to see if their beliefs are changed by their awareness of the policy or their exposure to it, regardless of their age. In the sample I include only women who were 25 or younger at the time of interview, to minimize the possibility of the effect motherhood itself or experience in the workplace confound the effect (as in Kuziemko et al. (2018)). Still, I control for whether the respondent has children, as well as some other demographic characteristics.

Table 5 shows the results of this specification for some variables related to women's dual roles as mothers and workers. Column 1 shows the estimated effect of the policy on how rarely women perceive work interfering with family life. Results show that the average effect of the policy on hispanic women is positive ans statistically significant. This means that hispanic women in the Pacific region report work interference with family life to happen less frequently (more rarely) after the implementation of

Table 5: Triple Differences Estimation on Variables of Women's Roles

	(1) How rarely does Work Interfere With Family	(2) Disagree: Family Life Suffers if Mother Works FT	(3) Disagree: Preschoolers Will Suffer Mom Works	(4) Disagree: Working Moms Can Be Warm	(5) Disagree: Most Women Really Want Home and Kids
DDD	2.402***	1.445	-0.494	-2.624**	0.151
	(0.771)	(1.655)	(1.267)	(1.021)	(1.141)
DD	-0.316	-0.348	-0.055	1.006**	1.319***
	(0.600)	(1.203)	(0.807)	(0.460)	(0.487)
TE Hispanic	2.185***	1.1222	-0.557	-1.606*	1.444
	(0.593)	(1.167)	(1.014)	(0.881)	(1.040)
H X A	-1.410***	-0.020	0.581	1.481**	0.076
	(0.504)	(0.745)	(0.721)	(0.734)	(0.562)
Hispanic N	23	23	23	23	23
N	91	149	148	148	147

Notes: standard errors in parentheses. Controls include number of children, time trend, racial categories, number of adults in the household, mother's education and having a working mother growing up. Sample includes female participants between 18 and 25 years of age.

the policy.

Column 2 finds no effect on how much women agree with the statement that family life suffers as a result of mothers working. This suggests that the motherhood side of the tradeoff was not worsened as a result of the policy. The same holds for Column 3, which estimates the effect on beliefs about preschoolers suffering when their mothers go to work. However, Column 4 estimates that women are more likely to believe that working women can have a warm relationship with their children. This effect is different for hispanic women in the Pacific region than for other women in the region. The total effect estimated for hispanic women is still estimated negative and statistically significant. This result is also consistent with the hypothesis of a perceived decrease on the cost of motherhood that is larger for hispanic women.

Finally, Column 5 estimates a positive difference-in-differences coefficient for disagreeing with the following statement: "A job is alright, but what most women really want is a home and children." The triple differences coefficient is not statistically significant, albeit also having a positive sign.

Overall, the triple differences estimations presented in this section are consistent with the mechanism rationalized in the model of Section 4. It is plausible that the effect found in Section 3 is driven by a reduction in the perceived cost of motherhood on labor supply. Women, especially hispanic women, as I find evidence that their opinions on topics related to the motherhood-work tradeoff. However, the evidence presented in this section should be interpreted with caution as this specific data set does not allow us to separate women living in California from other women in the Pacific region. Even though the hispanic marker may assist us in this analysis, the structure of the data is not ideal to answer these questions, and results in a small sample.

5.2 Google Trends

When estimating policy effects, it is common to question how much were eligible participants actually aware of the existence of these benefits. If the effect of this policy is indeed through women internalizing a decrease in family-work tradeoffs, it is not necessary that women are aware of the policy details and eligibility rules. A general message being spread would be sufficient, especially if youger women were exposed to it. For example, having more conversations around the topic of maternity leave, and becoming aware of the existence of paid leave could be enough for women to internalize the message.

In order to investigate whether there was interest around maternity leave happening around the time of the policy implementation in California, I use Google Trends data. Google Trends analyzes google web searches and computes an index of relative interest in the specified search terms over a determined period of time. The index takes a value of 100 when the number of searches was the maximum over the specified period of time, and a value of zero when there were none. This index measures interest in the search term over time, in a specific region.

Google Trends time series begin in January 2004, which means there is not much data on the time before the CPFLA began, in August 2004. However, by looking at the trends starting in January 2004 and comparing different geographical regions, we can get a sense of the relative trends in the conversations or topics that people were reading about.

To eliminate the noise in google trends data, I apply an HP filter to each series. This allows me to extract the underlying trend of the data. This is especially important since, perhaps unsurprisingly, the data is more volatile at the beginning of the series.

Figures 14 through 16 present the filtered series for different combinations of words related to CPFLA. The solid line represents the HP-filtered index for google searches of that combination of words in the entire United States, while the dashed line is the equivalent but only for searches in the state of California.

In Figure 14, we can see that there is a peak in interest in the words "working moms" for the state of California around 2005, close to when the policy began effect (August 2004). The pattern of interest in the United States looks remarkably different. It increases steadily before somewhat flattening around 2015. The difference in trends supports the idea that the topic gained relevance in public discourse in California around the time of the policy implementation. This combination of words is not policy-specific, but rather related to the content of the policy, which suggests that there was public discussion and interest around the topic of women's dual role as workers and mothers, not just about the specific legislation in question.

Figure 15 shows the HP-filtered index for the word combination "Paid Maternity Leave California," which is more specific to the CPFLA. The patterns of the state of California and the US don't look that different in this case, but because the word "California" is included in the search criteria, this is not surprising. The fact that interest peaks in 2004 and gradually decreases until after 2010 is encouraging for the hypothesis that policy implementation in fact generated interest in the topic.

Finally, Figure16 shows the HP-filtered index for the words "Paid Maternity Leave". Patterns differ strikingly between the US and the state of California. These patterns resemble those in 14, but are more directly related to CPFLA. What this plot shows is that the pattern of interest in this combination of words in the state of California had a peak around early 2005, decreased and started to gradually increase after around 2011. On the other hand, the entire country had a constant interest at first, and built up interest for this combination of words beginning around 2011. The fact that interest in California peaks around policy implementation, while interest in the rest of the country behaves very differently supports the idea that these issues were being locally discussed.

Specific knowledge of the policy and eligibility rules is not necessary for a more general message to seep into attitudes and gain interest in public discussion. The results shown in this section suggest that the policy had some implications in attitudes and public discourse, even if individuals were unaware of the specifics of the policy. Conversations around maternity leave caused by the implementation of the CPFLA may have influenced women's perceptions of work-motherhood tradeoffs, ultimately modifying their human capital investment decisions.

6 Conclusions

I find that the CPFLA induced a statistically significant increase in female college enrollment of roughly 2 percentage points that is persistent. This effect is consistent with women internalizing maternity leave policies as a decrease in the cost of motherhood on their labor supply. This paper argues that women's expectation of the effects of a policy are enough to drive behavior change (in particular, schooling choices) even if ex-post effects are not what they anticipated. I provide evidence that interest in these

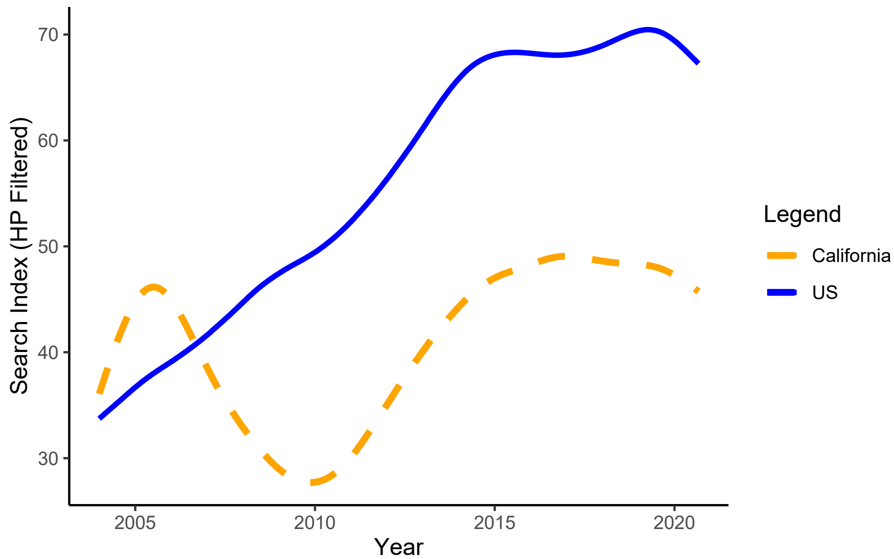

Figure 14: Filtered Google Search Index: "Working Mom"

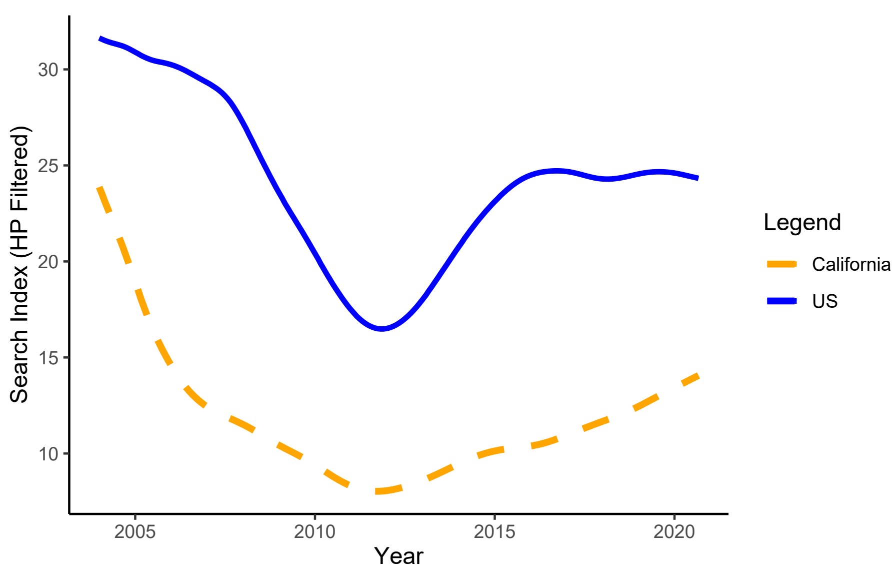

Figure 15: Filtered Google Search Index: "Paid Maternity Leave California"

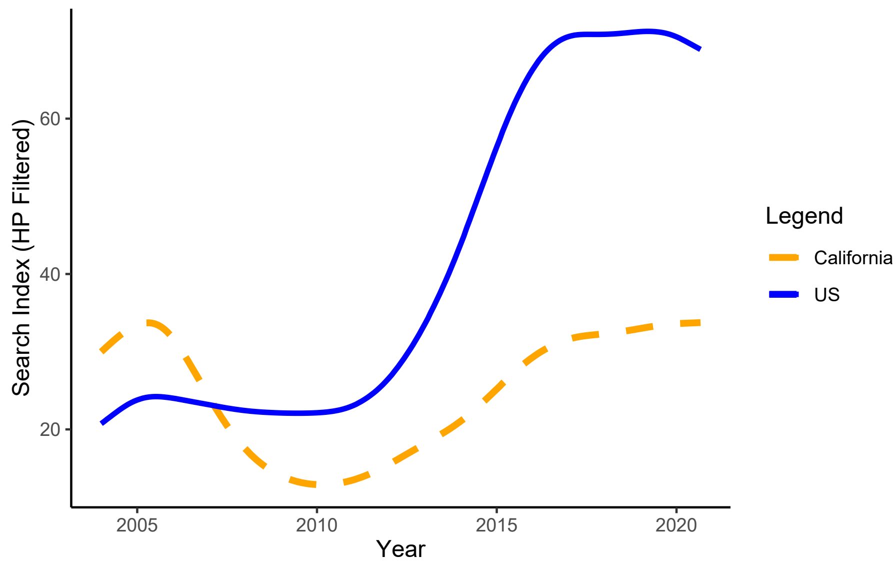

Figure 16: Filtered Google Search Index: "Paid Maternity Leave "

topics was generated around the time when the policy was implemented, and that attitudes around the topics were also affected.

I contribute to the literature of effects of maternity leave policy by studying women's changes in schooling decisions. Furthermore, my results provide more evidence of the fact that women's labor supply seems to be constrained by the work-family tradeoffs they face, and their schooling choices respond accordingly. This paper studies a particular wage replacement policy. As discussed before, job protection policies were already in place, albeit not accessible to all women. In this sense, the effect found cannot be generalized as an effect of all maternity leave policies. With this data I cannot study how eligibility rules played into the effects I find, but these are potentially important insights, especially for policy makers.

In light of other research finding that the gender gap in labor-market outcomes is stagnant while women's schooling keeps increasing, policymakers and researchers should pay more attention to the broad effects of these policies. Women seem to take maternity leave as a sign of a decrease in the cost of motherhood, and increase schooling in anticipation of higher future labor supply. If paid maternity leave policies don't ease these tradeoffs, or aren't accompanied by such an effect, this may result in women underestimating the cost of motherhood on their labor supply. Statements about the welfare effects of these policies may have to take this into consideration.

More research is needed on the relationship between maternity leave policies, women's expectations of their effects, and the ex-post effects on women's labor-market and related outcomes. In particular, studying the relationship between expectations and the ex-post limiting factors that contribute to persistent gender gaps in labor-market outcomes. It is also important to study how endogenous fertility plays into these mechanisms.

Another choice that these policies could be affecting is that of occupation. Future research should study how these policies may shift women from one occupation (or one college major) to another, and how that could be impacting the gender-wage gap, which has been documented to be related to occupational choices.

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