THE EFFECT OF PAID PARENTAL LEAVE IN THE UNITED STATES ON YOUNG WOMEN'S EMPLOYMENT AND EARNINGS, AND THE FAMILY WAGE GAP

by

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DEDICATION

I dedicate this thesis to my parents Dr. Alister and Emily Inglis. Mum, thank you for attempting to raise a functioning member of society with your “extended” maternity leave. I can assure you, your efforts were not in vain.

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TABLE OF CONTENTS

1. INTRODUCTION 1

2. LAWS 4

3. ECONOMIC THEORY 10

The Household's Perspective 10
Maternal Employment Decisions Model 10
Paid Parental Leave 14
Paid Parental Leave by Skill Level 17
Paid Parental Leave on the Family Wage Gap 17
Job Protection 18
The Firm's Perspective 18
Benefits of Paid Parental Leave 19
Costs of Paid Parental Leave 19
The Family Wage Gap 22

4. LITERATURE REVIEW 24

Leave Taking 24
Unpaid Leave 24
Paid Leave 26
Summary 28
Women's Labour Market Outcomes 28
Unpaid Leave 29
Paid Leave 30
Summary 35
The Family Wage Gap 35
The Motherhood Wage Penalty 36
The Fatherhood Wage Premium 41
The Effects of Leave on the Family Wage Gap 44
Summary 45

5. DATA 46

6. EMPIRICAL METHODOLOGY 50

Difference-in-difference with Control States 50
Young Women's Employment 51
Standard Errors 53
Young Women's Earnings 54

TABLE OF CONTENTS — CONTINUED

Difference-in-difference without Control States....55
Young Women's Employment....55
Young Women's Earnings....56
Mothers' Earnings....57
Fathers' Earnings....58
Difference-in-difference-in-difference....60
Young Women's Employment....60
Young Women's Earnings....62
Mothers' Earnings....62
Fathers' Earnings....63
Synthetic Control States....64
Estimations by Education Subgroup....65
Effects Over Time....65
Robustness Checks....67

7. RESULTS....70

Young Women's Employment....70
Summary....73
Young Women's Earnings....74
Summary....76
Young Mothers' Earnings....77
Summary....79
Young Fathers' Earnings....79
Summary....81
Effects Over Time....81
Summary....82

8. ROBUSTNESS CHECKS....113

Young Women's Employment....114
Summary....115
Young Women's Earnings....115
Summary....116
Young Mothers' Earnings....117
Summary....117
Young Fathers' Earnings....118
Summary....119

TABLE OF CONTENTS — CONTINUED

9. CONCLUSION....136

REFERENCES CITED....139

APPENDICES....150

APPENDIX A: Difference-in-difference for the Control Variables of Young Women's Employment....151
APPENDIX B: Synthetic Control States and Weights....155
APPENDIX C: Estimations Involving Men as Control Groups....164
APPENDIX D: Calculations for Raw Mean Differences....169
APPENDIX E: Summary Statistics for Control Variables Hispanic in Alternative Control States....173

LIST OF TABLES

Table Page

1. State Parental Leave Benefits in Addition to the FMLA 7

2. California and New Jersey Paid Parental Leave Laws 9

3. Summary Statistics for Sample of Young Women's Employment in California and Synthetic Control States Pre-2004 83

4. Summary Statistics for Sample of Young Women's Employment in California and Synthetic Control States Post-2004 84

5. Summary Statistics for Sample of Young Women's Employment in New Jersey and Synthetic Control States Pre-2009 85

6. Summary Statistics for Sample of Young Women's Employment in New Jersey and Synthetic Control States Post-2009 86

7. The Effect of Paid Parental Leave on Young Women's Employment 87

8. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Women's Employment 88

9. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Women's Employment by Education Subgroup 89

10. Summary Statistics for Sample of Young Women's Wages in California and Synthetic Control States Pre-2004 90

11. Summary Statistics for Sample of Young Women's Wages in California and Synthetic Control States Post-2004 91

12. Summary Statistics for Sample of Young Women's Wages in New Jersey and Synthetic Control States Pre-2009 92

13. Summary Statistics for Sample of Young Women's Wages in New Jersey and Synthetic Control States Post-2009 93

14. The Effect of Paid Parental Leave on Young Women's Wages 94

LIST OF TABLES — CONTINUED

Table Page

15. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Women's Wages 95

16. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Women's Wages by Education Subgroup 96

17. Summary Statistics for Sample of Young Mothers' Wages in California and Synthetic Control States Pre-2004 97

18. Summary Statistics for Sample of Young Mothers' Wages in California and Synthetic Control States Post-2004 98

19. Summary Statistics for Sample of Young Mothers' Wages in New Jersey and Synthetic Control States Pre-2009 99

20. Summary Statistics for Sample of Young Mothers' Wages in New Jersey and Synthetic Control States Post-2009 100

21. The Effect of Paid Parental Leave on Young Mothers' Wages 101

22. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Mothers' Wages by Education Subgroup 102

23. Summary Statistics for Sample of Young Fathers' Wages in California and Synthetic Control States Pre-2004 103

24. Summary Statistics for Sample of Young Fathers' Wages in California and Synthetic Control States Post-2004 104

25. Summary Statistics for Sample of Young Fathers' Wages in New Jersey and Synthetic Control States Pre-2009 105

26. Summary Statistics for Sample of Young Fathers' Wages in New Jersey and Synthetic Control States Post-2009 106

27. The Effect of Paid Parental Leave on Young Fathers' Wages 107

28. Difference-in-difference-in-difference for the Effect of Paid Parental Leave on Young Fathers' Wages by Education Subgroup 108

LIST OF TABLES — CONTINUED

Table Page

29. Pre-Paid Parental Leave Policy and Young Women's Employment and Earnings 110

30. Post-Paid Parental Leave Policy and Young Women's Employment and Earnings 110

31. Pre-Paid Parental Leave Policy and Earnings of Parents 111

32. Post-Paid Parental Leave Policy and Earnings of Parents 112

33. The Effect of Paid Parental Leave on Young Women's Employment Using Alternative Control States 120

34. Effect of Paid Parental Leave on Young Women's Employment Using Neighbour States by Subgroup 121

35. Young Women's Employment Using Alternative Age Group Definitions 122

36. Young Women's Employment by Subgroup Using Alternative Age Group Definition 123

37. Young Women's Earnings Using Alternative Control States 124

38. Young Women's Earnings Using Neighbour States by Education Subgroup 125

39. Young Women's Earnings Using Alternative Age Group Definitions 126

40. Young Women's Earnings by Subgroup Using Alternative Age Group Definition 127

41. Young Mothers' Earnings Using Alternative Control States 128

42. Young Mothers' Earnings Using Neighbour States by Education Subgroup 129

43. Young Mothers' Earnings Using Alternative Age Group Definitions 130

LIST OF TABLES — CONTINUED

Table Page

44. Young Mothers' Earnings by Subgroup Using Alternative Age Group Definition 131

45. Young Fathers' Earnings Using Alternative Control States....132

46. Young Fathers' Earnings Using Neighbour States by Education Subgroup 133

47. Young Fathers' Earnings Using Alternative Age Group Definitions 134

48. Young Fathers' Earnings by Subgroup Using Alternative Age Group Definition 135

A1. The Effect of Paid Parental Leave on Young Women's Employment Control Variables 152

B1. State Weights in Synthetic California 156

B2. State Weights in Synthetic New Jersey....157

B3. State Weights in Synthetic California by Education Subgroup 158

B4. State Weights in Synthetic New Jersey by Education Subgroup 159

B5. State Weights in Synthetic California for Redefined Age Groups....160

B6. State Weights in Synthetic New Jersey for Redefined Age Groups 161

B7. State Weights in Synthetic California by Education Subgroup for Redefined Age Groups 162

B8. State Weights in Synthetic New Jersey by Education Subgroup for Redefined Age Groups 163

C1. Young Women's Labour Market Outcomes Using Young Men as a Control Group....165

C2. Young Women's Labour Market Outcomes Using Older Men as a Control Group....166

LIST OF TABLES — CONTINUED

Table Page

C3. The Effect of Paid Parental Leave on Young Men's Wages 167

C4. Synthetic State Weights for Young Men's Labour Market Outcomes 168

E1. Means for Control Variable Hispanic in Neighbouring States.....174

E2. Means for Control Variable Hispanic in Florida, New York, and Texas 175

LIST OF FIGURES

Figure Page

1. Klerman and Leibowitz's (1999) Maternal Employment Decisions Model 23

2. Household Budget Constraint 23

ABSTRACT

Using March Current Population Survey data from 1994-2015, this paper examines the effect of paid parental leave in the United States on young women's employment and earnings, and the family wage gap. The family wage gap is the difference in earnings between parents and non-parents. Paid parental leave laws in California and New Jersey are exploited for a quasi-natural experiment using difference-in-difference-in-difference empirical models. Results show robust evidence that paid parental leave has negative impacts on young women's employment and earnings. Estimated impacts vary by education level, with employment effects concentrated among young women without a bachelor's degree, and earnings effects concentrated among young women with only some college experience. Additionally, results also show weakly suggestive evidence that paid parental leave decreases the family wage gap for both mothers and fathers.

CHAPTER ONE

INTRODUCTION

The United States is the only nation in the Organisation for Economic Cooperation and Development (OECD) that does not offer paid maternity or paternity leave (OECD, 2016). However, there are three states in the United States that do offer paid parental leave (PPL). Paid parental leave laws have been implemented in California in 2004, New Jersey in 2009, and Rhode Island in 2014. Washington passed PPL legislation in 2007, but has yet to implement it due to budgetary restrictions. Additionally, New York passed legislation in 2016, and the law will be implemented in 2018, while Washington D.C passed legislation in 2016, and the law will be implemented in 2020 (Public Service Broadcasting, 2016; National Partnership for Women and Families, 2017). Paid parental leave is a trending topic, as eighteen other states are considering PPL policies (United States Department of Labor, 2015). Additionally, recent surveys and polls indicate that paid parental leave is well supported among the public (Groden, 2016; Horowitz et al., 2017; National Partnership for Women and Families, 2016). Examining the potential impacts of PPL can be valuable for policy makers.

Paid parental leave has far reaching impacts across many margins. Proponents of PPL policies would point to the potential positive impacts that it may have on several margins such as child bonding, child education, child health, and parental health (Baker and Milligan, 2010; Bernal, 2008; Broadway et al., 2015; Chatterji and Markowitz, 2012). With PPL affecting so many margins, it is conceivable to believe that a PPL will influence the behaviour of households and firms. The behaviour change from households and firms will have consequences on young women's labour market outcomes, and the family wage gap. The family wage gap is the

difference in earnings between parents and non-parents, which has been found to be negative for mothers, and positive for fathers.

The effect of PPL on the family wage gap is an important consideration because of the long-run effects it has on both parents and children. In the long-run, PPL may help alter gender equality in the household. Gender equality allows for more labour market opportunities for mothers, and more bargaining for mothers when making decisions with their husbands (Kahn et al., 2015). Additionally, PPL may impact households' child raising decisions, especially for single mothers. If PPL policies can assist households raising children, this could improve childhood outcomes and have positive impacts for society (Budig and England, 2001). To date, no other paper has investigated the effect of PPL on the family wage gap in the United States.

Research on the effect of PPL on young women's labour market outcomes in the United States is growing, but it has received less attention than research on unpaid leave. The majority of research on parental leave in the United States has focused on unpaid leave (Baum, 2003a; Han and Waldfogel, 2003; Han et al., 2009; Waldfogel, 1999). The majority of studies on PPL focus on other OECD nations (Asai, 2015; Edwards, 2006; Lalive and Zweimuller, 2009; Schönberg and Ludsteck, 2014).

Using March Consumer Population Survey (CPS) data, this paper contributes to the literature by using a difference-in-difference-in-difference (DDD) strategy with a synthetic controls method that exploits the implementation of PPL laws in California and New Jersey, in order to examine the effect of PPL on young women's employment and earnings, and the family wage gap.[1] To date, no other studies have primarily used a synthetic controls method to investigate PPL in the United States. Additionally, no other studies have investigated the changes to earnings for young women in New Jersey as a result of PPL.

[1] Rhode Island is not examined due to the relative infancy of its programme.

This paper finds that PPL in the United States has a negative effect on young women's employment and earnings, and decreases the family wage gap for both mothers and fathers. Results vary by education level. Employment effects are concentrated among young women without a bachelor's degree. Earnings of young women with only some college experience incur the largest negative effects of PPL. Results on the family wage gap are not robust, but provide weak suggestive evidence that PPL may decrease the family wage gap between young mothers and young childless women, and between young fathers and young childless men.

CHAPTER TWO

LAWS

American parents seeking leave from their job to care for family members can utilize private employer benefits or the Family and Medical Leave Act (FMLA). The FMLA was implemented in August 1993. The FMLA is an unpaid gender-neutral leave law that grants 12 weeks of job protected unpaid leave from work to care for ill family members, or to care for newborn, adopted, or foster children.[2] To be eligible, a person must be a public employee or be employed at a private firm with at least 50 employees, and must have worked at least 1250 hours in the previous 12 months (United States Department of Labor, 2016).

In addition to coverage by the FMLA, several states and the District of Columbia also provide expanded parental leave benefits by covering smaller firms, providing longer leaves, or reducing firm size and work time eligibility requirements. These benefits are summarized in Table 1. There is a large degree of variation in firm sizes covered, number of weeks provided, and work requirements to qualify for the leave. Six states have also passed legislation that provides for paid leave benefits. These benefits have two forms. First, five states offer paid benefits that fall under temporary disability insurance (TDI) programmes. The TDI programmes are not job protected and they treat mothers recovering from pregnancy as a temporarily disabled.[3] These states allow mothers to take approximately six weeks of paid unprotected job leave (Ruhm, 2011). The payment

[2] Job protected leave means that an employer is obliged to retain an employee who decides to take leave.
[3] In California, TDI, is referred to as State Disability Insurance (Applebaum and Milkman, 2011).

during the leave period is usually one-half to two-thirds of mothers' wages (Rossin-Slater et al., 2013).

The second form of paid leave benefit comes in the form of explicit paid parental leave (PPL). Five states plus Washington D.C. have passed legislation providing PPL. As can be seen in Table 1, the five states are California, New Jersey, New York, Rhode Island, and Washington State. Washington State passed a PPL policy in 2007, but has been unable to implement the policy due to budgetary limitations. New York passed its legislation in 2016 but the policy will not go into effect until 2018. At the end of 2016, Washington D.C. passed what will be the United States' most generous PPL, to be implemented in 2020. The PPL policy will offer eight weeks leave with up to a 90 percent weekly wage replacement rate for some workers, and up to a $1,000 weekly maximum benefit (National Partnership for Women and Families, 2017). States that provide both PPL and TDI designed their PPL such that when the TDI benefits expire, the PPL policies will take over seamlessly (Ruhm, 2011).

The empirical analysis focusses on the California Paid Family Leave (CA-PFL) and the New Jersey Paid Family Leave Insurance (NJ-FLI), but not the Rhode Island mandate due to its relative infancy. Both the CA-PFL and NJ-FLI are similar, as outlined in Table 2. The CA-PFL was the first PPL policy in the United States and went into effect in July 2004, while the NJ-FLI was implemented in August 2009. Both policies offer six weeks of paid leave benefits. The CA-PFL weekly payment is 55 percent of an individual's weekly wage with a $728 weekly maximum, and the NJ-FLI weekly payment is 66 percent weekly wage replacement with a $546 weekly maximum. Unlike

the FMLA, there are no minimum working tenure durations, earnings amount, or firm size for an employee to qualify for leave benefits in both states. Neither PPL policy offers job protection, meaning an employer is not obliged to retain employees once they go out on leave. However, if employees can qualify for the FMLA, they can use the PPL policy and the FMLA at the same time to have a job protected PPL. Both PPL policies are financed with payroll taxes to employees, so firms are not contributing funding to PPL. The payroll taxes for both California and New Jersey have low maximum contribution caps (Fass, 2009).

Table 1: State Parental Leave Benefits in Addition to the FMLA

	Unpaid Leave Expansions						Paid Leave Expansions			
State	Effective Year	Number of employees at firm size	Work Requirements	Number of Weeks Granted	Law	Law Code	Temporary Disability Insurance	Law Code	Paid Leave	Source(s)
CA	1992	50+	1250 hrs. in the past 12 months	12 for parental leave and 4 for maternity disability leave	CA Family Rights Act	Cal. Gov. Code § 12945	1996	Cal. Unemp. Ins. Code § 3300-3306 (S.B. 1661)	2004	Ruhm, Han, NCSL, DOL
	1980	5+	None	up to 16 weeks	Pregnancy Disability Leave	Cal. Gov't Code 12945(b)(2)	-	-	-	
CT	1990	75+	1000 hrs. in the past 12 months	16	CT FMLA	Conn. Gen. Stat. §31-51kk	-	-	-	Ruhm, Han, NCSL, DOL
	2005	3+	None; only for pregnant women	Not specified	CT's Fair Employment Practices Act	Conn. Gen. Stat. §46a-60	-	-	-	
DC	1991	All firm sizes	1000 hrs. in the past 12 months	16	D.C FMLA	D.C. Code Ann. §32-501-517	-	-		Ruhm, Han, NCSL, DOL, PBS
HI	1992	100+	Worked for past 6 months full-time	4	HI Family Leave Law	Haw. Rev. Stat. § 398	1969	Haw. Rev. Stat § 392-3, § 392-21	-	Ruhm, Han, NCSL, DOL
IA	1987	4+	None	8	IA Civil Rights Act	Iowa Code § 216.6	-	-	-	IA
KS	1972	All firm sizes	None	Not specified	Pregnancy and Childbirth	Kan. Admin. Regs. § 21-32-6	-	-	-	KS
LA	1997	25+	None	6 weeks for normal pregnancy	Pregnancy Disability Leave	La. Rev. Stat. Ann. §§ 23:341	-	-	-	LA
ME	1988	25+	Worked for past 12 months at the same employer	10	ME FMLA	Me. Rev. Stat. Ann. § 843	-	-	-	Ruhm, Han, NCSL, DOL
MA	1972	6+	Have worked for the past 3 months at the same employer	8	MA Maternity Leave Act	(Mass. Gen. Laws ch. 149, § 105D	-	-	-	Ruhm, Han, NCSL
MN	1987	21+	Have worked for past 12 continuous months	6	MN FMLA and Parental Leave Act	Minn. Stat. 181.941-942	-	-	-	Ruhm, Han, NCSL, DOL
MT	1987	All firm sizes	None	Not specified	MT Maternity Leave Act	Mont. Code Ann. §49-2-310-311	-	-	-	Ruhm

Table 1 (continued): State Parental Leave Benefits in Addition to the FMLA

	Unpaid Leave Expansions						Paid Leave Expansions			
State	Effective Year	Number of employees at firm size	Work Requirements	Number of Weeks Granted	Law	Law Code	Temporary Disability Insurance	Law Code	Paid Leave	Source(s)
NH	1965[d]	6+	None	Not specified	Pregnancy Disability	N.H. Rev. Stat. §§ 354-A:2, 354-A:7	-	-	-	B
NJ	1990	50+	1000 hrs. in the past 12 months	12	NJ Family Leave Act	N.J.S.A. § 34:11B-1	1948[a]	NJ. Rev. Stat. § 43:21-25 et seq.	2009	Ruhm, Han, NCSL, DOL, Lerner
NY	-	-	-	-	-	-	1950[b]	S. 6406C, Part SS, 239th Leg., Reg. Sess	2018	Ruhm, NCSL, NY
OR	1988	25+	25 hrs. in per week in the past 180 days	12	Oregon Family and Medical Leave Act	Or. Rev. Stat. § 659A.150-186	-	-	-	Ruhm, Han, NCSL, DOL
RI	1987	50+	30 hrs. per week in the past 12 months	13	RI FMLA	RI § 28-42-2	1942	R.I. Gen. Laws Sec. 28-41 et seq	2014	Ruhm, Han, NCSL, DOL
TN	1988	100+	Worked for past 12 months at the same employer	16	TN Maternity Leave Act	Tenn. Code Ann. § 4-21-408	-	-	-	Ruhm, Han, TN
VT	1992	10+	30 hrs. in the past 12 months	12	Parental and Family Leave Act	VT stat. Ann. Tit. 21 Sections 470-472	-	-	-	Ruhm, Han, NCSL, DOL
WA	1989	100+	680 hrs. during his or her qualifying year	12	WA State Family Leave Act	Wash. Rev. Code § Sec. 49.78	-	Wash. Rev. Code § 49.86.010(8)	2007[c]	Ruhm, Han, NCSL, DOL
WI	1988	50+	1000 hrs. in the past 12 months	6	WI FMLA	Wis. Stat. § 103.10	-	-	-	Ruhm, Han, NCSL, DOL

Sources: National Partnership for Women and Families (2017) and Presagia (2016) are sources used for all states. Key to other sources: NY= Boldiston (1999); B= Bond (1965); Ruhm= Ruhm (2011); DOL= United States Department of Labor (2017); Han= Han & Waldfogel (2003); IA= Iowa State Legislature; KS= Kansas Human Rights Commission; Lerner= Lerner & Applebaum (2014); LA = Louisiana State Legislature; NCSL= National Conference of State Legislatures; TN= Tennessee State Government (2017); PBS= PBS (2016) . Note: This table excludes leave laws that cover only state employees.

a TDI began covering pregnant women or women recovering from pregnancy in 1970

b TDI began covering pregnant women or women recovering from pregnancy in 1977.

c Although Washington passed the law in 2007, it has yet to implement it due to budgetary restrictions.

d The law in NH began covering pregnancy related leave around 1975.

Table 2: California and New Jersey Paid Parental Leave Laws

	California	New Jersey
Weeks of Leave	6	6
Payment Rate of Weekly Wage	55%	66%
Initial Maximum Weekly Payment	$728	$546
Cost to Employees	$64 per year cap (2005)	$33 per year cap (2009)
Average Benefits per Week	$555	$487
Employer Contribution	None	None
Job Protection	No	No
Part-time Worker Coverage	Yes	Yes
Firm Size for Eligibility	All	All

Source: Fass (2009), the California Loading Industry Association (2004), and the United States Department of Labor (2015).

CHAPTER THREE

ECONOMIC THEORY

Paid parental leave policy theory can be explored from the household's perspective and the firm's perspective. The household's perspective focuses on the supply side of the labour market, while the firm's perspective focuses on the demand side of the labour market.

The Household's Perspective

The household's perspective focuses on the supply side of the labour market. It is explored beginning with Klerman and Leibowitz's (1999) maternal employment decisions model in an unpaid maternity leave world. Their model is then expanded to introduce paid parental leave (PPL). The model discusses the timing of return to work decisions faced by parents as a result of PPL. This has direct impacts on job continuity, employment, and wages. Job continuity is defined as a mother returning to her pre-birth employer after maternity leave.

Maternal Employment Decisions Model

Klerman and Leibowitz's (1999) theoretical model of maternal employment decisions provides the foundation for analysis of PPL's effect on mothers' labour market outcomes. Their model evaluates a mother's choice set after childbirth, which involves the tradeoff between staying on leave and returning to work. The model makes three assumptions. First, a mother consumes savings while on leave. Second, a mother has a

binary choice set. She can either return to her pre-birth employer after using the maximum allotted leave time, or quit her pre-birth employer in order to have a longer maternity leave. Third, the longer a mother is on leave, the larger her human capital depreciation will be.

Mothers experience tradeoffs when deciding on the timing of their return to work. On one hand, wages incentivize a mother to go back to work after childbirth because she consumes savings and forgoes wages while on maternity leave. On the other hand, a mother gains utility from spending time with her newborn. Therefore, a mother prefers not to return to work too quickly. A mother will trade time at home for wages and savings. A mother's decision will depend on her pre-birth wage, alternative wage, and utility function.

Figure 1 graphically displays a mother's choice.[4] The x-axis represents weeks on leave since childbirth. The y-axis represents wages. Wage W_o is the wage from a mother's pre-birth employer. Wage W_a is the alternative wage that a mother attains if she chooses to quit her pre-birth employer to take longer leave. Wage $W_o > W_a$ because of the loss of firm-specific human capital associated with quitting the pre-birth employer for an alternative job. Ceteris paribus, higher wages are preferred to lower wages, generating the indifference curves with the relationship $U_o > U_a$. Utility increases monotonically with wage, but not for leave length, as will be explained below.

Consider the case when no maternity leave law is present. Optimally, a mother would like to have leave length L_2 and remain at her pre-birth employer to receive wage

[4] The Klerman and Leibowitz (1999) model only focusses on mothers and not their spouses.

W_o. Leave length L_2 and wage W_o is preferred to any other point. Despite gaining utility from being on maternity leave, a mother may prefer not to have a leave length longer than L_2 because she depletes savings while on maternity leave. The upward sloping indifference curves reflect this notion. She will be indifferent between point A and B, despite point B providing a longer leave, because the longer leave length consumes more savings.

Now consider the case when the pre-birth employer offers leave length L_1. Indifference curve U_a is shaped such that the mother is indifferent between taking leave L_1 to receive wage W_o with the pre-birth employer and quitting to take leave L_3 to receive wage W_a from another employer. The mother quits if the leave length offered by the pre-birth employer is less than L_1 weeks. Alternatively, suppose the pre-birth employer offers a short leave length less than L_1. The mother will quit the pre-birth employer and will take leave length L_3 to receive wage W_a upon re-entry to the workforce. The forgone earnings associated with quitting are $(W_o\text{-}W_a) \times L_3$.

Klerman and Leibowitz (1999) extend the model to introduce an unpaid job-protected maternity leave law. Let the maternity leave law guarantee leave length L_{UML}. An unpaid maternity leave law affects several groups of mothers differently:

Group 1. If an employer originally offers less than leave L_{UML}, mothers may take leave L_{UML}, and return to their pre-birth employer. As a result, job continuity, employment, and wages increase due to the leave law.

Group 2. If an employer offers between leave L_1 and L_{UML}, the mother may take L_{UML}. This group of mothers would have returned to their pre-birth employer with or without the leave law. Job continuity, employment, and wages are unaffected by the leave law.

Group 3. When an employer offers leave between L_{UML} and up to leave L_2, mothers may take the maximum allotted leave offered by the pre-birth employer. These mothers are unaffected by the leave law. Job continuity, employment, and wages are unaffected by the leave law.

Group 4. When an employer offers above leave L_2, mothers may take leave L_2 because it is their preferred leave time given the indifference curve's shape. Job continuity, employment, and wages are unaffected by the leave law.

Group 5. Some mothers may have strong tastes and preferences for staying at home. With or without an unpaid maternity leave policy, these mothers will quit their pre-birth employers. These mothers' indifference curves in figure 1 will have steeper slopes such that their indifference curve U_a will be lower than is currently displayed. This implies that their preferred leave length is greater than L_2, the leave length that these mothers would take if they quit the pre-birth employer is greater than L_3, and the alternative wage these mothers will receive is lower than W_a. Job continuity, employment, and wages are unaffected by the leave law.

Group 6. Han et al. (2009) observe that some mothers may change their tastes and preferences during maternity leave in favour of more leave time. These mothers may quit their pre-birth employers to spend more time on leave. In figure 1, these mothers' indifference curves will change to resemble indifference curves of mothers in group 5. As a result job continuity, employment, and wages decrease due to an unpaid maternity leave policy.

In sum, the model predicts that mothers in group 1 see increased job continuity, employment, and wages as a result of leave taking. Mothers in group 6 see decreased job continuity, employment, and wages as a result of leave taking. The leave policy does not affect job continuity, employment, or wages for mothers in other groups. As a result of these divergent theoretical impacts, the effect of an unpaid maternity leave policy on mothers' employment and wages is ambiguous. What is not ambiguous, however, is that fertility and leave take up rates will increase because leave benefits give marginal families more incentive to have a child. Ceteris paribus, this increases employment for mothers on the margin because mothers must work in order to meet leave eligibility requirements.

Paid Parental Leave

The theoretical predictions described above resulted from unpaid maternity leave policies. The introduction of PPL increases the size of the groups described above for several reasons. First, PPL incentivizes families on the margin to have children because it lowers the marginal cost (MC) of fertility. Second, PPL laws also cover fathers,

providing them with the same choice set as mothers, at least qualitatively. The original Klerman and Leibowitz (1999) model can be transformed into a parental employment decisions model to introduce the paid aspect of the policy, and to include both parents in the groups described above. It is important to note that PPL policies in the United States provide only partial, not full, wage replacement. Partial wage replacement implies that parents must consume savings even with PPL. However, savings are not depleted as much with PPL compared to an unpaid parental leave. Because savings are consumed, parents still face the U-shaped indifference curves depicted in figure 1.

The impact of PPL on the relative sizes of the five groups is theoretically unknown. Therefore, no definitive conclusions can be reached regarding changes in job continuity, employment, and wages resulting from PPL. It is not theoretically unknown, however, that fertility and leave take up rates increase. Because parents must be employed to be eligible for the leave benefits, employment increases for parents on the margin for the same reason marginal mothers' employment increases with unpaid maternity leave.

A simple household budget constraint yields insight as to why PPL incentivizes increased female labour supply. Employment may increase because parents must work in order to qualify for PPL benefits. Figure 2 graphically displays a household's budget constraint. In figure 2, the x-axis measures number of children, which is denoted by C. Assume children are normal goods. Let M denote total household income, and let parameter α denote the MC of raising a child. The y-axis measures consumption. The implementation of a PPL policy decreases the MC of having children. Parameter α

decreases such that $\alpha_0 > \alpha_1$. This pivots budget curve BC_0 out to BC_1, and increases the number of children from C_0 to C_1 for the household. The household is better off because indifference curve $U_0<U_1$. Note that both the substitution and income effects are positive, but their magnitudes will vary by household. From this simple budget constraint diagram, it is clear fertility increases as a result of PPL. In addition, leave take up rates increase because there are more families utilizing the PPL when having children.

Paid parental leave affects mothers more than fathers because mothers will utilize leave more for two reasons. First, mothers on average have a lower MC for leave taking than fathers because mothers have lower wages on average (Blau and Kahn, 1992). As such, mothers will experience a lower average wage loss for taking leave than fathers would. Additionally, Patnaik (2016) observes that fathers are more likely to experience social stigma costs for leave taking. This contributes to fathers having a higher MC for leave taking.[5]

The second reason mothers are predicted to be more likely to utilize leave is that traditionally labour supply models assume that mothers have have comparative advantage in home production compared to fathers. According to the Becker model of household allocation, households would be behaving most efficiently if the spouses allocate their time according to their comparative advantages (Becker, 1981). The Becker model assumes that mothers have comparative advantage for household labour due to biological reasons such the ability to breastfeed newborns. The Becker model also assumes that fathers have comparative advantage in market labour due to higher average wages. This

[5] As noted by Patnaik (2016), social stigma costs incorporate several things such as social norms, peer-pressure, and preferences against leave taking.

model implies that mothers have the most incentive to qualify for PPL benefits. Thus, the Becker household allocation model implies that mothers have the most incentive to qualify for PPL, and that PPL could increase employment for young women because PPL benefits are conditional on work. Note, however, that the Becker household allocation model was developed in the 1980s. Since then, household dynamics, societal norms and women's labour market opportunities have changed, with the implication that the Becker model may be less effective at explaining the household allocation patterns in more recent times.

Paid Parental Leave by Skill Level

In theory, PPL impacts low-skilled workers differently than high-skilled workers. Because high-skilled workers have higher wages, high-skilled workers have higher opportunity costs for taking unpaid leave relative to low-skilled workers because the wage loss for high-skilled workers taking parental leave is larger. Based on this reasoning, high-skilled workers could have more to gain than low income families with the introduction of PPL. Alternatively, low-skilled workers could gain more with a PPL policy because low-skilled workers have smaller budget constraints than high-skilled workers. Therefore, the PPL policy's reduction in the MC of having children as a proportion of total income is larger for low-skilled workers than for high-skilled workers.

Paid Parental Leave on the Family Wage Gap

A paid parental leave policy can decrease both the motherhood wage penalty and fatherhood wage premium. Decreasing the motherhood wage penalty is conditional on

PPL increasing job continuity for mothers. Job continuity increases mothers' wages because mothers retain firm-specific human capital by staying with their pre-birth employers, which decreases the motherhood wage penalty. Decreasing the fatherhood wage premium is also conditional on fathers taking paternity leave. If a PPL incentivizes fathers to trade time at work with time for childcare, they will experience a reduction in firm-specific human capital by taking leave. Ceteris paribus, the fatherhood wage premium will decrease as a result of PPL. The opposing impacts of PPL for mothers and fathers result from a relative increase in female firm-specific human capital via increased job continuity, but a decrease in male firm-specific human capital via decreased time at work. This assumes that PPL generates a larger relative increase in firm-specific human capital for mothers via job continuity than the decrease in human capital from the leave itself.

Job Protection

Outcomes described above have assumed that the PPL is job protected leave. As noted by Sarin (2016), in the absence of job protection, individuals would be less incentivized to use PPL. An unprotected PPL would benefit high-skilled individuals more than low-skilled individuals because it is easier for employers to replace low-skilled workers for taking leave.

The Firm's Perspective

The theoretical impact of PPL from the firm's perspective focuses on the demand side of the labour market. A PPL policy is associated with costs and benefits for firms. A

firm's profit maximization behaviour has several implications for young women's earnings, the motherhood wage penalty, and the fatherhood wage premium.

Benefits of Paid Parental Leave

A PPL policy is associated with two benefits for firms. First, job continuity increases, conditional on parental tastes and preferences being held constant.[6] Increases in job continuity protect the firm's worker-specific investments (Klerman and Leibowitz, 1997). A firm invests training, time, and other resources in workers, which leads to increased firm-specific human capital. The worker's firm-specific human capital is retained with job continuity that results from PPL. Additionally, the firm does not incur search costs for hiring a permanent replacement.

Second, a PPL policy can increase worker job satisfaction. It is in the firm's interest for employees to have high job satisfaction, as it is a strong predictor for quitting (Freeman, 1978; Akerlof and Yellen, 1988). Worker turnover is costly for a firm, and could be reduced if sufficient leave time is granted. Additionally, workers with higher job satisfaction are more productive (Oswald et al., 2009).

Costs of Paid Parental Leave

Conversely, a PPL policy is associated with disruptive labour costs, human capital depreciation costs, and uncertainty costs in the hiring process. Disruptive labour costs are defined as costs firms incur to cover projects of workers who are absent due to parental

[6] Tastes and preferences need to remain constant. Otherwise, parents could change their tastes and preferences in favour for leave and quit their jobs, as noted by Han et al. (2009).

leave. As Summers (1989) examines, mandated benefits create deadweight loss much like a tax, which is disruptive to firms.

Firms incur increased disruptive labour costs for covering the workloads left behind by parents on PPL in three ways. First, firms can train other workers to perform projects left behind by employees on leave. Firms must invest in both training and additional compensation for workers' supplementary labour. Second, firms may hire permanent full-time supplementary workers that they otherwise would not have hired absent the PPL policy. The firm will incur a search cost during the hiring process. Third, firms can hire temporary workers. Temporary workers incur both a search cost and a training cost for the firm. Additionally, temporary workers may have a lower marginal product of labour than full-time workers because temporary workers have less incentive to increase their competence and invest in firm-specific human capital relative to full-time workers (Guadalupe, 2003).

Second, firms also incur human capital depreciation costs as a result of PPL. Paid parental leave increases time away from work, which leads to human capital depreciation (Edin and Gustavsson, 2007; Mincer and Ofek, 1982). Upon return to work, a firm must re-train a returning worker to both refresh existing skills, and to train in new technology or processes introduced during the leave period. This is especially costly if the firm is in an industry that undergoes frequent technological changes.

Lastly, firms will incur increased uncertainty costs in the hiring process due to a PPL. A firm must invest more resources and rely on signaling to determine if a potential

worker is non-career orientated, or is career orientated.[7] Ceteris paribus, firms prefer career orientated workers. During the hiring process, the firm is unable to observe productivity. Productivity levels are only known to the firm once the applicant is hired and begins work (Spence, 1973). However, the firm can observe personal attributes and characteristics to help determine whether or not to hire a worker.

Firms may engage in statistical discrimination as a result of increased uncertainty due to PPL. Firms may discriminate against observable attributes that are associated with non-career orientated workers (Spence, 1973). In this context, firms have incentive to discriminate against hiring potential workers who may have a child in the near future and take parental leave. Non-career orientated workers become relatively more expensive than career orientated workers as a result of the costs associated with a PPL policy for firms. Because they are unlikely to bear children, older men and older women should thus be less affected by a PPL policy than young women. Young women have higher probabilities of imposing costs on firms because they are potential mothers, are more likely to take leave than fathers, and to take longer leaves than fathers. Firms may reduce the relative demand for low-skilled young women the most because this group has more substitutes. Thus, firms may engage in statistical discrimination against young women in order to avoid hiring non-career orientated workers due to the increased labour costs, human capital depreciation, and uncertainty costs associated with PPL. Young men may also impose costs to firms, but the expected costs are lower because the probability of leave taking, and the leave length, is likely to be smaller than for young women.

[7] In this context, non-career orientated is defined as an individual applying for a job primarily to qualify for parental leave benefits.

Therefore, a PPL policy may more negatively affect young women's labour market outcomes, particularly earnings and employment, relative to older women and men.

The Family Wage Gap

From the firms' perspective, the effect of a PPL policy on the motherhood wage penalty is unclear. A firm may be uncertain whether a mother will have subsequent children or not, and therefore uncertain which mothers may incur future costs for the firm. Additionally, firms may treat young childless women similarly to young mothers because firms may anticipate young childless women to have children in the future. Therefore, some young childless women will be treated similarly to young mothers, which leaves predictions for the effect of PPL on the motherhood wage penalty unclear from the firm's perspective.

For similar reasons, the effect of a PPL policy on the fatherhood wage premium is unclear from the firms' perspective. Firms may treat young fathers and young childless men the same if they anticipate that both groups may have a child in the near future. This leaves predictions for the effect of PPL on the fatherhood wage penalty ambiguous from the firm's perspective.

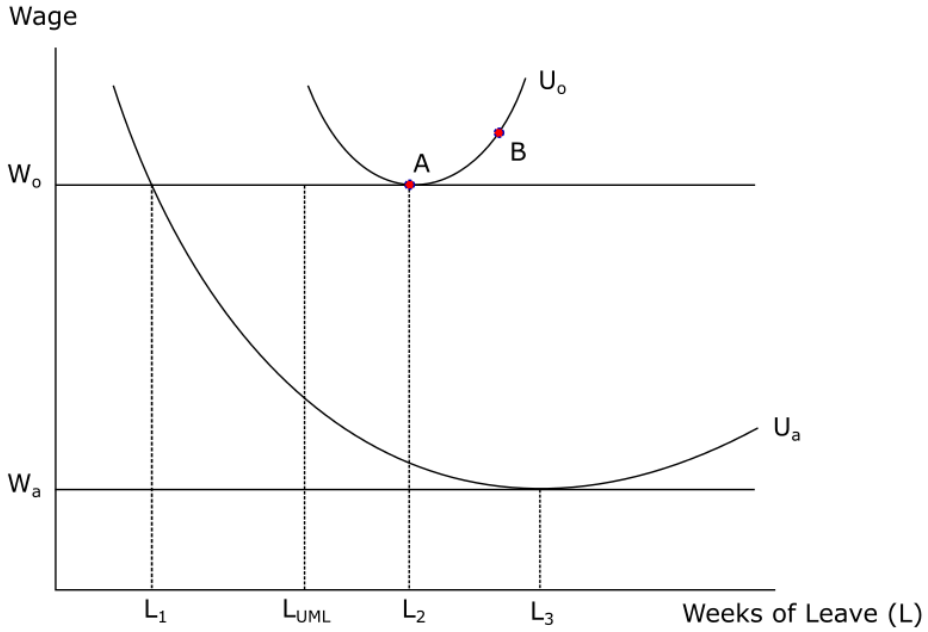


Figure 1: Klerman and Leibowitz's (1999) Maternal Employment Decisions Model

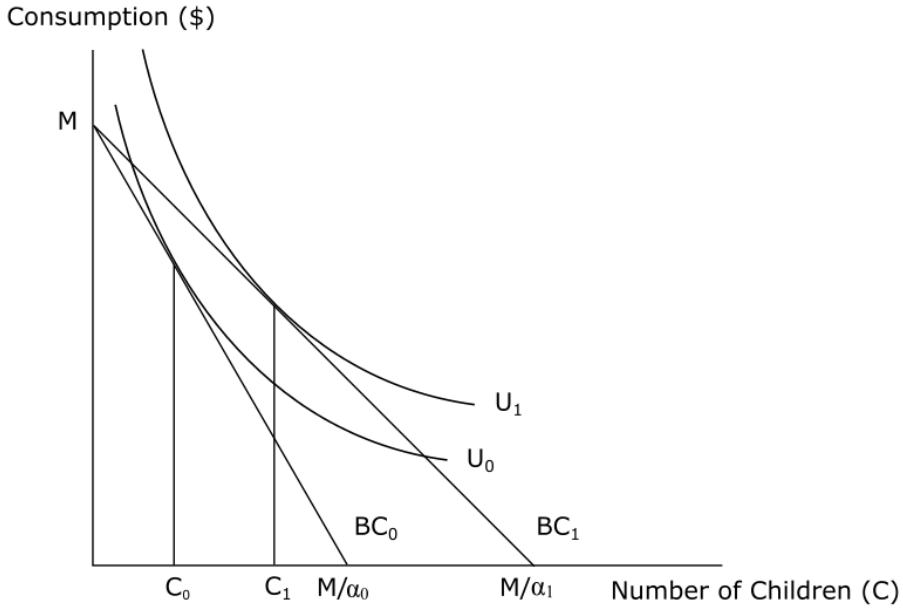


Figure 2: Household Budget Constraint

CHAPTER FOUR

LITERATURE REVIEW

Previous research provides evidence that the introduction of a paid parental leave policy (PPL) can affect leave taking, young women's labour market outcomes, and the family wage gap. Young women's labour market outcomes include employment, working hours, labour force participation (LFP), wages, and job continuity. This chapter summarizes prior studies of both paid and unpaid leave on women's labour market outcomes, and summarizes reasons for the family wage gap. The family wage gap discussion has three parts: the motherhood wage penalty, the fatherhood wage premium, and the effect of leave on the family wage gap.

Leave taking

It is important to understand how leave laws affect leave taking before analyzing the effect leave laws have on other outcomes. Leave laws provide incentive for individuals to take leave, although the extent of those impacts may vary widely. This section summarizes prior literature on leave laws' effect on leave taking.

Unpaid Leave

Research on the impact of unpaid leave on leave taking has found mixed results that vary on several dimensions. Baum (2003a) utilizes National Longitudinal Survey of Youth 1979 Cohort (NLSY-79) data to examine the impact of maternity leave laws using pre-FMLA state law variation. Using probit and logit models, Baum (2003a) finds no

evidence that unpaid maternity leave laws have an effect on leave taking. Han and Waldfogel (2003) also use a probit model to examine maternity leave laws' effect on parental leave taking. They use Survey of Income and Program Participation (SIPP) data for the years 1991 to 1999 to exploit state and federal leave law variation. Although they find positive effects on mothers' leave taking in some specifications, the significance of the results disappears when controlling for both state fixed effects and mothers' pre-birth working hours.[8] Additionally, they find that unpaid parental leave had no impact on fathers' leave taking.

Alternatively, Klerman and Leibowitz (1997) use 1980 and 1990 Census Public Use Microdata and find that unpaid state maternity leave laws have a positive impact on mothers' leave taking. Mothers' leave taking in states with maternity leave laws increased by two weeks relative to mothers who were not in states with maternity leave laws. Waldfogel (1999) employs a difference-in-difference (DD) and difference-in-difference-difference (DDD) approach with March Current Population Survey (CPS) data to exploit state variation in leave laws before and after the FMLA. Results show leave taking increased for mothers at medium and large sized firms in states with leave laws compared to states without leave laws.[9] On the other hand, fathers who worked at medium sized firms in states with parental leave laws did not increase leave taking relative to fathers in states without parental leave laws. However, because the CPS data

[8] Leave law coverage that Han and Waldfogel (2003) examine is dependent on working above a threshold number of hours prior to the birth. The threshold number of hours varies by state.
[9] Waldfogel (1999) defines medium firms as having 100-499 workers, and large firms as having 500 or more workers. Using different definitions for firm sizes may yield different results because the FMLA covers firms with 50 or more employees.

used by Waldfogel (1999) does not identify employees specifically on parental leave, the sample potentially includes employees absent from work for other reasons. This would bias results to be larger than the true effect of leave laws on leave taking. Han et al. (2009) use June CPS data to examine state leave mandates and the FMLA between 1987 and 1994. Their results are mixed. Mothers in states with leave laws were 5-9 percentage points more likely to take leave. However, the results are only significant for married or college educated mothers, and not mothers without a college education. This could be because more educated mothers are better able to take advantage of unpaid time off than less educated mothers possibly because they have less binding budget constraints. Additionally, Han et al. (2009) find that fathers in states with leave laws increased leave taking by approximately two days relative to fathers in states without leave laws.

Paid Leave

Contrary to the mixed evidence of unpaid leave's impact on leave taking, strong evidence exists that PPL has a positive impact on leave taking after the birth of a child. The magnitudes of leave taken vary based on the national context and the generosity of leave policies. Several papers examine the issue in European countries typically using DD and DDD models. Schönberg and Ludsteck (2014) find that in Germany, the five paid maternity leave expansions that occurred between 1979 and 1992 increased mothers' leave taking and delayed mothers' return to work. In 2007, Germany implemented new PPL expansions called *Elterngeld*.[10] *Elterngeld* offers 67 percent wage replacement up to €1,800 per month for up to 14 moths (Tamm, 2013). A host of papers find that *Elterngeld*

[10] *Elterngeld* literally translates to "parent's money."

increased parental leave taking (Kluve et al., 2008; Bergemann and Riphahn, 2011; Kluve and Tamm, 2013; Kluve and Schmitz, 2014). Lalive and Zweimuller (2009) examine Austrian parental leave expansions including a 1996 policy that increased PPL time from one year to two years, but did not increase the partial wage replacement of €340 per month. Lalive and Zweimuller (2009) find that the policy significantly increased leave taking by eligible mothers, increasing the average leave length from 9 months to 19 months. Carneiro et al. (2015) examine Norway's 1977 introduction of 18 weeks of paid leave at full pre-birth salary. This policy led to 100 percent leave take up rate for the full 18 weeks amongst eligible mothers.[11] Carneiro et al. (2015) also report that between April 1992 and April 1993, additional PPL expansions led to mothers increasing average paid leave days from 266 days to 310 days. Dahl et al. (2016) also investigate PPL in Norway. Between 1987 and 1992, Norway expanded PPL from 18 weeks to 35 weeks. Dahl et al. (2016) find that the expanded leave resulted in parents lengthening their parental leave by almost three weeks (22.7 days).

Several studies investigate the effect of PPL on parental leave taking in the United States. These papers use DD and DDD strategies to measure the impact of the passage of the CA-PFL on leave taking. Using NLSY-97 data, Baum and Ruhm (2016) find that both parents' leave taking increased as a result of the CA-PFL; the average mother increased leave by 2.4 weeks and the average father increased leave by 4.7 days. Rossin-Slater et al. (2013) utilize March CPS data from 1999 to 2010, and find robust evidence that mothers' leave taking doubled from three to six weeks as a result of the CA-PFL.

[11] This is based on survey evidence. Norway offered mothers 12 weeks of unpaid leave before the 1977 introduction of 18 weeks paid leave.

Using American Community Survey (ACS) data, Bartel et al. (2015) find that the parental leave participation rate increased by 50 percent, and that joint leave taking (both parents taking time off at the same time) increased by 28 percent as a results of the CA-PFL.[12]

Summary

Research uniformly shows either a zero or positive effect of leave policies on parental leave taking. Researchers have found that unpaid parental leave mostly has positive effects on mothers' leave taking, with the exception of Baum (2003a), and Han and Waldfogel (2003), who find no effect. Studies of PPL also consistency find a positive effect of leave policies on mothers' leave taking. European policies offer more generous benefits than the United States, and the effect of these policies in Europe are larger. Research in Europe and the United States indicates that fathers take only limited leave under both unpaid and paid parental leave policies.

Women's Labour Market Outcomes

This section reviews prior research on the effect of leave laws on women's labour market outcomes. Women's labour market outcomes include job continuity, employment, wages, working hours, and LFP. The literature focuses on unpaid leave laws almost exclusively the United States, while literature on paid leave focuses on Europe, Asia, and the United States.

[12] These studies only focus on the CA-PFL and do not include the NJ-FLI for additional variation.

Unpaid Leave

Researchers typically use a DD or DDD approach when evaluating the effect of unpaid leave on job continuity for women. Prior research exploits state leave law variation and the FMLA to measure the effects of unpaid leave on women's labour market outcomes. Research on the effect of leave laws on job continuity find consistent positive impacts (Baum 2003a; Hofferth and Curtin, 2006; Waldfogel, 1997a). As demonstrated by Klerman and Leibowitz (1999), increases in job continuity resulting from leave laws should theoretically lead to higher employment and wages for mothers via its impact on firm-specific human capital retention. However, empirical findings show mixed results.

Several studies find no significant effect of unpaid leave on women's employment and wages. Although some specifications in Klerman and Leibowtiz (1997) indicate that state maternity leave mandates improved women's employment, the result is not robust. Klerman and Leibowtiz (1997) suggest that the positive result is due to endogeneity because states that passed maternity leave legislation also had stronger economies than states without maternity leave legislation. Baum (2003b) uses NLSY-79 data and the passage of the FMLA to measure impacts of state maternity leave mandates on women's employment and wages. His results show that unpaid maternity leave mandates have statistically insignificant impacts on women's employment and wages. This result is consistent with Waldfogel (1999), who finds that the FMLA did not affect women's employment or wages. Han et al. (2009) additionally find no effect of the FMLA on women's employment.

The findings of no impact of unpaid leave on women's labour market outcomes described above contrast to research by Edwards (2006) and Gruber (1994), who find that leave laws have adverse effects on women's labour market outcomes, particularly among young women. Edwards (2006) examines the impact of an Australian unpaid maternity leave mandate on women's wages. Using state leave law variation, she finds evidence that employed women eligible for leave received lower wages relative to women who were not eligible for leave. Although he does not focus on leave laws per se, Gruber (1994) finds results suggesting that because leave laws increase the costs of hiring women, they could generate unintended consequences on the demand for female labour. Gruber (1994) examines state and federal mandates in the United States that require childbirth to be covered in health insurance plans. His findings show that the mandates increased the number of hours worked, decreased wages, and decreased employment for married women. He concludes that this is because the mandates raised firms' costs of hiring women who have high probabilities of having a child.[13]

Paid Leave

Research that investigates the effect of paid leave on women's labour market outcomes in Europe yields varying results. In Germany, Kluve and Schmitz (2014) use a regression discontinuity (RD) approach to measure the impact of *Elterngeld* on women's labour market outcomes. They find that *Elterngeld* significantly increased both job continuity and employment in the medium-term.[14] Schönberg and Ludsteck (2014) study

[13] Gruber (1994) examines women ages 20-40 years old.
[14] Kluve and Schmitz (2014) define the medium-term as 3-5 years after childbirth.

a series of five German paid maternity leave expansions. Four out of the five expansions only marginally increased employment rates and job continuity three to six years after childbirth. Conversely, one of the policies had a negative effect on mothers' employment, LFP and wages two to six years after childbirth. Puhani and Sonderhof (2011) investigate West German PPL expansions. They find that the policies caused women in general to receive less on-the-job training relative to men. Their findings could be an explanation for Ejrnæs and Kunze's (2013) results. Ejrnæs and Kunze (2013) study West German PPL expansions between the late 1980s and 1990s. They find that mothers' wages fell three to six percent per year of leave. Ruhm (1998) investigates leave laws in nine European countries.[15] He finds that short leave length laws (three months or less) increased women's employment without lowering wages, but longer leave length laws lowered women's wages. Lalive and Zweimuller (2009) investigate a 1990 Austrian paid parental leave reform that increased leave from one to two years. They find that the reform caused mothers' employment and wages to decrease in the short-term, but not the long-term.[16]

Several papers study the effect of PPL on women's labour market outcomes in Scandinavian countries. Dahl et al. (2016) find that maternity leave expansions in Norway had little effect on parental earnings and LFP. Gupta et al. (2008) summarize previous literature examining the effect of family-friendly policies in Scandinavian countries on women's labour market outcomes. They report that PPL expansions have

[15] Ruhm (1998) uses data from nine European countries including Denmark, Finland, France, Germany, Greece, Ireland, Italy, Norway, and Sweden.
[16] Lalive and Zweimuller (2009) define the short-term as 0-36 months after childbirth, and the long-term as 37-120 months after childbirth.

positive effects on employment, but negative effects on wages, especially among higher educated women. Gupta et al. (2006) investigate the effect of family-friendly policies in Denmark between 1983 and 1995. In 1984, Denmark expanded paid parental leave by 10 additional weeks to total 24 weeks of parental leave. Gupta et al. (2006) find evidence that Danish women's wages stalled during this time period and attribute the stall to generous family friendly policies.

Papers that investigate the effects of PPL on women's labour market outcomes in Asia also find mixed results. Lai and Masters (2005) examine a 1984 Taiwanese paid maternity leave law that required firms to pay mothers full wage replacement for eight weeks of leave. Using DDD models, Lai and Masters (2005) find that the law had a negative effect on young women's employment and wages relative to young men and older women. Zveglich and Rodgers (2003) also examine the same law using a DDD strategy. They find that the paid maternity leave law increased young women's working hours and employment, but decreased their wages slightly. Asai (2015) uses a DDD approach to investigate a 2001 Japanese maternity leave reform. The reform increased leave wage replacements from 25 percent to 40 percent and kept leave length fixed. Asai (2015) finds no evidence that the reform increased job continuity for mothers. He attributes this finding to Japanese work and social cultural norms that include lack of support for working mothers and lack of help for childcare from husbands.

In the United States, the literature on the impact of paid leave on mothers' labour market outcomes focuses on the effect of the CA-PFL on mothers. Baum and Ruhm (2016) find that the CA-PFL increased job continuity. Additionally, their results show

that mothers' number of working hours and wages increased in the child's second year of life. Rossin-Slater et al. (2013) find results consistent with Baum and Ruhm (2016) in regards to job continuity, working hours, and wages. Although both papers find positive impacts of the CA-PFL on mothers' labour market outcomes, neither paper examines the impact of the CA-PFL on young women more generally.

Several recent studies in the United States examine the changes in the labour market outcomes of young women that result from PPL. The first is by Curtis et al. (2016), who examine the impacts of the CA-PFL. Using Quarterly Workforce Indicators (QWI) data at the county level, they estimate the effect of the CA-PFL with a DDD model. They compare pre-CA-PFL and post-CA-PFL outcomes for young women relative to both men and older women in counties that are located in control states. They find that the CA-PFL is associated with increased job separations, and increased hiring of young women.[17] They did not find that young women's wages or employment decreased as a result of the CA-PFL.

The second study is by Das and Polachieck (2015) who find different results from Curtis et al. (2016). Das and Polachieck (2015) use CPS data and a quadruple difference strategy that accounts for before and after the CA-PFL, different demographics, different ages, and shocks specific to California. They find that the CA-PFL increased LFP, unemployment, and the length of unemployment spells for young women in California. The results are robust to various specifications and placebo policies. Das and Polachieck (2015) do not investigate the effect of the CA-PFL on young women's wages.

[17] Job separations refer to young women leaving their employer.

The third study is by Byker (2016). Byker (2016) uses a DD model and SIPP data to examine both the CA-PFL and NJ-FLI. She finds that the two policies increased labour force attachment for women. Byker (2016) uses separate models for women with and without a bachelor's degree, and her estimates indicate that increased labour force attachment is driven by women without a bachelor's degree. This is because women who would have temporarily exited the labour force without a paid parental leave policy remain in the labour force when a paid parental leave policy is available.

The fourth study is by Sarin (2016) who examines both the CA-PFL and NJ-FLI using a DDD model strategy. She finds that the PPL policies reduce hiring of child-bearing aged women working at firms with 50 or more employees by about 2 percent. Sarin (2016) distinguishes between young women working at firms with 50 or more employees and young women working at firms with fewer than 50 employees because of FMLA job protection. Only women working at firms with 50 or more employees potentially qualify for job protection under the FMLA at the same time as the NJ-FLI paid benefits.

The fifth study is by Reed and Vandegrift (2016) who find that the NJ-FLI reduces overall employment by about 3.3 percent, and has larger negative effects on young women's employment for higher skilled workers, but no effect on unskilled workers. Women aged 22-24 and 25-34 experience an 8.8 percent and 7.8 percent employment decrease respectively. College educated women experience a 5.9 percent employment decrease. Reed and Vandegrift (2016) suggest that the NJ-FLI affects skilled workers more because skilled workers are more likely to qualify for job protection under

the FMLA, resulting in paid job protected leave. They cite Kerr (2016) who shows that unskilled workers have a higher probability of working for firms with less than 50 employees. The findings of Sarin (2016) and Reed and Vandegrift (2016) suggest that job protection is an important aspect of leave policy that strongly influences behaviour.

Summary

Research consistently finds positive impacts of paid and unpaid leave on job continuity for women, with the exception of Asai (2015), who finds no impact. Additionally, studies on both paid and unpaid leave find non-positive effects on women's wages generally. However, Baum and Ruhm (2016), and Rossin-Slater et al. (2013) find that mothers' wages increased as a result of the CA-PFL. Evidence of unpaid leave's effect on employment show no effect, but the evidence on paid leave's effect on employment are in general mixed, but negative in the United States. The mixed results are likely due to the great policy variation among different countries. Most of this research of leave on employment and wages focusses on mothers and not young women.

The Family Wage Gap

Becoming a parent has dichotomous labour market effects for mothers and fathers. For women, prior research finds that becoming a mother is associated with a wage penalty. For men, previous research shows that becoming a father is associated with a wage premium. These differential impacts lead to a "family wage gap" for men and women. The family wage gap is comprised of the motherhood wage penalty and the fatherhood wage premium. The motherhood wage penalty is defined as the wage

difference between mothers and childless women, ceteris paribus. The fatherhood wage premium is defined as the wage difference between fathers and childless men, ceteris paribus. This section first summarizes existing literature on the motherhood wage penalty and the fatherhood wage premium, and then summarizes research on the effect of leave laws on the family wage gap.

The Motherhood Wage Penalty

Studies show that the motherhood wage penalty usually ranges between five to ten percent for young mothers (Kahn et al., 2014). There are several possible explanations for the motherhood wage penalty. Three key explanations include the time constrains of motherhood, self-selection of mothers into lower pay employment, and self-selection of lower pay women into motherhood. Additionally the motherhood wage penalty varies by education level.

Prior research indicates that time constraints of motherhood are an important factor influencing the motherhood wage penalty. Using female Danish twin data, Simonsen and Skipper (2010) examine the motherhood wage penalty. Female twins were included in the study conditional on only one of the twins having a child. Although they find a four to five percent wage difference among sets of twins, when comparing mothers and non-mothers who work the same amount of hours, the motherhood wage penalty disappears. Simonsen and Skipper (2010) conclude that mothers' high levels of absence from work are responsible for the motherhood wage penalty. Avellar and Smock (2003) use a fixed effects model with National Longitudinal Survey of Young Women (NLSYW) data from 1975-1985 and NLSY data from 1986-1998 to investigate the

motherhood wage penalty. After controlling for human capital, they find 3.8 percent and 3.3 percent motherhood wage penalties for mothers in the NLSYW cohort and NLSY cohort, respectively. Avellar and Smock (2003) attribute this to mothers being the parents who are taking primary responsibility for childcare.

The effect of time constraints on the motherhood wage penalty varies by education level. Using National Longitudinal Survey of Labor Market Experience of Young Women data between 1968 and 1988, Anderson et al. (2003) use a fixed effects model to investigate the motherhood wage penalty. They find that high school dropouts incur a three percent motherhood wage penalty when returning to work while the child is an infant or toddler, but they do not incur a motherhood wage penalty for returning to work when their child is older. This suggests that the motherhood wage penalty dissipates over time for high school drop outs. Additionally, Anderson et al. (2003) find that high school graduates incur a four to six percent motherhood wage penalty, but college educated women do not incur a motherhood wage penalty. Anderson et al. (2003) conjecture that high school graduates and high school dropouts with young children have a higher probability of having less flexible working hours, causing costs due to time constraints of motherhood to be higher for these women than for others.

Anderson et al. (2002) investigate the effects of time constraints on the motherhood wage penalty by education level and race. They use National Longitudinal Survey of Labor Market Experience of Young Women data and a fixed effects model. They find white high school dropouts and white high school graduates do not incur a motherhood wage penalty when accounting for human capital and years out of the

workforce. College educated mothers incur a four percent wage penalty for the first child, and a 15 percent wage penalty for subsequent children when controlling for education and experience. However, once years out of the workforce is controlled for, the motherhood wage penalty for college educated whites disappear, but a motherhood wage penalty still persists for college educated blacks. It is possible that groups of mothers that incur a motherhood wage penalty have less flexible jobs, which makes time constraints more costly.

Self-selection into family-friendly employment also contributes to the motherhood wage penalty. Using Danish register data, Nielson et al. (2004) divide the economy into a family friendly public sector (because the public sector offers more benefits), and a non-family friendly private sector where wages are higher than in the family friendly public sector.[18] Nielson et al. (2004) find that mothers in the family friendly public sector do not incur a motherhood wage penalty, but mothers in the non-family friendly sector do. This suggests that mothers self-select into employment based on their tastes and preferences for trading family friendly policies and wages. In the United States, Amuedo-Dorantes and Kimmel (2005) conjecture that the wage penalty is because college educated women self-select into higher quality jobs that provide mothers with more opportunities for advancement. Firms have incentive to provide family friendly policies for high quality jobs in order to encourage job continuity and potentially attract high quality workers. However, Amuedo-Dorantes and Kimmel (2005) do not observe job characteristics to support this claim further.

[18] Benefits include such things as more generous pensions, fewer working hours, more vacation days, more parental leave policies, and more sick care days to aid family members.

Mothers self-selecting into lower paying jobs contributes to the motherhood wage penalty. Low and Sanchez (2015) use an equilibrium quantitative life-cycle model to simulate paid parental leave in the United States. Their simulation is based on data and findings from previous studies. They postulate that mothers who are induced by maternity leave to entre the labour market are less productive. Therefore, these mothers self-select into lower skilled jobs and receive lower wages. Additionally, mothers who take longer leave do not accumulate as much firm-specific human capital. Low and Sanchez (2015) postulate that these two notions contribute towards the motherhood wage penalty.

Women self-selecting into motherhood contributes to the motherhood wage penalty. That is, women who become mothers are systematically different from those who do not. Korenman and Neumark (1992) use NLSYW data for 28-38 year old women to explore this notion. They use family background variables and measures of attitudes and expectations for an instrumental variable approach. They find that work experience and tenure are endogenous. That is, estimates that include work experience and tenure understate the true effect of children on mothers' wages because lower work experience and tenure are associated with motherhood. Thus, women who self-select into motherhood are systematically different from women who do not, and the self-selection is based on unobserved characteristics correlated with wage.

Kahn et al. (2014) find evidence that self-selection into higher fertility has a lasting effect on the motherhood wage penalty.[19] Kahn et al. (2014) find a wage penalty

[19] Higher fertility refers to having more children.

for women in their 20s and 30s similar to Budig and England (2001), who found a three to five percent wage penalty per child. Using NLSYW data and a fixed effects model, Kahn et al. (2014) find a motherhood wage penalty of four percent that endures among mothers into their 40s and 50s who have three or more children. However, the motherhood wage penalty for mothers with fewer than three children dissipates by the time they reach their 40s. This implies that mothers who self-select into having more children will endure a longer wage penalty.

Despite the majority of prior research finding evidence of a motherhood wage penalty, several papers do not find evidence of a motherhood wage penalty. These papers focus on Denmark. Using Danish Longitudinal data between 1980 and 1995, Gupta and Smith (2002) utilize a generalized estimating equation. After controlling for work experience, they do not find any significant or lasting effect of children on mothers' wages. Their result is robust towards the presence of children and the number of children. Their result reinforce earlier studies by Rosholm and Smith (1996), and Naur and Smith (1997), who also do not find that children have a negative impact on mothers' wages in Denmark. Gupta and Smith (2002) note that statistical discrimination based on motherhood in Denmark is minimalized because publicly paid maternity leave coverage is almost 100 percent. However, instead of statistical discrimination being based on motherhood, Gupta and Smith (2002) suggest statistical discrimination could be based on motherhood potential, therefore, all young women may be statistically discriminated against.

The Fatherhood Wage Premium

Studies find that the fatherhood wage premium ranges between three to ten percent (Killewald, 2012). There are several possible explanations for the fatherhood wage premium. The most cited explanation is household specialization, where fathers specialize in labour market production as opposed to household production (Becker, 1981).[20] Other explanations for the fatherhood wage premium include a treatment effect of fatherhood, self-selection of fathers into employment, and self-selection of men into fatherhood.

Several papers find that household specialization is a key explanation for the fatherhood wage premium. Using Danish register data, Gupta et al. (2007) find that the fatherhood wage premium exists only for one to two years after the birth of a child. Because Danish fathers allocate .65 hours per one hour of childcare allocated by mothers, Gupta et al. (2007) postulate that household specialization allows fathers to focus on market labour.[21] Simonsen and Skipper (2010) show descriptive findings that Danish fathers allocate more time towards market labour corresponding to mothers allocating more time to household labour after childbirth. Using Panel survey of Income Dynamics (PSID) data and a fixed effects model, Lundberg and Rose (2000) find a nine percent fatherhood wage premium when the mother does not remain attached to the labour force after first childbirth. Additionally, fathers' annual working hours also increase by 118

[20] Household Specialization and the time constraint of motherhood are equivalent. This paper uses different terminology in order to preserve consistency with prior literature. The time constraint of motherhood in the labour market is a result of household specialization.

[21] Gupta et al. (2007) attain household childcare allocation ratios by sex from a Danish 2001 time use survey.

hours. This suggests that when mothers reallocate time towards household labour, fathers reallocate time towards market labour. This is consistent with Lundberg and Rose (2002). Lundberg and Rose (2002) use a fixed effects model and PSID data. They find that the average fatherhood wage premium is 4.2 percent, and fathers increase annual working hours by an average of 38 hours.[22] Using the 1980 U.S Census, Pencavel (1986) finds an association between children and longer working hours for fathers. This implies that men with children dedicate more time to market labour than men without children. This provides evidence of the household specialization theory.

Hersh and Stratton (2000) find evidence that challenges the household specialization theory. Using a fixed effects model and data from the National Survey of Families and Household (NSFH), they find that having children under the age of six increases wages for fathers. However, there is little difference between married and single men's time allocation for household labour. Based on the results of Hersh and Stratton (2000), the only way that household specialization impacts the fatherhood wage premium is if different types of household work have different effects on fathers' wages. The composition of household labour is different for single men relative to fathers. For example, Hersh and Stratton (2000) report that single men devote more time to cooking and cleaning relative to fathers. It is possible that mothers perform more labour intensive and energy consuming household tasks than fathers, which potentially allows for fathers to allocate energy towards market labour.

[22] Interestingly, Lundberg and Rose (2002) find that the birth of a son raises fathers' wages and working hours more than the birth of a daughter.

Killewald (2012) views the treatment effect of fatherhood as an explanation for the fatherhood wage premium. In other words, having a child changes men's behaviour in ways that make fathers more productive at work. Using a fixed effects model with NLSY-79 data, Killewald (2012) finds that fathers who live with their biological children and wives experience a four percent wage premium when their wives are working less than full-time. Fathers do not experience any wage premium when their wives are working full-time. Additionally, he finds that stepfathers and fathers who do not live with their biological children do not experience a wage premium. However, his findings are also consistent with the increased household specialization theory because fathers' wages increase only when mothers are working less than full-time.

Previous research shows that fathers self-selecting into higher paying jobs contributes to the fatherhood wage premium. Peterson et al. (2011) investigate the fatherhood wage premium in Norway. They use matched employee-employer data between 1979 and 1996. During this time, Norway expanded family friendly policies, including PPL. Peterson et al. (2011) find that the fatherhood wage premium is a phenomenon of self-selection of fathers into higher paying occupations. Supportive of this notion, Simonsen and Skipper (2010) find that Danish fathers have on average six more months of work experience than non-fathers, and earn a four percent wage premium. This suggests that fathers self-select into better jobs.

Other research suggests that self-selection into fatherhood is an explanation for the fatherhood wage premium. Kunze (2014) addresses the issue by comparing Norwegian brothers born between 1955 and 1965, conditional on only one brother in the

family being a father. Initially, Kunze (2014) finds a 3.2 percent to 4.4 percent fatherhood wage premium. However, she then controls for individual and family fixed effects by examining a twin brother only data set, and finds that the fatherhood wage premium is statistically zero. Kunze (2014) concludes that typical estimates of fatherhood wage premium are biased upward because men with strong family values self-select into fatherhood.

The Effect of Leave on the Family Wage Gap

Three papers investigate the effect of leave on the motherhood wage penalty and the fatherhood wage premium. Waldgofel (1998a), using a first difference model, investigates the impact of maternity leave on the motherhood wage penalty. She finds that mothers in the United States and Great Britain experienced wage premiums of approximately six percent and eight percent, respectively, as result of leave policy. Ceteris paribus, this is because mothers who have job-protected maternity leave have a higher probability of returning to their pre-birth employer. The resulting premiums found by Waldfogel (1998a) offset some but not all of the motherhood wage penalty.

Although Waldfogel (1999) does not explicitly examine the motherhood wage penalty, she uses young women as one of her control groups when investigating the effect of the FMLA on mothers' wages. Her results show that the impact of the FMLA on the motherhood wage penalty varies by firm size, and whether or not the state had a maternity leave law pre-FMLA. She finds some evidence that the FMLA decreased the motherhood wage penalty for mothers working at large sized firms in states with no prior maternity leave laws. Waldfogel (1998b) does a review of the family wage gap literature.

She suggests that short a maternity leave will likely have small negative effects on employment and wages, but the positive effects of leave, including decreasing the motherhood wage penalty, could offset the negative effects.

Alternatively, Albrecht et al. (1999) use Swedish data and find that parental leave has no effect on mother's wages, but can have an effect on fathers' wages. Fathers who take large amounts of leave experience a wage penalty, while fathers who do not take large amounts of leave do not experience a wage penalty. A large number of Swedish women included in the sample worked in the public sector, which is more family friendly. Additionally, almost all women in Sweden take generous parental leave. Therefore, a mother taking leave does not signal anything negative to an employer. Conversely, a father taking significant leave could signal undesirable attributes to an employer, explaining the negative effect of leave on the fatherhood wage premium.

Summary

The motherhood wage penalty is usually around five to ten percent for mothers in their 20s and 30s (Kahn et al., 2014) while the fatherhood wage premium is between three to ten percent (Killewald, 2012). The family wage gap is attributed to household specialization and self-selection. The motherhood wage penalty is largely, if not entirely, accounted for when controlling for time out of the workforce. Self-selection incorporates self-selection into parenthood, and selection into different careers relative to non-parents. Results vary by national context, race, number of children, and education levels. The limited research on the effect of leave on the family wage gap suggest leave could reduce the family wage gap.

CHAPTER FIVE

DATA

March CPS data from 1994-2015 is used, and was accessed via the Integrated Public Use Microdata Series (IPUMS) (Flood et al., 2015). The year 1994 was chosen as the first year of data because it is the first year after the implementation of the FMLA.

Several definitions of age are common throughout the main estimations. *Young* women and men are defined as those between the ages of 24-40 years old, while *older* women and men are defined as those between the ages of 41-65 years old. The age of 24 is chosen to be the lower bound for younger individuals because by this age the majority of individuals will not move across defined education groups.[23]

In the employment analyses, employed is a binary variable. A value of one indicates employed, and a value of zero indicates otherwise. *Employed* is defined as individuals who responded that they are at work, or have a job but not at work last week. For all estimations, individuals who report being in the armed forces are excluded from the analysis because of systematic differences between armed service members and civilians.

The earnings analysis for young women restricts the sample to full-time workers because there are systematic differences between full-time workers and part-time workers. Additionally, full-time workers have greater ability to qualify for job protected

[23] The definitions of *young* and *older* groups are altered as a robustness check in Chapter 8.

PPL than part-time workers.[24] Full-time workers are defined as individuals who usually worked 35-60 hours in the previous year and worked at least 40 weeks in the previous year.

The March CPS provides several work characteristic control variables. These include usual hours worked in the previous year, the industry an individual works in (categorical industry values are converted into ten industry indicator variables), and an individual's occupation (categorical values defined by IPUMS are converted into 25 occupation indicator variables). These work characteristics are only used for estimations involving earnings, and not used for estimations involving employment, because they are not observed for unemployed individuals in the sample.

One limitation to the CPS dataset is that it provides the age and number of children only at the year level rather than month level. *Age of the youngest child* within the household is provided by the data, and utilized for forming parental treatment groups for estimations. However, the age of other children residing in the household is unknown.

Treatment groups for parents are defined by the variable *age of own youngest child. Own child* is defined by the CPS as a biological, foster or adopted child. Mothers aged between 24-40, and whose youngest child is aged one, two, three, or four years old at the time of the survey year are used to form the treatment group *young mothers*; the treatment group *young fathers* is formed in the same manner.[25] Parents of older children

[24] Recall that the CA-PFL and NJ-PFI provide unprotected paid parental leave, and there is no minimum firm size or work requirement to qualify for benefits. However, the FMLA can be used co-currently as the paid parental leave policies for qualifying parents, but the FMLA does have firm size limitations and work requirements. The combination of the paid leave policies and the FMLA constitutes job protected PPL.
[25] The age definition of parents are altered as a robustness check in Chapter 8.

are included in control groups for estimations involving young women's employment and earnings, but not included in estimations involving mothers and fathers. This is because one purpose of this paper is to investigate the effect of PPL on the incidence of the family wage gap, which is primarily taken in the first years after the birth of a child.

There are several personal binary control variables. These include marital status (*married spouse present or absent*, *single*, or *other*), race (*white*, *black*, or *other races*), Hispanic, education level (*high school education or less*, *some college*, *bachelor degree or more*), and urban status.[26]

The March CPS dataset reports useful household characteristic information used as controls. These include number of own children under five years old in the household, number of own children in the household, and total number of own family members in the household. Total number of own family members in the household is defined in the CPS to include extended kin related by blood, marriage, or adoption.

Average seasonally adjusted state unemployment rates from the Bureau of Labor Statistics are used to control for labour market conditions. Labour market conditions influence behaviour and employment decisions for both firms and households, and therefore labour market conditions are important to control for, especially because the analysis spans recession years 2007-2009.

[26] The category *some college* is comprised of individuals who have some college experience but no degree, individuals with an associate's degree in an occupational or vocational field, and individuals with an associate's degree in an academic programme.

Inter-census estimates for state populations are used from the United States Census Bureau. It is important to control for population because this affects labour supply, and labour supply impacts employment and earnings.

CHAPTER SIX

EMPIRICAL METHODOLOGY

Three approaches are used to measure the effect of paid parental leave (PPL) on *young* women's labour market outcomes and the family wage gap. First, difference-in-difference (DD) models are used to compare the young women's employment and earnings in treatment states (California and New Jersey) and control states. Second, DD models without control states compare the demographic group of interest (young women, young mothers, or young fathers) to a different demographic group within a treatment state. Lastly, a preferred difference-in-difference-in-difference (DDD) approach will combine the two DD approaches. All models account for time constant state characteristics. The models for of California and New Jersey are estimated separately because of their different lengths of time since implementation, different wage replacement rates, different maximum benefit levels, and other potential systematic differences between California and New Jersey.

Difference-in-difference with Control States

Difference-in-difference (DD) ordinary least squares (OLS) estimations using control states compare the change in an outcome variable in a treatment state to the change in the same outcome variable in a control state. Only one demographic group is involved in each estimation, and only young women's employment and earnings are estimated using a DD.

Young Women's Employment

A DD model is used to compare the change in young women's employment in treatment states to the change in young women's employment in control states before and after the implementation of PPL. These OLS models use data on only young women, and are based on equation (1.1).[27]

$$Employed_{ijt} = \alpha_0 + \delta_1 PPL_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (1.1)$$

The subscript notation refers to young woman *i*, in state *j*, at time *t*. The dependent variable $Employed_{ijt}$ is a binary variable and equals one if young woman *i* is employed and zero otherwise. The policy variable PPL_{ijt} equals one if young woman *i* is in a treatment state during a time after a PPL has been implemented and zero otherwise. The vector $\boldsymbol{X}_{ijt}$ includes the personal characteristics age, age squared, marital status, race, ethnicity, and education. The vector $\boldsymbol{U}_{jt}$ includes state population and unemployment rates to control for labour supply and for labour market conditions unique to each state in each year that may affect $Employed_{ijt}$. The vector $\boldsymbol{S}_j$ includes state fixed effects to control for time constant characteristics unique to each state. The vector $\boldsymbol{T}_t$includes year fixed effects to control for macroeconomic changes in a given year that occur both in treatment and control states. The variable $\boldsymbol{S}_j * Trend_t$ is a state-specific linear time trend that controls for different trends in $Employed_{ijt}$ over time that may vary by state. Including the variable $\boldsymbol{S}_j * Trend_t$ is allows for a relaxation of the parallel trends

[27] As noted in Chapter 5, *young women* are defined here as women between 24-40 years old. The impact of altering this definition to instead include women 24-33 years old is examined as a robustness check in Chapter 8.

assumption (Mora and Reggio, 2013). This is important because any potential difference in the dependent variable between treatment and control states is controlled for.

The DD estimator is δ_1, and it measures the average treatment effect of PPL on young women's employment status in treatment states, while controlling for changes in young women's employment in control states over the same period of time. It can be expressed as

$$\delta_1 = \mathrm{E}[\mathrm{employment}_{\text{Treatment State, Post Policy}} - \mathrm{employment}_{\text{Treatment State, Pre Policy}}] - \mathrm{E}[\mathrm{employment}_{\text{Control State, Post Policy}} - \mathrm{employment}_{\text{Control State, Pre Policy}}].$$

This captures the difference in employment among young women in treatment states before and after the PPL policy, minus the difference in employment among young women in control states over the same time period. The expected sign of estimate δ_1 is ambiguous. On one hand, a PPL policy incentivizes young women to return to their pre-birth employer, and thus increases the supply of young women's labour. This leads to a positive estimate of δ_1. On the other hand, the relative cost of employing young women increases. Firms may therefore decrease the relative demand for young women. This leads to a negative estimate of δ_1.

Standard Errors

Standard errors are clustered at the state level for the estimations in accordance to Bertrand et al. (2004).[28] Clustering standard errors allows for arbitrary correlation between errors within clusters of observations (Baum et al., 2010).

Clustering at the largest observation level (state level) comes with a tradeoff. Failing to cluster at the largest observation level ignores correlations among the observations within clusters (Ibragimov and Muller, 2016). Additionally, using default standard errors may overstate the significance of estimators (Cameron and Miller, 2015). According to Cameron and Miller (2015), using clustered standard errors at the largest observation level is the most conservative approach to avoid bias in the precision of estimators, even when lack of clusters is a concern. Clustering when there are a small amount of treatment groups relative to the amount of control groups over-rejects the null hypothesis (Conley and Taber, 2011). Therefore, a tradeoff exists between being more conservative with regards to the significance of the estimators and an increase in type I error when clustering on the state level.

Young Women's Earnings

A different DD OLS model is used to compare changes in young women's earnings in treatment states to changes in young women's earnings in control states before and after the implementation of PPL.[29] These models are based on equation (1.2).

[28] A DD without using controls states is estimated below. By construction, clustering on the state level is not possible in that model, so standard errors that are robust towards heteroskedasticity are used instead.
[29] Only *young* women who are employed and working full-time are included in the model. Full-time workers are individuals who report working between 35-60 hours per week, and were employed for at least 40 weeks in the previous year.

$$Ln(Wage)_{ijt} = \alpha_0 + \delta_1 PPL_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (1.2)$$

Equation (1.2) is different from (1.1) in two ways. First, the dependent variable is now $Ln(Wage)_{ijt}$ rather than $Employed_{ijt}$. Second, the employment characteristics vector ($\boldsymbol{Z}_{ijt}$) is included because work controls are observed for employed workers (non-employed workers are excluded from the regression). Note that PPL_{ijt} is defined the same way as in equation (1.1).

The DD estimator is δ_1, and measures the average treatment effect of PPL on young women's earnings, while controlling for changes in young women's earnings in control states over the same time period. It can be expressed as

$$\delta_1 = E[\ln(\text{wages})_{\text{Treatment State, Post Policy}} - \ln(\text{wages})_{\text{Treatment State, Pre Policy}}] - E[\ln(\text{wages})_{\text{Control State, Post Policy}} - \ln(\text{wages})_{\text{Control State, Pre Policy}}].$$

The expected sign of δ_1 is ambiguous. On one hand, a PPL policy incentivizes young women to return to their pre-birth employer, which increases relative job continuity and reduces firm-specific human capital depreciation. This increases young women's earnings and leads to a positive estimate of δ_1. On the other hand, a PPL increases the supply of women working because many are incentivized to work in order to qualify for benefits. This implies a negative estimate of δ_1. Additionally, because the relative cost of employing young women increases, firms may decrease the relative demand for young women, which also leads to a negative $\delta_1$estimate.

Difference-in-difference without Control States

Difference-in-difference estimations without using control states compare the change in an outcome variable among a treatment demographic to the change in the same outcome variable in among a control demographic group in the same states and time. Thus the analyses takes place in treatment states that pass PPL.

Young Women's Employment

A DD OLS model is used to compare changes in young women's employment status in treatment states before and after the implementation of PPL to changes in older women's employment status in treatment states before and after the passage PPL. These models use data on younger and older women in treatment states only, and are based on equation (2.1).[30]

$$Employed_{it} = \alpha_0 + \delta_1 PPL_{it} + \boldsymbol{X}_{it}\beta + \boldsymbol{U}_{jt}\eta + \boldsymbol{T}_t\theta + Trend_t\theta + e_{it} \qquad (2.1)$$

Equation (2.1) differs from equation (1.1) in several ways. First, the subscript *j* is no longer present because the analysis occurs only within the treatment state. For the same reason, state fixed effects $\boldsymbol{S_j}$ and state fixed effects interacted with a time trend $\boldsymbol{S}_j * Trend_t$ are omitted. The vector $\boldsymbol{S}_j * Trend_t$ is replaced by a linear time trend variable $Trend_t$. The variable of interest PPL_{it} equals one if individual *i* is a young woman during a time period *t* after PPL has been implemented and zero otherwise. The year

[30] As noted in Chapter 5, *young women* are defined here as women between 24-40 years old, while *older women* are defined here as women between 41-65 years old. Estimates that use alternative definition for *young* and *older* women are presented in Chapter 8.

fixed effects vector $\boldsymbol{T}_t$controls for state level macroeconomic changes in a given year that may affect $Employed_{it}$.

The DD estimator is δ_1, and measures the average treatment effect of PPL on young women's employment while controlling for changes in employment during the same time period among older women. It can be expressed as

$$\delta_1 = \text{E}[\text{employment}_{\text{Young Women, Post Policy}} - \text{employment}_{\text{Young Women, Pre Policy}}] - \text{E}[\text{employment}_{\text{Older Women, Post Policy}} - \text{employment}_{\text{Older Women, Pre Policy}}].$$

The expected sign of the estimate is ambiguous for the same reasons discussed above. One threat to the identification of equation (2.1) would be if older women were substitute labour for younger women. This would render older women an inappropriate control group because they may also be affected by PPL. However, several papers show that older women and younger women should not be considered substitute workers (Munnel and Wu, 2012; Gruber and Wise, 2010; Gruber and Milligan, 2008).

Young Women's Earnings

A DD OLS model is used to compare changes in young women's earnings in treatment states to changes older women's earnings in treatment states before and after the passage of PPL. These models are based on equation (2.2).

$$Ln(Wage)_{it} = \alpha_0 + \delta_1 PPL_{it} + \boldsymbol{X}_{it}\beta + \boldsymbol{Z}_{it}\lambda + \boldsymbol{U}_t\eta + \boldsymbol{T}_t\theta + Trend_t\theta + e_{it} \qquad (2.2)$$

Equation (2.2) is different from equation (2.1) in two ways. First, the dependent variable is now $Ln(Wage)_{it}$. Second, the employment characteristics vector $\boldsymbol{Z}_{it}$is included because work characteristics are observed only for employed workers and only full-time workers are included in the sample.

The DD estimator is δ_1, and measures the average treatment effect of PPL on young women's earnings. It can be expressed as

$\delta_1 = \text{E}[\ln(\text{wages})_{\text{Young Women, Post Policy}} - \ln(\text{wages})_{\text{Young Women, Pre Policy}}] -$
$\text{E}[\ln(\text{wages})_{\text{Older Women, Post Policy}} - \ln(\text{wages})_{\text{Older Women, Pre Policy}}].$

The expected sign of the estimate is ambiguous for the same reasons as discussed above.

Mothers' Earnings

A DD OLS model is used to compare changes in young mother's earnings in treatment states to changes in young childless women's earnings in treatment states before and after the implementation of a PPL policy.[31] These models use data on mothers and young childless women, and are based on equation (2.3).

$$Ln(Wage)_{it} = \alpha_0 + \delta_1 PPL_{it} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{it}\lambda + \boldsymbol{U}_t\eta + \boldsymbol{T}_t\theta + Trend_t\theta + e_{it} \qquad (2.3)$$

Equation (2.3) is different from equation (2.2) because the variable PPL_{it} equals one if woman *i* is a young mother in a time period *t* after a PPL policy has been implemented and zero otherwise.

The DD estimator is δ_1, and measures the average treatment effect of PPL on the young mothers' earnings relative to similar changes in young childless women's earnings during the same time period. It can be expressed as

$\delta_1 = \text{E}[\ln(\text{wages})_{\text{Young Mothers, Post Policy}} - \ln(\text{wages})_{\text{Young Mothers, Pre Policy}}] -$
$\text{E}[\ln(\text{wages})_{\text{Young Childless Women, Post Policy}} - \ln(\text{wages})_{\text{Young Childless Women, Pre Policy}}].$

The expected sign of the estimate is ambiguous. On one hand, job continuity has been empirically shown to increase as a result of PPL. This increases young mothers' earnings,

[31] Estimations involving earnings of mothers and non-mothers measure the motherhood wage penalty. To avoid confusion, the *motherhood wage penalty* may be referred to as simply *mothers' relative earnings.*

and would lead to a positive estimate of δ_1. On the other hand, the relative cost of employing young mothers increases because the probability that young mothers may have subsequent children increases. Firms may decrease their relative demand for young mothers. This would lead to a negative estimate of δ_1. However, young childless women's probability of becoming young mothers and taking leave also increases, so it is unclear how firms will adjust their relative demand for young childless women relative to that for young mothers.

All estimations involving young mothers' earnings are associated with three caveats. First, young childless women may be a contaminated control group for young mothers. There may be young childless women planning to have a child, or pregnant at the time of the survey such that firms treat them the same as young mothers. In other words, there are layers of heterogeneity among young childless women that have not been accounted for. Second, this paper does not control for the selection into parenthood, which the previous literature has indicated is a relevant consideration for estimations involving the family wage gap. Third, there is low sample size. Most of the observations in the estimates involving young mothers are actually composed of the control demographic (*young childless* women) and not young mothers (i.e., there are relatively few young mothers in the treatment states in the sample). Sample sizes can be seen in summary statistic tables presented in Chapter 7.

Father's Earnings

A DD OLS model is used to compare changes in young fathers' earnings in treatment states to changes in young childless men's earnings in treatment states before

and after the implementation of a PPL policy.[32] These models use data on fathers and young childless men, and are based on equation (2.4).

$$Ln(Wage)_{ijt} = \alpha_0 + \delta_1 PPL_{it} + \boldsymbol{X}_{it}\beta + \boldsymbol{Z}_{it}\lambda + \boldsymbol{U}_t\eta + \boldsymbol{T}_t\theta + Trend_t\theta + e_{it} \qquad (2.4)$$

Equation (2.4) is different from equation (2.3) in two ways. First, subscript *i* refers to man *i*. Second, the variable PPL_{it} equals one if man *i* is a young father in a time period *t* after the implementation of a PPL policy, or equals zero otherwise.

The DD estimator is δ_1, and measures the average treatment effect of PPL on the fatherhood wage premium. It can be expressed as

$$\delta_1 = \text{E}[\ln(\text{wages})_{\text{Young Fathers, Post Policy}} - \ln(\text{wages})_{\text{Young Fathers, Pre Policy}}] - \text{E}[\ln(\text{wages})_{\text{Young Childless Men, Post Policy}} - \ln(\text{wages})_{\text{Young Childless Men, Pre Policy}}].$$

The expected sign of the estimate is ambiguous. Empirical findings show that fathers take only small amounts of parental leave with parental leave expansions. This may lead to a zero estimate of δ_1. On the other hand, if fathers utilize leave, a negative δ_1 may occur due to a loss in firm-specific human capital. At the same time, young childless men's probability of becoming fathers and taking leave also increases, so it is unclear how firms will adjust their relative demand for young childless men relative to young fathers.

All estimations involving young fathers' earnings are associated with the same three caveats as estimations involving young mothers' earnings. The three caveats are (1) young childless men may be a contaminated control group for young fathers, (2) there is

[32] Estimations involving earnings of fathers and non-fathers measure the fatherhood wage premium. To avoid confusion, the *fatherhood wage premium* may be referred to as simply *fathers' relative earnings*.

no control for the selection into parenthood, and (3) the sample of young fathers in the treatment states is relatively small.[33]

Difference-in-difference-in-difference

The DDD model is the preferred approach. It combines the two DD approaches by using control states and control demographic groups. The DDD approach exploits variation between time, states, and different demographic groups. It is able to control for labour market outcomes for individuals both in the treatment and control demographic groups, national macroeconomic shocks that may affect the labour market for all individuals, and state macroeconomic shocks that may affect labour market outcomes for all individuals.

Young Women's Employment

A series of DDD OLS models compare percentage point changes in employment for young women in treatment states to percentage point changes in employment for young women in control states before and after the implementation of PPL, while using older women as a control group. These models use data on young women and older women, and are based on equation (3.1).

$$Employed_{ijt} = \alpha_0 + \gamma_1 PPL_{ijt} + \gamma_2 YW_{ijt} + \gamma_3 PPL_{ijt} * YW_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{U}_{jt}\eta + \boldsymbol{S_j}\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j\theta * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (3.1)$$

The subscript notation refers to woman *i*, in state *j*, at time *t*. The variable $Employed_{ijt}$ is a binary variable, and equals one if young woman *i* is employed and zero

[33] Sample sizes can be seen in summary statistics tables presented in Chapter 7.

otherwise. The variable PPL_{ijt} equals to one if woman *i* (of any age) is in a treatment state during time *t* after a PPL has been passed and zero otherwise. The variable YW_{ijt} equals one if woman *i* is a young woman and zero otherwise.[34] The variable $PPL_{ijt} * YW_{ijt}$ is the variable of interest, and equals one if individual *i* is a young woman in a treatment state during time *t* after a PPL has been implemented in a treatment state and zero otherwise. All other control variables are the same as equation (1.1). The vector $\boldsymbol{S}_j * \boldsymbol{T}_t$ is state by year fixed effects and allows for more flexibility in the model because it controls for time effects that are unique to each state in each year. The vector $\boldsymbol{S}_j * \boldsymbol{T}_t$ is not included in the DD models because of multicollinearity.

The DDD estimator is γ_3, and measures the average treatment effect of PPL on *young* women's employment while controlling for changes in young women's employment in control states and also for changes in older women's employment in treatment and control states over time. It can be expressed as

$\gamma_3 =$ {E[young women's employment$_{\text{Treatment State, Post}}$ - young women's employment$_{\text{Treatment State, Pre}}$] −
E[young women's employment$_{\text{Control State, Post}}$ - young women's employment$_{\text{Control State, Pre}}$]} −
{E[older women's employment$_{\text{Treatment State, Post}}$ - older women's employment$_{\text{Treatment State, Pre}}$] −
E[older women's employment$_{\text{Control State, Post}}$ - older women's employment$_{\text{Control State, Pre}}$]}.

The expected sign of the estimate is ambiguous for the same reasons as described above.

[34] As noted in Chapter 5, *young* and *older* are defiend here as ages 24-40, and 41-65, respectively. Estimates that use alternative definitions of young and older are presented in Chapter 8 as a robustness check.

Young Women's Earnings

A series of DDD models compare percent changes in earnings for young women in treatment states to percent changes in earnings for young women in control states before and after the implementation of PPL while using older women as a control group. These models are based on equation (3.2).

$$\text{Ln}(\text{W}age)_{ijt} = \alpha_0 + \gamma_1 PPL_{ijt} + \gamma_2 YW_{ijt} + \gamma_3 PPL_{ijt} * YW_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j\theta * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (3.2)$$

Equation (3.2) is different from equation (3.1) in two ways. First, the dependent variable is now $\text{Ln}(\text{W}age)_{ijt}$. Second, the employment characteristics vector $\boldsymbol{Z}_{ijt}$ is included because work controls are observed for employed workers, and only full-time workers are included in the sample.

The DDD estimator is γ_3, and measures the average treatment effect of PPL on young women's earnings relative to older women's earnings. It can be expressed as

γ_3 = {E[young women's ln(wages)$_{\text{Treatment State, Post}}$ - young women's ln(wages)$_{\text{Treatment State, Pre}}$] − E[young women's ln(wages)$_{\text{Control State, Post}}$ - young women's ln(wages)$_{\text{Control State, Pre}}$]} − {E[older women's ln(wages)$_{\text{Treatment State, Post}}$ - older women's ln(wages)$_{\text{Treatment State, Pre}}$] − E[older women's ln(wages)$_{\text{Control State, Post}}$ - older women's ln(wages)$_{\text{Control State, Pre}}$]}.

The expected sign of the estimate is ambiguous for the same reasons as described above.

Mothers' Earnings

A series of DDD OLS models compare the change in earnings for young mothers in treatment states relative to young mothers in control states before and after the implementation of PPL while using young childless women as a control group. These models use data on young mothers and young childless women, and are based on equation (3.3).

$$\text{Ln}(\text{W}age)_{ijt} = \alpha_0 + \gamma_1 PPL_{jt} + \gamma_2 YM_{ijt} + \gamma_3 PPL_{ijt} * YM_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j\theta * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (3.3)$$

Equation (3.3) is different from equation (3.2) in two ways. The variable YM_{ijt} equals one if young woman *i* is a young mother and zero otherwise. The variable $PPL_{ijt} * YM_{ijt}$ equals one if young woman *i* is a young mother in a treatment state during a time period *t* after a PPL policy has been implemented in the respective treatment state and zero otherwise. The other control variables are the same as equation (3.2).

The DDD estimator is γ_3, and measures the average treatment effect of PPL on the motherhood wage penalty. It can be expressed as

γ_3 = {E[young mothers' ln(wages)$_{\text{Treatment State, Post}}$ - young mothers' ln(wages)$_{\text{Treatment State, Pre}}$] − E[young childless women's ln(wages)$_{\text{Control State, Post}}$ - young childless women's ln(wages)$_{\text{Control State, Pre}}$]} − {E[young mothers' ln(wages)$_{\text{Treatment State, Post}}$ - young mothers' ln(wages)$_{\text{Treatment State, Pre}}$] − E[young childless women's ln(wages)$_{\text{Control State, Post}}$ − young childless women's ln(wages)$_{\text{Control State, Pre}}$]}.

The expected sign of the estimate is ambiguous for the same reasons as described above.

Fathers' Earnings

A series of DDD models compare the change in earnings for young fathers in treatment states relative to young fathers in control states before and after the implementation of PPL while using young childless men as a control group. These models use data on young fathers and young childless men, and are based on equation (3.4).

$$\text{Ln}(\text{W}age)_{ijt} = \alpha_0 + \gamma_1 PPL_{jt} + \gamma_2 YF_{ijt} + \gamma_3 PPL_{ijt} * YF_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (3.4)$$

Equation (3.4) is different from equation (3.2) in two ways. The variable YF_{ijt} equals one if man *i* is a young father and zero otherwise. The variable $PPL_{ijt} * YF_{ijt}$ equals to one if

man *i* is a young father in treatment state *j* during a time period *t* after a PPL policy has been passed in the state and zero otherwise. The other control variables are the same as equation (3.2).

The DDD estimator is γ_3, and measures the average treatment effect of PPL on the fatherhood wage premium. It can be expressed as

$\gamma_3 = \{E[\text{young fathers' ln(wages)}_{\text{Treatment State, Post}} - \text{young fathers' ln(wages)}_{\text{Treatment State, Pre}}] -$
$E[\text{young childless men's ln(wages)}_{\text{Control State, Post}} - \text{young childless men's ln(wages)}_{\text{Control State, Pre}}]\} -$
$\{E[\text{young fathers' ln(wages)}_{\text{Treatment State, Post}} - \text{young fathers' ln(wages)}_{\text{Treatment State, Pre}}] -$
$E[\text{young childless men's ln(wages)}_{\text{Control State, Post}} - \text{young childless men's ln(wages)}_{\text{Control State, Pre}}]\}.$

The expected sign of the estimate is ambiguous for the same reasons as described above.

Synthetic Control States

Several sets of synthetic control states are chosen for each estimation. The synthetic control method was first developed by Abadie and Gardeazabal (2003), and extended by Abadie et al. (2010). The synthetic control method positively weights several states such that they sum to one. The selected weighted states are representative of the treatment states (California or New Jersey), and approximate the pre-treatment trends for the treated groups of interest (young women, young mothers, or young fathers). The synthetic control states provide a counterfactual to the treatment states. This ensures that the parallel trends assumption, necessary for identifying causal inferences of DD models, is upheld in order to observe what would have occurred absent a PPL policy. All control variables are used for determining the chosen control states' weights displayed in Tables B1 and B2 in Appendix B. With the exception of New Jersey and Rhode Island, all states were considered as potential synthetic control state candidates for estimations involving California, and with the exception of California and Rhode Island, all states were

considered as potential synthetic control state candidates for estimations involving New Jersey.

Estimations by Education Subgroup

Additional DDD models are estimated by education subgroups. Dissecting the main sample by education subgroup is insightful because prior literature and theory suggest that the impacts of PPL will vary based on workers' education level.[35] Education subgroup models are estimated separately for those individuals with (1) a high school degree or less, (2) some college, and (3) a bachelor's degree or more. Each estimation by subgroup has its own set of synthetic control states in order ensure that the parallel trends assumption is satisfied.[36] Tables B3 and B4 in Appendix B display the synthetic control groups for estimations by subgroup.

Effects Over Time

All main DDD estimations are also altered to measure how earnings and employment respond in the years before and after the implementation of PPL. This serves two purposes. First, it acts as a quasi-placebo test. A significant estimate for the years prior to the implementation of PPL could indicate that the PPL estimates during the post-

[35] Estimations for the effect of PPL on employment and earnings for young women who work in a female dominated occupations were also obtained. Female dominated occupations are defined by the United States Department of Labor as occupations with at least 50,000 workers, and where 75 percent of the workers are female. The estimates of the impact of the PPL on earnings were negative and significant in California, but statistically insignificant in New Jersey. This analysis was not included in the paper because sample sizes for investigating young women in female dominated occupations by education subgroup were small. These results are available upon request.

[36] Estimations by subgroup using the same synthetic control states as in the main DDD results outlined in tables 1 and 2 were obtained. The results are both qualitatively and quantitatively similar to results presented in this paper, and are available upon request.

policy period equations are spurious. Second, it allows for examination of the effect that the implementation of PPL has over time. This provides a richer understanding for the effects of PPL because it separates the short-run (1-3 years after PPL implementation) and the long-run (4 or more years after PPL implementation) effects. The DDD equation for the year prior to the implementation of PPL takes the following form:

$$\mathrm{Y}_{ijt} = \alpha_0 + \gamma_1 Law_{jt} * (Year\ Prior)_{ijt} + \gamma_2 Group\ of\ Interest_{ijt} + \gamma_3 Law_{jt} * (Year\ Prior)_{ijt} * Group\ of\ Interest_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (4.1),$$

and the DDD equation for investigating the short-run and long-run effect of PPL takes the following form:

$$\mathrm{Y}_{ijt} = \alpha_0 + \gamma_1 Law_{jt} * (1\ to\ 3\ Years\ Post)_{ijt} + \gamma_2 Law_{jt} * (4\ or\ More\ Years\ Post)_{ijt} + \gamma_3 Group\ of\ Interest_{ijt} + \gamma_4 Law_{jt} * (1\ to\ 3\ Years\ Post)_{ijt} * Group\ of\ Interest_{ijt} + \gamma_5 Law_{jt} * (4\ \ or\ More\ Years\ Post)_{ijt} * Group\ of\ Interest_{ijt} + \boldsymbol{X}_{ijt}\beta + \boldsymbol{Z}_{ijt}\lambda + \boldsymbol{U}_{jt}\eta + \boldsymbol{S}_j\theta + \boldsymbol{T}_t\theta + \boldsymbol{S}_j * \boldsymbol{T}_t\theta + \boldsymbol{S}_j * Trend_t\theta + e_{ijt} \quad (4.2).$$

The subscript notation refers to individual *i*, in state *j*, at time *t*. The variable Y_{ijt} is either logged earnings or employment. The variables $Law_{jt} * (Year\ Prior)_{ijt}$, $Law_{jt} * (1\ to\ 3\ Years\ Post)_{ijt}$, and $Law_{jt} * (4\ or\ More\ Years\ Post)_{ijt}$ are equal to one for those in the treatment state in particular years. The variable $Group\ of\ Interest_{ijt}$ refers to either young women, young mothers, or young fathers, depending on which group is being examined. All controls are the same as equation (3.2), with the exception that estimations involving employment will not have work control vector $\boldsymbol{Z}_{ijt}$.

The coefficient γ_3 in equation (4.1) is the coefficient of interest that acts as a quasi-placebo test, and measures how the dependent variable is affected prior to the

implementation of PPL. The coefficient γ_4 in equation (4.2) measures the short run effects 1-3 years after the implementation of PPL. The coefficient γ_5 in equation (4.2) measures the long run effects four or more years after the implementation of PPL. A non-significant coefficient, or a coefficient of value zero signifies that PPL had no impact in the particular time period. A small significant coefficient signifies that PPL had a small impact in the particular time period. A large significant coefficient signifies that PPL had a large impact in the particular time period.

Robustness Checks

All DDD estimations are repeated with several alternative specifications for robustness. These robustness specifications use several alternative sets of control states, alter the definitions for *young* and *older* individuals, and use alternative demographic groups rather than older women as a control group for estimations involving young women's employment and earnings.

Three alternative sets of control states are used as a robustness check. First, all DDD specifications are estimated using neighbouring states as control states. Neighbouring states for California are Arizona, Nevada, and Oregon while neighbouring states for New Jersey are Delaware, New York, and Pennsylvania. Second, Florida, New York, and Texas are used as alternative control states. These states are used by both Rossin-Slater et. al (2013) and Byker (2016). Rossin-Slater et. al (2013) explains that these states were chosen in their study of the CA-PFL because these states are the next three largest states to California. The third set of control states uses all states plus Washington D.C.

All synthetic DDD specifications are also estimated with variation in age definitions. *Young* individuals are defined as individuals between the ages of 24-33, and *older* individuals are defined as individuals between the ages of 50-65. Because this tighter age definition generates a starker gap between the "young" and "old" than used in the base regressions, it is more likely to generate significant estimates, and thus is a less conservative estimation strategy. Because this also changes the individuals included in the sample, new synthetic control states are attained for these estimates. Tables B5 and B6 in Appendix B display the new synthetic control states, and Tables B7 and B8 in Appendix B display the new synthetic control states that are used for estimations by education subgroup.

All DDD specifications for young women's employment and earnings are also estimated using young men and older men rather than older women as control groups. These results can be found in Tables C1 and C2 in Appendix C. These estimates are suspect, however, since using young men, and older men as control groups is not necessarily appropriate. There are unobserved differences between young women and men (especially older men) that may affect labour market outcomes. Additionally, there is evidence that PPL may affect young men's employment and earnings, making them a contaminated control group for young women. When using a DDD model comparing young men's employment and earnings in treatment states to young men's labour market outcomes in control states while using older men as a control group, there are several significant estimates as a result of PPL. These results can be found in Table C3 in

Appendix C. Synthetic control states used for this estimation can be found in Table C4 in Appendix C.

CHAPTER SEVEN

RESULTS

This section provides estimation results. Results are organised in the order of (1) young women's employment, (2) young women's earnings, (3) mothers' earnings, and (4) fathers' earnings, with each section having a summary. Each of these sections includes a discussion of summary statistics by state, DD results, DDD results, and DDD results by education subgroup.

Young Women's Employment

Tables 3 and 4 display summary statistics for estimations in California involving young women's employment pre-PPL and post-PPL, respectively. The raw unconditional mean differences in employment are 0.009 for the DD with control states (DDa), 0.006 for the DD without control states (DDb), and 0.023 for the DDD.[37] The unconditional DDD implies that approximately 1 out 50 young women would gain employment as a result of PPL. All of the mean employment differences are positive and statistically significantly different from zero, indicating that a comparison of the average changes in employment without controlling for other factors would misleadingly imply that the CA-PFL increased young women's employment. As will be shown in the regression results, once sociodemographic and other factors are controlled for, the CA-PFL is estimated to reduce young women's employment by 2.1 percentage points.

[37] Calculation for all raw unconditional mean differences performed can be found in Appendix D.

In both the pre-2004 and post-2004 periods, young women in California appear to differ from young women in control states along several dimensions, including having slightly larger households and being more likely to live in a metro area. Young women in California also appear to be more likely to be white, less likely to be black, and more likely to be Hispanic than young women in control states. They also appear to have lower average levels of education than young women in control states. Although these differences in the treatment and control groups are statistically significant, with the exception of metro and race/ethnicity variables, they are all of small magnitude.

Nonetheless, to the extent that they are correlated with other variables, they may be of concern. However, as shown in Chapter 8, estimates that use several different sets of control states produce similar results to those in the base specifications based on the samples described in tables 3-6.

Tables 5 and 6 display summary statistics for estimations involving young women's employment in New Jersey pre-PPL and post-PPL, respectively.[38] The raw unconditional mean differences in employment are 0.001 for the DDa, -0.012 for the DDb, and 0.005 for the DDD. The unconditional DDD implies that approximately 1 out 1000 young women would gain employment as a results of PPL. Again, the mean employment differences signify that a simple comparison of mean employment differences may be misleading.

[38] Because all respondents in New Jersey and its synthetic control states report being in a metro area, this variable is excluded from the analysis of the NJ-PPL

Table 7 displays the DD results for the effect of PPL on young women's employment in California and New Jersey.[39] The DDa for California implies a positive effect of PPL on young women's employment relative to young women's employment in control states, but the DDa for New Jersey implies a negative effect of PPL on young women's employment relative to young women in control states. With the inclusion of state-by-time-trends, the California DDa coefficient becomes more positive, and the New Jersey DDa coefficient becomes more negative. This suggests that there are more negative linear employment trends in California relative to its control states, and that there are more positive linear employment trends in New Jersey relative to its control states. This underscores the importance for controlling for state-specific employment trends, and allowing for flexibility in the models. The DDb coefficients for California and New Jersey are negative and significant. This implies a negative effect of PPL on young women's earnings relative to older women's earnings in treatment states. The coefficients are unresponsive to the inclusion of a linear time trend.

Table 8 displays DDD results for the effect of PPL on young women's employment in California and New Jersey. The coefficients indicate that PPL decreases employment of young women in California and New Jersey compared to employment of young women in control states, while using older women as a control group, by 2.1 percentage points in California and 2.8 percentage points in New Jersey. The coefficients are significant at the five percent level and unresponsive to the inclusion of state-by-year fixed effects. This result proves to be relatively robust in Chapter 8.

[39] All control variables have expected signs and magnitudes, and are displayed in Table A1 in Appendix A.

Table 9 displays DDD results for the effect of PPL on employment of young women by education subgroup.[40] All coefficients for young women without a bachelor's degree are negative and significant, with larger effects being experienced in New Jersey than California. This signifies that young women without a bachelor's degree experience a decrease in employment as a result of PPL. The effect is more negative for young women with a high school degree or less than for young women with some college experience. Alternatively, there does not appear to be an impact of PPL on the employment of young women with a bachelor's degree. All estimates are unresponsive to the inclusion of state-by-year fixed effects. This result proves to be relatively robust in Chapter 8.

Summary

Preferred DDD results show a negative impact of PPL on employment of young women. This result is consistent with previous literature. The negative impact has heterogeneous effects by subgroup as PPL policy coefficients are significant and negative for young women without a bachelor's degree in both treatment states. This result is consistent with several theoretical predictions discussed in Chapter 3. From the household's perspective, PPL is likely to have stronger impacts on women with lower skills and lower earnings (proxied here by education) since the laws allow those with more binding budget constraints to afford leave.

[40] As a further robustness check, estimates of the effect of PPL on employment for young women with a high school degree or less (and not enrolled in school) were obtained while redefining *young* to include those aged between18-40. Results are qualitatively and quantitatively similar to those in Table 9 columns 1 and 2.

From the firm's perspective, PPL raises the relative cost of employing young women, particularly among those most incentivized to take up PPL, i.e., low-skilled workers for whom there are relatively more substitutes available.

Young Women's Earnings

Tables 10 and 11 display summary statistics for estimations in California involving young women's earnings pre-PPL and post-PPL, respectively. As was the case with the employment estimations, although there are several statistically significant differences between in sociodemographic characteristics of young women in the treatment and control states, most of these differences are quantitatively small. Estimates that utilize several alternative control groups yield similar results, as shown in Chapter8. The raw unconditional mean differences are 0.015 for the DDa, 0.003 for the DDb, and 0.006 for the DDD. The unconditional DDD implies that for every $500 earned by young women, PPL increases young women's earnings by $3. All of the mean earnings differences are positive, and signify that without controlling for any variables young women's earnings in California increased as a result of PPL.

Tables 12 and 13 display summary statistics for estimations in New Jersey involving young women's earnings pre-PPL and post-PPL, respectively. The raw unconditional mean differences are 0.015 for the DDa, -0.002 for the DDb, and -0.001 for the DDD. The DD across state is positive and implies that an increase occurs in young women's earnings in New Jersey relative to young women's earnings in control states without controlling for any variables. The DD across state and DDD are negative, and

imply a decrease in young women's earnings as a result of PPL without controlling for any variables. The unconditional DDD implies that for every $1000 earned by young women, PPL increases young women's earnings by $1. As was the case with the employment estimations, although there are several statistically significant differences between in sociodemographic characteristics of young women in the treatment and control states, most of these differences are quantitatively small. Estimates that utilize several alternative control groups yield similar results, as shown in Chapter8.

Table 14 displays DD results for the effect of PPL on young women's earnings in California and New Jersey. The DDa for California implies a positive effect of PPL on young women's earnings relative to young women's earnings in control states, but the DDa for New Jersey implies a negative effect of PPL on young women's earnings relative to young women in control states. With the inclusion of state-by-time-trend, the California DDa coefficient becomes more positive, and the New Jersey DDa coefficient becomes negative. This suggests that there are more negative linear wage trends in California relative to its control states, and that there are more positive linear wage trends in New Jersey relative to its control states. This underscores the importance of controlling for state-specific wage trends, and allowing for flexibility in the models. Additionally, the relatively large magnitudes of the DDa coefficients imply that there are shocks specific to young women's earnings present. The DDb coefficients for California and New Jersey are negative but insignificant.

Table 15 displays the DDD results for the effect of PPL on young women's earnings in California and New Jersey. The coefficients indicate that PPL decreases

earnings of young women in California and New Jersey, by 2.2 percent and 3.2 percent, respectively. The coefficients are unresponsive to the inclusion of state-by-year fixed effects. This result proves to be relatively robust in Chapter 8.

Table 16 displays DDD results for the effect of PPL on young women's earnings by education subgroup.[41] Several coefficients are significant, including the estimated effect of PPL among young women with a high school degree or less in New Jersey, young women with some college in both states, and young women with a bachelor's degree or more in both treatment states. All significant coefficients are negative with the exception of young women with a bachelor's degree or more in New Jersey, which is 0.034. This is in contrast the corresponding coefficient in California, which is -0.036. The coefficients are relatively unresponsive to the inclusion of state-by-year fixed effects. All results, with the exception of those for young women with a bachelor's degree or more in New Jersey, prove to be robust in Chapter 8.

Summary

Results show a zero or negative effect of PPL on earnings of young women with the exception of young women with a bachelor's degree or more in New Jersey. All results that show a negative result prove to be robust in Chapter 8. This is consistent with prior literature, particularly the notion of Summers (1989), who proposes that mandates may cause unintended consequences on specific groups it is intended to aid.

[41] As a further robustness check, estimates for the effect of PPL on earnings for young women with a high school degree or less (not enrolled in school) were obtained while redefining *young* to include those aged 18-40. Results for earnings for California are roughly the same as Table 16 columns 1 and 2. Results for earnings for New Jersey are positive and significant, which indicates that the definition of age and enrollment status may influence these results.

Young Mothers' Earnings

Tables 17 and 18 display summary statistics for estimations involving young mothers' earnings in California pre-PPL and post-PPL, respectively. The raw unconditional mean differences are 0.124 for the DD, and 0.09 for the DDD. The unconditional DDD implies that for every $100 earned by young mothers, PPL increases young mothers' earnings by $9. Both mean wage differences are positive, and signify that without controlling for any variables, young mothers' earnings in California increased as a result of PPL.[42]

Tables 19 and 20 display summary statistics for estimations involving young mothers' earnings in New Jersey pre-PPL and post-PPL, respectively. The raw unconditional mean differences are -0.011 for the DD, and -0.047 for the DDD. The unconditional DDD implies that for every $1000 earned by young mothers, PPL decreases young mothers' earnings by $47. Both mean wage differences are negative and signify that, young mothers' earnings in New Jersey decreased as a result of PPL without controlling for any variables.

Table 21 displays results for the effect of PPL on young mothers' earnings in California and New Jersey. All DD and DDD coefficients in California are positive and significant. Coefficients for the California DDD specification are smaller than coefficients for the DD specification, which indicates that national trends or shocks have a negative impact on young mothers' earnings. The DD coefficients for New Jersey are

[42] As with the regressions for young women's employment and earnings, estimates that utilize alternative control groups are presented in Chapter 8.

zero, and the DDD coefficients for New Jersey are positive but insignificant. The DDD estimation indicates that mothers' earnings in California increased by 4.9 percent, and mothers' earnings in New Jersey did not change compared to mothers' earnings in control states, while using young childless women as a control group, as a result of PPL. This indicates that the motherhood wage penalty decreases as a result of PPL in California, but does not change in New Jersey. This result proves to be relatively robust in Chapter 8.

Table 22 displays DDD results for the effect of PPL on young mothers' earnings by education subgroup. Table 22 shows that mothers with a high school degree or less experience a 2.8 percent earnings increase in California and a 16.2 percent earnings increase in New Jersey as a result of PPL when compared to mothers in control states with a high school degree or less, while using young childless women as a control group. Mothers in California with a bachelor's degree or more incur an 8.7 percent earnings increase compared to earnings of young childless women with a bachelor's degree or more. Mothers in California with only some college experience a 3 percent earnings increase when compared to mothers in control states, while using young childless women as a control group, as a results of PPL. In contrast, young mothers in New Jersey with some college experience incur a 28.5 percent wage decrease as a result of PPL when compared to young mothers in control states, while using young childless women as a control group. This large negative coefficient in New Jersey results from few mothers included in the sample. All earnings results by education subgroup prove to be robust or relatively in Chapter 8 with the exception of earnings of mothers in California with a high

school degree or less. Mothers' earnings results are associated with caveats previously mentioned.

Summary

Results show a positive effect of PPL on earnings of young mothers. This is consistent with increased job continuity associated with PPL. However, the effects by subgroup show mixed results. The positive effects are concentrated among young mothers with a bachelor's degree or more in California, and young mothers with a high school degree or less in New Jersey. Negative effects are found for young mothers in New Jersey with some college experience. This suggests that job continuity may occur, but not for all mothers.

Young Fathers' Earnings

Tables 23 and 24 display summary statistics for estimations involving young fathers' earnings in California pre-PPL and post-PPL, respectively. The raw unconditional mean differences are 0.06 for the DD, and -0.015 for the DDD. The DD signifies that an increase occurs for young fathers' earnings in California relative to young childless men in California as a result of PPL without controlling for any other differences between the groups. The unconditional DDD implies that for every $1000 earned by young fathers, PPL decreases young fathers' earnings by $15. The DDD signifies that, as a result of PPL, a decrease occurs for young fathers' earnings in

California relative to young fathers' earnings in control states while using young childless as men a control group without controlling for any variables.[43]

Tables 25 and 26 display summary statistics for estimations involving young fathers' earnings in New Jersey pre-PPL and post-PPL, respectively. The raw unconditional mean differences are -0.037 for the DD, and -0.038 for the DDD. The unconditional DDD implies that for every $1000 earned by young fathers, PPL decreases young fathers' earnings by $38. Both mean earnings differences are negative and signify that young fathers' earnings in New Jersey decrease as a result of PPL without controlling for any variables.

Tables 27 displays results for the effect of PPL on young fathers' earnings in California and New Jersey. All DD and DDD coefficients in California are positive, but not significant. The DD coefficients in New Jersey is not significant, but the DDD coefficients in New Jersey is significant and indicates that young fathers' earnings in New Jersey decreases by 5.5 percent compared to young fathers' earnings in control states, while using young childless men as a control group. This result proves to be robust in Chapter 8, but is associated with several caveats discussed previously.

Tables 28 displays DDD results for the effect of PPL on young fathers' earnings by education subgroup. All coefficients in Table 28 are negative with the exception of earnings of young fathers with some college experience in California, and earnings of fathers with a bachelor degree or more in New Jersey when state-by-year fixed effects are

[43] As with the regressions for young women's employment and earnings, estimates that utilize alternative control groups are presented in Chapter 8.

included. Only the result for young fathers in New Jersey with come college education prove to be robust in chapter 8, but is associated with caveats previously mentioned.

Summary

Results show a negative effect of PPL on earnings of young fathers with the exception of young fathers with some college education in California. The negative impact of PPL on fathers' earnings is consistent with results from Albrecht et al. (1999) who found a negative wage impact on fathers' earnings as a result of PPL in Sweden.

Effects Over Time

Table 29 displays results for the pre-PPL effect on *young* women's employment and earnings. The DDD policy estimator is included in Table 29 for comparison. All pre-PPL estimators are both small in magnitude and statistically insignificant.

Table 30 displays results for the post-PPL effect on young women's employment and earnings. Employment results for California are negative and significant which is consistent with the main DDD results. Earnings estimates for California do not gain significance until four or more years post-PPL, and is not significant in the short run (1-3 years post-PPL). This is consistent with Applebaum and Milkman (2011), who report that the CA-PFL was not well-advertised at the time of implementation and that PPL participation took several years. Employment estimates for New Jersey are not significant for both 1-3 years post-PPL, and four or more years post-PPL, while earnings estimates for New Jersey are negative and significant for both both 1-3 years post-PPL, and four or more years post-PPL.

Table 31 displays results for the pre-PPL effect on young parents' earnings. The DDD policy estimator is included in the Table 31 for comparison. Several pre-PPL estimators are significant which indicates that these estimations are spurious, and no definitive conclusions can be made. The magnitudes are larger for New Jersey than for California. The only coefficient that is not significant is the coefficient for young fathers' earnings in California.

Table 32 displays results for the displays results for the prost-PPL effect on young parents' earnings. Table 32 indicates that Earnings for young mothers in California increase over time as a result of PPL. Earnings coefficients for young mothers in New Jersey are negative, but not significant. Earnings for young fathers in New Jersey are unaffected in the short-run 1-3 years post-PPL, but in the long- run 4 or more years the estimator is significant and positive. Earnings coefficients for young fathers in New Jersey are negative, but not significant.

Summary

Investigating the effects of PPL over time strengthens main findings on young women's employment and earnings, but further casts doubt on estimations involving the family wage gap. The effect of PPL on young women's labour market over time provides both qualitatively, and relative quantitatively consistent results with the main findings. Conversely, the effect of PPL on the family wage gap is inconsistent because several pre-PPL estimators are significant, or because several post-PPL estimators are not significant.

Table 3: Summary Statistics for Sample of Young Women's Employment in California and Synthetic Control States Pre-2004

	Young Women				Older Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variable								
Employed	0.636	0.481	0.702	0.457	0.682	0.466	0.697	0.460
Household (hh)								
Family members in hh	3.767	1.856	3.502	1.624	3.193	1.708	2.904	1.505
Children in hh	1.511	1.374	1.481	1.277	1.152	1.243	0.950	1.118
Children under 5 in hh	0.469	0.688	0.430	0.674	0.045	0.233	0.026	0.181
Metro	0.990	0.099	0.830	0.376	0.985	0.120	0.836	0.370
Demographics								
Age	32.325	4.858	32.465	4.877	49.726	6.422	50.316	6.575
White	0.809	0.393	0.710	0.453	0.783	0.412	0.730	0.444
Black	0.055	0.229	0.197	0.398	0.070	0.256	0.183	0.386
Other Race	0.135	0.342	0.091	0.287	0.147	0.354	0.087	0.282
Hispanic	0.466	0.499	0.047	0.211	0.325	0.468	0.031	0.175
Education								
High school or less	0.481	0.500	0.475	0.499	0.463	0.499	0.543	0.498
Some college	0.286	0.452	0.276	0.447	0.284	0.451	0.233	0.423
Bachelor degree or more	0.233	0.423	0.249	0.432	0.254	0.435	0.224	0.417
Marital Status								
Married	0.266	0.442	0.256	0.436	0.090	0.286	0.085	0.279
Single	0.611	0.488	0.611	0.488	0.647	0.478	0.658	0.474
Other	0.138	0.345	0.145	0.352	0.283	0.450	0.267	0.443
State								
Unemployment (%)	6.487	1.055	5.622	0.896	6.460	1.033	5.593	0.899
Population (millions)	33.600	1.403	7.473	4.095	33.700	1.409	7.556	4.124
Observations	22,083		24,960		19,382		26,060	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The pre-2004 period refers to years 1994-2004.

Table 4: Summary Statistics for Sample of Young Women's Employment in California and Synthetic Control States Post-2004

	Young Women				Older Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variable								
Employed	0.636	0.481	0.693	0.461	0.676	0.468	0.705	0.456
Household (hh)								
Family members in hh	3.790	1.810	3.589	1.635	3.304	1.680	2.985	1.512
Children in hh	1.415	1.344	1.480	1.313	1.204	1.209	0.988	1.113
Children under 5 in hh	0.435	0.664	0.464	0.698	0.047	0.241	0.028	0.191
Metro	0.987	0.113	0.818	0.386	0.983	0.129	0.814	0.389
Demographics								
Age	32.299	4.906	32.279	4.903	50.680	6.511	51.080	6.604
White	0.765	0.424	0.623	0.485	0.744	0.437	0.627	0.484
Black	0.058	0.234	0.224	0.417	0.067	0.250	0.222	0.415
Other Race	0.177	0.382	0.153	0.360	0.189	0.392	0.151	0.358
Hispanic	0.493	0.500	0.071	0.257	0.368	0.482	0.044	0.206
Education								
High school or less	0.403	0.491	0.380	0.485	0.416	0.493	0.461	0.498
Some college	0.282	0.450	0.284	0.451	0.277	0.448	0.272	0.445
Bachelor degree or more	0.314	0.464	0.336	0.472	0.306	0.461	0.267	0.443
Marital Status								
Married	0.322	0.467	0.345	0.475	0.116	0.320	0.117	0.321
Single	0.579	0.494	0.539	0.498	0.648	0.478	0.626	0.484
Other	0.118	0.323	0.129	0.336	0.257	0.437	0.269	0.443
State								
Unemployment (%)	8.280	2.563	6.251	1.663	8.358	2.543	6.247	1.692
Population (millions)	37.400	1.042	6.938	4.259	37.400	1.037	7.039	4.332
Observations	26,924		24,477		30,496		30,328	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The post-2004 period refers to years 2005-2015.

Table 5: Summary Statistics for Sample of Young Women's Employment in New Jersey and Synthetic Control States Pre-2009

	Young Women				Older Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variable								
Employed	0.691	0.462	0.727	0.446	0.732	0.443	0.746	0.435
Household (hh)								
Family members in hh	3.462	1.542	3.373	1.505	3.102	1.453	2.933	1.402
Children in hh	1.315	1.195	1.393	1.269	1.146	1.130	1.046	1.134
Children under 5 in hh	0.454	0.683	0.451	0.696	0.040	0.235	0.034	0.208
Metro	1.000	0.000	0.906	0.292	1.000	0.000	0.901	0.299
Demographics								
Age	32.738	4.821	32.716	4.843	50.072	6.496	50.118	6.487
White	0.775	0.417	0.862	0.344	0.793	0.405	0.886	0.318
Black	0.135	0.342	0.090	0.286	0.140	0.347	0.080	0.272
Other Race	0.089	0.285	0.048	0.213	0.067	0.250	0.034	0.180
Hispanic	0.212	0.409	0.100	0.300	0.154	0.361	0.058	0.234
Education								
High school or less	0.396	0.489	0.404	0.491	0.463	0.499	0.478	0.500
Some college	0.247	0.431	0.248	0.432	0.214	0.410	0.226	0.418
Bachelor degree or more	0.357	0.479	0.348	0.476	0.323	0.468	0.296	0.456
Marital Status								
Married	0.280	0.449	0.279	0.448	0.100	0.300	0.093	0.291
Single	0.621	0.485	0.608	0.488	0.676	0.468	0.673	0.469
Other	0.112	0.315	0.125	0.330	0.239	0.426	0.244	0.430
State								
Unemployment (%)	5.468	1.236	5.120	1.089	5.450	1.291	5.164	1.127
Population (millions)	8.432	0.244	9.220	3.460	8.459	0.240	9.349	3.456
Observations	10,006		32,244		11,390		36,550	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The pre-2009 period refers to years 1994-2009.

Table 6: Summary Statistics for Sample of Young Women's Employment in New Jersey and Synthetic Control States Post-2009

	Young Women				Older Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variable								
Employed	0.673	0.469	0.708	0.454	0.726	0.446	0.724	0.447
Household (hh)								
Family members in hh	3.523	1.490	3.413	1.516	3.208	1.454	3.032	1.439
Children in hh	1.274	1.204	1.379	1.257	1.249	1.165	1.105	1.160
Children under 5 in hh	0.456	0.666	0.478	0.701	0.038	0.224	0.038	0.224
Metro	1.000	0.000	0.892	0.310	1.000	0.000	0.889	0.314
Demographics								
Age	32.437	4.904	32.349	4.878	51.019	6.518	51.055	6.566
White	0.753	0.431	0.815	0.388	0.763	0.425	0.841	0.366
Black	0.124	0.329	0.107	0.309	0.131	0.338	0.105	0.307
Other Race	0.123	0.329	0.078	0.268	0.105	0.307	0.054	0.226
Hispanic	0.320	0.467	0.142	0.349	0.201	0.401	0.089	0.285
Education								
High school or less	0.324	0.468	0.321	0.467	0.384	0.486	0.388	0.487
Some college	0.227	0.419	0.251	0.433	0.220	0.414	0.249	0.432
Bachelor degree or more	0.448	0.497	0.429	0.495	0.396	0.489	0.363	0.481
Marital Status								
Married	0.361	0.480	0.347	0.476	0.134	0.341	0.122	0.327
Single	0.556	0.497	0.560	0.496	0.666	0.472	0.655	0.475
Other	0.099	0.299	0.104	0.305	0.220	0.414	0.235	0.424
State								
Unemployment (%)	8.123	1.480	6.962	1.287	8.120	1.479	6.966	1.260
Population (millions)	8.878	0.047	9.393	3.629	8.878	0.047	9.379	3.637
Observations	2,691		11,377		4,054		16,252	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The post-2009 period refers to years 2010-2015.

Table 7: The Effect of Paid Parental Leave on Young Women's Employment

	Difference-in-difference with Control States (DDa)				Difference-in-difference without Controls States (DDb)			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.002*	0.141*	-0.004	-0.017***	-0.017***	-0.017***	-0.028**	-0.028**
	(0.001)	(0.065)	(0.007)	(0.002)	(0.005)	(0.005)	(0.013)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	-	-	-	-
Time Trend	Yes	Yes	Yes	Yes	No	Yes	No	Yes
State x Time Trend	No	Yes	No	Yes	-	-	-	-
Observations	98,444	98,444	56,318	56,318	98,885	98,885	28,141	28,141
R-squared	0.106	0.106	0.079	0.080	0.092	0.092	0.056	0.056

Standard errors are in parenthesis and are clustered at the state level for columns 1-4, while standard errors for columns 5-8 are robust towards heteroskedasticity. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between the ages 24-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used for columns 1-4. The policy estimator variable for columns 1-4 is defined as post-policy time period interacted with the treatment state, and for columns 5-8 is defined as post-policy time period interacted with variable *young women*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 8: Difference- in-difference-in difference for the Effect of Paid Parental Leave on Young Women's Employment

	CA		NJ	
	1	2	3	4
Policy Estimator	-0.021**	-0.021**	-0.028**	-0.028**
	(0.007)	(0.007)	(0.006)	(0.006)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes
Observations	204,710	204,710	124,564	124,564
R-squared	0.089	0.089	0.059	0.059

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between 24-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 9: Difference-in-difference-in-difference for Effect of Paid Parental Leave on Young Women's Employment by Education Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	CA		NJ		CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.019***	-0.019***	-0.058***	-0.058***	-0.008*	-0.008*	-0.028*	-0.028*	0.003	0.003	0.005	0.005
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.012)	(0.009)	(0.009)	(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	85,160	85,160	68,582	68,582	62,719	62,719	32,400	32,400	69,802	69,802	48,030	48,030
R-squared	0.051	0.051	0.039	0.039	0.036	0.036	0.033	0.034	0.042	0.042	0.067	0.067

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between 24-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B3 and B4 in Appendix B for synthetic control states and weights used. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with young women. The variables *other race* and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 10: Summary Statistics for Sample of Young Women's Earnings in California and Synthetic Control States Pre-2004

	Young Women				Older Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.129	0.697	10.110	0.665	10.280	0.695	10.209	0.675
Wage	31,698	29,544	30,156	24,454	36,536	31,115	33,930	31,121
Work variables								
Hours worked	41.383	4.511	41.261	4.968	41.670	4.915	41.201	5.146
Household (hh)								
Family members in hh	3.330	1.785	3.148	1.619	2.968	1.573	2.882	1.541
Children in hh	1.142	1.227	1.105	1.183	1.026	1.130	0.960	1.082
Children under 5 in hh	0.292	0.550	0.279	0.552	0.036	0.209	0.028	0.182
Metro	0.993	0.083	0.855	0.352	0.988	0.109	0.845	0.362
Demographics								
Age	32.509	4.832	32.540	4.854	49.185	6.027	49.520	6.058
White	0.780	0.414	0.728	0.445	0.767	0.423	0.727	0.445
Black	0.067	0.250	0.128	0.334	0.081	0.273	0.131	0.338
Other Race	0.153	0.360	0.144	0.351	0.152	0.359	0.141	0.348
Hispanic	0.409	0.492	0.223	0.416	0.278	0.448	0.174	0.379
Education								
High school or less	0.366	0.482	0.352	0.478	0.369	0.483	0.417	0.493
Some college	0.332	0.471	0.314	0.464	0.329	0.470	0.284	0.451
Bachelor degree or more	0.302	0.459	0.334	0.472	0.302	0.459	0.299	0.458
Marital Status								
Married	0.324	0.468	0.332	0.471	0.102	0.303	0.107	0.310
Single	0.531	0.499	0.517	0.500	0.591	0.492	0.611	0.488
Other	0.161	0.368	0.168	0.374	0.326	0.469	0.300	0.458
State								
Unemployment (%)	6.454	1.040	5.627	0.941	6.409	1.001	5.599	0.945
Population (millions)	33.600	1.388	11.200	7.641	33.800	1.384	11.300	7.696
Observations	8,858		14,973		8,255		16,260	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The pre-2004 period refers to years 1994-2004.

Table 11: Summary Statistics for Sample of Young Women's Earnings in California and Synthetic Control States Post-2004

	Young Women				Older Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.467	0.672	10.433	0.675	10.615	0.726	10.535	0.677
Wage	44,010	38,798	42,411	40,372	53,126	53,984	47,820	49,411
Work variables								
Hours worked	41.219	4.461	41.161	4.735	41.510	4.842	41.253	4.965
Household (hh)								
Family members in hh	3.440	1.751	3.255	1.710	3.133	1.580	2.983	1.521
Children in hh	1.130	1.231	1.139	1.226	1.106	1.123	1.013	1.086
Children under 5 in hh	0.306	0.560	0.323	0.582	0.037	0.213	0.032	0.201
Metro	0.990	0.100	0.859	0.348	0.986	0.119	0.847	0.360
Demographics								
Age	32.506	4.846	32.416	4.835	50.396	6.287	50.682	6.363
White	0.730	0.444	0.646	0.478	0.720	0.449	0.643	0.479
Black	0.062	0.242	0.130	0.336	0.072	0.259	0.131	0.337
Other Race	0.208	0.406	0.224	0.417	0.208	0.406	0.225	0.418
Hispanic	0.453	0.498	0.238	0.426	0.327	0.469	0.185	0.389
Education								
High school or less	0.295	0.456	0.268	0.443	0.324	0.468	0.333	0.471
Some college	0.295	0.456	0.284	0.451	0.296	0.457	0.296	0.456
Bachelor degree or more	0.410	0.492	0.447	0.497	0.380	0.485	0.371	0.483
Marital Status								
Married	0.372	0.483	0.396	0.489	0.129	0.335	0.133	0.340
Single	0.516	0.500	0.482	0.500	0.609	0.488	0.609	0.488
Other	0.132	0.338	0.141	0.348	0.281	0.449	0.279	0.448
State								
Unemployment (%)	8.245	2.553	6.546	2.084	8.265	2.540	6.510	2.114
Population (millions)	37.400	1.046	10.600	7.951	37.400	1.045	10.700	7.996
Observations	10,532		15,219		12,770		19,883	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The post-2004 period refers to years 2005-2015.

Table 12: Summary Statistics for Sample of Young Women's Earnings in New Jersey and Synthetic Control States Pre-2009

	Young Women				Older Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.297	0.666	10.244	0.625	10.429	0.676	10.328	0.669
Wage	36,917	35,463	34,309	30,543	42,445	37,398	38,279	35,682
Work variables								
Hours worked	40.994	4.817	41.374	4.765	40.837	4.932	41.382	5.003
Household (hh)								
Family members in hh	3.108	1.521	3.011	1.479	3.006	1.439	2.813	1.370
Children in hh	0.975	1.088	1.040	1.138	1.076	1.079	0.948	1.039
Children under 5 in hh	0.276	0.532	0.285	0.556	0.033	0.208	0.020	0.155
Metro	1.000	0.000	0.893	0.310	1.000	0.000	0.884	0.320
Demographics								
Age	32.504	4.883	32.547	4.891	49.866	6.184	49.876	6.122
White	0.758	0.428	0.819	0.385	0.775	0.418	0.835	0.371
Black	0.152	0.359	0.106	0.308	0.157	0.364	0.098	0.297
Other Race	0.090	0.286	0.074	0.262	0.067	0.251	0.067	0.250
Hispanic	0.214	0.410	0.061	0.239	0.142	0.349	0.036	0.186
Education								
High school or less	0.350	0.477	0.356	0.479	0.409	0.492	0.445	0.497
Some college	0.252	0.434	0.250	0.433	0.227	0.419	0.238	0.426
Bachelor degree or more	0.398	0.490	0.394	0.489	0.364	0.481	0.317	0.465
Marital Status								
Married	0.343	0.475	0.333	0.471	0.107	0.309	0.110	0.312
Single	0.545	0.498	0.544	0.498	0.645	0.479	0.634	0.482
Other	0.127	0.333	0.135	0.341	0.264	0.441	0.266	0.442
State								
Unemployment (%)	5.459	1.236	5.206	1.083	5.431	1.296	5.215	1.138
Population (millions)	8.433	0.244	10.100	3.595	8.470	0.235	10.200	3.576
Observations	4,650		16,598		5,615		19,665	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The pre-2009 period refers to years 1994-2009.

Table 13: Summary Statistics for Sample of Young Women's Earnings in New Jersey and Synthetic Control States Post-2009

	Young Women				Older Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.594	0.660	10.526	0.640	10.728	0.669	10.643	0.675
Wage	48,751	38,063	45,138	32,583	58,121	60,263	52,393	46,695
Work variables								
Hours worked	40.585	3.866	41.319	4.691	41.086	4.862	41.601	5.071
Household (hh)								
Family members in hh	3.271	1.423	3.114	1.524	3.108	1.369	2.947	1.398
Children in hh	1.063	1.115	1.103	1.145	1.168	1.065	1.010	1.067
Children under 5 in hh	0.360	0.605	0.355	0.608	0.032	0.193	0.030	0.199
Metro	1.000	0.000	0.869	0.337	1.000	0.000	0.865	0.342
Demographics								
Age	32.553	4.800	32.381	4.887	50.966	6.459	50.945	6.431
White	0.762	0.426	0.765	0.424	0.754	0.431	0.779	0.415
Black	0.121	0.326	0.119	0.324	0.133	0.340	0.120	0.325
Other Race	0.117	0.322	0.116	0.321	0.112	0.316	0.101	0.301
Hispanic	0.290	0.454	0.084	0.277	0.205	0.404	0.053	0.225
Education								
High school or less	0.242	0.429	0.227	0.419	0.343	0.475	0.344	0.475
Some college	0.217	0.412	0.259	0.438	0.233	0.423	0.260	0.439
Bachelor degree or more	0.541	0.498	0.513	0.500	0.424	0.494	0.396	0.489
Marital Status								
Married	0.374	0.484	0.375	0.484	0.128	0.334	0.121	0.327
Single	0.535	0.499	0.532	0.499	0.648	0.478	0.643	0.479
Other	0.108	0.311	0.104	0.305	0.246	0.431	0.250	0.433
State								
Unemployment (%)	8.150	1.480	6.828	1.337	8.098	1.475	6.775	1.300
Population (millions)	8.877	0.047	10.000	4.155	8.879	0.047	10.300	3.930
Observations	1,210		6,954		2,012		8,725	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young* women are defined as women between the ages of 24-40, and *older* women are defined as women between the ages of 41-65. The post-2009 period refers to years 2010-2015.

Table 14: The Effect of Paid Parental Leave on Young Women's Earnings

	Difference-in-difference with Control States (DDa)				Difference-in-difference without Control States (DDb)			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.010	0.121*	0.001	-0.036**	-0.005	-0.005	-0.029	-0.029
	(0.018)	(0.062)	(0.005)	(0.012)	(0.010)	(0.010)	(0.027)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	-	-	-	-
Time Trend	-	-	-	-	No	Yes	No	Yes
State x Time Trend	No	Yes	No	Yes	-	-	-	-
Observations	49,582	49,582	29,412	29,412	40,415	40,415	13,487	13,487
R-squared	0.409	0.410	0.397	0.398	0.423	0.423	0.409	0.409

Standard errors are in parenthesis and are clustered at the state level for columns 1-4 while standard errors for columns 5-8 are robust towards heteroskedasticity. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between 24-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used for columns 1-4. Only full-time workers are included in the sample, and are defined as individuals working 35-60 hours in the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state for columns 1-4, and for columns 5-8 is defined as post-policy time period interacted with variable *young women*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 15: Difference- in-difference-in difference for the Effect of Paid Parental Leave on Young Women's Earnings

	CA		NJ	
	1	2	3	4
Policy Estimator	-0.022***	-0.022***	-0.032***	-0.032***
	(0.004)	(0.004)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes
Observations	106,750	106,750	65,429	65,429
R-squared	0.414	0.414	0.398	0.398

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between 24-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 16: Difference-in-difference-in-difference Effect of Paid Parental Leave on Young Women's Earnings by Education

	High School or Less Education				Some College Education				Bachelor or More Education			
	CA		NJ		CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.009	-0.009	-0.047***	-0.048***	-0.037***	-0.037***	-0.163***	-0.161***	-0.036**	-0.036**	0.034***	0.034***
	(0.007)	(0.007)	(0.004)	(0.005)	(0.003)	(0.002)	(0.018)	(0.018)	(0.008)	(0.008)	(0.007)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	43,134	43,134	21,522	21,522	37,705	37,705	37,997	37,997	38,052	38,052	40,108	40,108
R-squared	0.281	0.281	0.270	0.270	0.259	0.259	0.269	0.270	0.283	0.283	0.285	0.285

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* women are defined as women aged between 20-40. *Older* women are used as a control group and are defined as women aged between 41-65. See Tables B3 and B4 in Appendix B for synthetic control states and weights used. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, and *marital status other* are omitted due to multicollinearity.
Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01

Table 17: Summary Statistics for Sample of Young Mothers' Earnings in California and Synthetic Control States Pre-2004

	Young Mothers				Young Childless Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.086	0.704	10.144	0.620	10.200	0.696	10.188	0.621
Wage	30,617	28,969	30,991	27,156	33,830	30,926	31,796	23,946
Work variables								
Hours worked	40.900	3.732	40.847	4.195	41.939	5.023	41.936	5.159
Household (hh)								
Family members in hh	4.277	1.470	4.160	1.459	2.255	1.629	2.116	1.369
Children in hh	2.042	0.992	2.009	1.030	0.000	0.000	0.000	0.000
Children under 5 in hh	1.148	0.375	1.152	0.376	0.000	0.000	0.000	0.000
Metro	0.992	0.087	0.877	0.329	0.997	0.056	0.916	0.277
Demographics								
Age	31.982	4.428	31.965	4.492	30.882	4.770	30.789	4.836
White	0.780	0.414	0.714	0.452	0.766	0.423	0.766	0.423
Black	0.062	0.241	0.127	0.333	0.060	0.237	0.095	0.293
Other Race	0.158	0.365	0.159	0.366	0.174	0.379	0.139	0.346
Hispanic	0.507	0.500	0.213	0.409	0.315	0.465	0.126	0.331
Education								
High school or less	0.424	0.494	0.413	0.492	0.237	0.425	0.276	0.447
Some college	0.333	0.471	0.310	0.462	0.320	0.467	0.280	0.449
Bachelor degree or more	0.243	0.429	0.277	0.448	0.443	0.497	0.444	0.497
Marital Status								
Married	0.141	0.348	0.127	0.333	0.585	0.493	0.535	0.499
Single	0.757	0.429	0.759	0.428	0.308	0.462	0.347	0.476
Other	0.117	0.321	0.131	0.338	0.122	0.327	0.130	0.336
State								
Unemployment (%)	6.447	1.042	5.246	0.850	6.461	1.055	5.275	0.842
Population (millions)	33.600	1.384	8.955	6.316	33.600	1.382	9.830	6.318
Observations	1,825		3,641		3,770		8,429	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young mothers* are defined as women between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are defined as women between the ages of 20-40 without children. The pre-2004 period refers to years 1994-2004.

Table 18: Summary Statistics for Sample of Young Mothers' Earnings in California and Synthetic Control States Post-2004

	Young Mothers				Young Childless Women			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.506	0.720	10.424	0.664	10.496	0.654	10.434	0.681
Wage	47,527	44,895	41,822	37,864	44,580	38,342	41,374	31,566
Work variables								
Hours worked	40.928	4.068	40.750	4.156	41.615	4.818	41.694	5.020
Household (hh)								
Family members in hh	4.338	1.430	4.173	1.446	2.427	1.627	2.234	1.538
Children in hh	2.020	1.019	2.000	1.007	0.000	0.000	0.000	0.000
Children under 5 in hh	1.148	0.370	1.170	0.390	0.000	0.000	0.000	0.000
Metro	0.988	0.110	0.855	0.352	0.994	0.079	0.916	0.277
Demographics								
Age	32.634	4.553	32.384	4.494	30.593	4.684	30.468	4.809
White	0.732	0.443	0.674	0.469	0.690	0.463	0.633	0.482
Black	0.062	0.241	0.102	0.303	0.057	0.231	0.108	0.311
Other Race	0.206	0.405	0.224	0.417	0.253	0.435	0.259	0.438
Hispanic	0.482	0.500	0.220	0.414	0.375	0.484	0.161	0.368
Education								
High school or less	0.320	0.467	0.319	0.466	0.202	0.402	0.221	0.415
Some college	0.305	0.460	0.282	0.450	0.256	0.437	0.253	0.435
Bachelor degree or more	0.376	0.484	0.399	0.490	0.542	0.498	0.525	0.499
Marital Status								
Married	0.155	0.362	0.185	0.388	0.632	0.482	0.608	0.488
Single	0.764	0.425	0.729	0.444	0.291	0.454	0.303	0.460
Other	0.098	0.297	0.102	0.303	0.094	0.292	0.109	0.312
State								
Unemployment (%)	8.348	2.567	6.990	2.662	8.234	2.538	6.896	2.592
Population (millions)	37.400	1.031	8.616	6.350	37.400	1.054	8.964	6.641
Observations	2,223		4,233		4,561		7,360	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young mothers* are defined as women between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are defined as women between the ages of 20-40 without children. The post-2004 period refers to years 2005-2015.

Table 19: Summary Statistics for Sample of Young Mothers' Earnings in New Jersey and Synthetic Control States Pre-2009

	Young Mothers				Young Childless Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.358	0.688	10.348	0.646	10.309	0.663	10.302	0.632
Wage	40,086	41,325	39,044	39,038	36,786	32,440	35,628	26,975
Work variables								
Hours worked	40.627	4.423	40.830	4.286	41.513	5.174	41.860	5.261
Household (hh)								
Family members in hh	4.004	1.184	3.938	1.212	2.221	1.379	2.079	1.252
Children in hh	1.836	0.859	1.888	0.941	0.000	0.000	0.000	0.000
Children under 5 in hh	1.126	0.338	1.163	0.395	0.000	0.000	0.000	0.000
Metro	1.000	0.000	0.883	0.322	1.000	0.000	0.922	0.268
Demographics								
Age	32.674	4.407	32.511	4.358	30.571	4.735	30.884	4.882
White	0.739	0.440	0.762	0.426	0.791	0.407	0.791	0.406
Black	0.161	0.368	0.123	0.329	0.125	0.330	0.102	0.303
Other Race	0.100	0.300	0.115	0.320	0.085	0.278	0.107	0.309
Hispanic	0.250	0.433	0.088	0.284	0.163	0.369	0.053	0.224
Education								
High school or less	0.349	0.477	0.321	0.467	0.277	0.448	0.248	0.432
Some college	0.253	0.435	0.266	0.442	0.232	0.422	0.243	0.429
Bachelor degree or more	0.398	0.490	0.413	0.492	0.491	0.500	0.510	0.500
Marital Status								
Married	0.135	0.341	0.143	0.350	0.568	0.495	0.551	0.497
Single	0.798	0.402	0.763	0.425	0.356	0.479	0.361	0.480
Other	0.080	0.271	0.108	0.310	0.093	0.291	0.097	0.297
State								
Unemployment (%)	5.486	1.277	5.082	1.163	5.481	1.219	5.121	1.129
Population (millions)	8.451	0.244	8.376	4.694	8.408	0.248	8.699	4.623
Observations	892		2,074		2,152		4,284	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young mothers* are defined as women between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are defined as women between the ages of 20-40 without children. The pre-2009 period refers to years 1994-2009.

Table 20: Summary Statistics for Sample of Young Mothers' Earnings in New Jersey and Synthetic Control States Post- 2009

	Young Mothers				Young Childless Women			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.621	0.744	10.552	0.735	10.561	0.635	10.542	0.603
Wage	54,166	59,010	47,623	36,273	45,128	23,887	45,481	33,402
Work variables								
Hours worked	40.396	3.697	41.036	4.482	40.955	4.178	41.845	5.073
Household (hh)								
Family members in hh	4.051	1.228	4.079	1.341	2.365	1.233	2.138	1.315
Children in hh	1.857	0.899	1.938	0.954	0.000	0.000	0.000	0.000
Children under 5 in hh	1.177	0.409	1.195	0.404	0.000	0.000	0.000	0.000
Metro	1.000	0.000	0.865	0.342	1.000	0.000	0.907	0.290
Demographics								
Age	33.283	4.314	32.683	4.285	30.176	4.526	30.351	4.740
White	0.805	0.397	0.742	0.438	0.787	0.410	0.717	0.450
Black	0.085	0.280	0.094	0.293	0.093	0.290	0.107	0.310
Other Race	0.109	0.312	0.164	0.370	0.120	0.326	0.175	0.380
Hispanic	0.314	0.465	0.108	0.311	0.239	0.427	0.090	0.287
Education								
High school or less	0.239	0.427	0.220	0.414	0.191	0.394	0.183	0.387
Some college	0.222	0.416	0.274	0.446	0.185	0.389	0.224	0.417
Bachelor degree or more	0.539	0.499	0.506	0.500	0.623	0.485	0.592	0.492
Marital Status								
Married	0.191	0.394	0.174	0.379	0.606	0.489	0.605	0.489
Single	0.761	0.427	0.750	0.433	0.325	0.469	0.329	0.470
Other	0.061	0.241	0.082	0.275	0.091	0.288	0.079	0.269
State								
Unemployment (%)	8.101	1.483	7.138	1.399	8.022	1.540	7.133	1.405
Population (millions)	8.879	0.046	7.790	4.865	8.881	0.046	7.802	4.930
Observations	293		940		507		1,582	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young mothers* are defined as women between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are defined as women between the ages of 20-40 without children. The post-2009 period refers to years 2010-2015.

Table 21: The Effect of Paid Parental Leave on Young Mother's Earnings

	Difference-in-difference				Difference-in-difference-in-difference			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.069***	0.069***	0.000	0.000	0.049***	0.049***	0.004	0.008
	(0.020)	(0.020)	(0.048)	(0.048)	(0.008)	(0.008)	(0.009)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	-	-	-	-	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	Yes	-	-	-	-
State x Time Trend	-	-	-	-	Yes	Yes	Yes	Yes
State x Year FE	-	-	-	-	No	Yes	No	Yes
Observations	12,379	12,379	3,844	3,844	36,042	36,042	12,724	12,724
R-squared	0.422	0.422	0.406	0.406	0.407	0.407	0.394	0.395

Standard errors are in parenthesis and are robust towards heteroskedasticity for columns 1-4, while standard errors for columns 5-8 are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 24-40. *Young mothers* are defined as young individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are used as a control group. See Tables B1 and B2 in Appendix B for synthetic control states and weights used for columns 5-8. Only full-time workers are included in the sample and are defined as individuals working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable for columns 1-4 is defined as post-policy time period interacted with *young mothers*, while the policy variable for columns 5-8 is defined as post-policy time period interacted with the treatment state interacted with variable *young mothers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 22: Difference-in-difference-in-difference Effect of Paid Parental Leave on Young Mothers' Earnings by Education Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	CA		NJ		CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	0.042***	0.028*	0.141**	0.162**	0.029	0.030*	-0.306***	-0.285***	0.087**	0.087**	0.031	0.005
	(0.012)	(0.014)	(0.040)	(0.032)	(0.016)	(0.015)	(0.030)	(0.021)	(0.027)	(0.027)	(0.023)	(0.037)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,389	9,389	3,861	3,861	11,091	11,091	3,691	3,691	14,232	14,232	9,856	9,856
R-squared	0.295	0.298	0.252	0.260	0.235	0.237	0.252	0.256	0.305	0.305	0.317	0.319

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. Young individuals are defined as individuals aged between 24-40. *Young mothers* are defined as young individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are used as a control group. See Tables B3 and B4 in Appendix B for synthetic control states and weights used. Only full-time workers are included in that sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young mothers.* The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 23: Summary Statistics for Sample of Young Fathers' Earnings in California and Synthetic Control States Pre-2004

	Young Fathers				Young Childless Men			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.331	0.749	10.401	0.658	10.239	0.733	10.258	0.638
Wage	41,087	41,709	40,910	37,275	36,338	33,387	35,113	29,755
Work variables								
Hours worked	43.053	6.001	42.949	5.698	42.705	5.777	42.566	5.674
Household (hh)								
Family members in hh	4.458	1.443	4.364	1.361	2.404	1.842	2.057	1.462
Children in hh	2.116	1.009	2.133	1.053	0.000	0.000	0.000	0.000
Children under 5 in hh	1.202	0.427	1.213	0.453	0.000	0.000	0.000	0.000
Metro	0.990	0.098	0.847	0.360	0.994	0.075	0.891	0.311
Demographics								
Age	32.674	4.332	32.361	4.349	31.013	4.707	31.385	4.858
White	0.861	0.346	0.903	0.296	0.804	0.397	0.833	0.373
Black	0.027	0.163	0.049	0.216	0.053	0.224	0.081	0.274
Other Race	0.112	0.315	0.048	0.214	0.143	0.350	0.086	0.280
Hispanic	0.568	0.495	0.310	0.463	0.428	0.495	0.219	0.414
Education								
High school or less	0.544	0.498	0.544	0.498	0.414	0.493	0.495	0.500
Some college	0.233	0.423	0.244	0.430	0.268	0.443	0.243	0.429
Bachelor degree or more	0.223	0.416	0.212	0.409	0.318	0.466	0.262	0.440
Marital Status								
Married	0.062	0.241	0.048	0.213	0.627	0.484	0.543	0.498
Single	0.919	0.273	0.905	0.294	0.272	0.445	0.293	0.455
Other	0.022	0.146	0.052	0.222	0.139	0.346	0.193	0.395
State								
Unemployment (%)	6.414	1.017	4.722	0.739	6.449	1.054	4.719	0.767
Population (millions)	33.700	13.757	1.928	1.079	33.500	1.374	1.943	1.196
Observations	3,392		1,858		5,972		4,554	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young fathers* are defined as men between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are defined as men without children between the ages of 20-40. The pre-2004 period refers to years 1994-2004.

Table 24: Summary Statistics for Sample of Young Fathers' Earnings in California and Synthetic Control States Post-2004

	Young Fathers				Young Childless Men			
	CA		Control States		CA		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.675	0.753	10.694	0.674	10.523	0.740	10.476	0.666
Wage	58,568	62,925	55,759	55,263	49,621	55,880	44,328	43,597
Work variables								
Hours worked	42.575	5.601	42.517	5.567	42.058	5.215	42.010	5.421
Household (hh)								
Family members in hh	4.462	1.429	4.231	1.162	2.519	1.792	1.985	1.282
Children in hh	2.119	1.037	2.064	0.951	0.000	0.000	0.000	0.000
Children under 5 in hh	1.213	0.444	1.255	0.471	0.000	0.000	0.000	0.000
Metro	0.987	0.115	0.859	0.348	0.993	0.086	0.919	0.272
Demographics								
Age	33.224	4.272	33.035	4.411	30.858	4.780	31.031	4.795
White	0.826	0.379	0.800	0.400	0.753	0.432	0.758	0.428
Black	0.032	0.177	0.087	0.282	0.044	0.206	0.120	0.325
Other Race	0.142	0.349	0.113	0.317	0.203	0.402	0.122	0.327
Hispanic	0.545	0.498	0.291	0.454	0.457	0.498	0.292	0.455
Education								
High school or less	0.477	0.500	0.465	0.499	0.378	0.485	0.453	0.498
Some college	0.237	0.425	0.230	0.421	0.263	0.440	0.250	0.433
Bachelor degree or more	0.286	0.452	0.305	0.460	0.359	0.480	0.297	0.457
Marital Status								
Married	0.073	0.260	0.077	0.267	0.668	0.471	0.640	0.480
Single	0.908	0.289	0.895	0.306	0.261	0.439	0.245	0.430
Other	0.024	0.152	0.032	0.175	0.107	0.309	0.157	0.364
State								
Unemployment (%)	8.170	2.599	7.089	3.009	8.198	2.548	7.213	3.097
Population (millions)	37.300	1.041	2.146	1.130	37.300	1.054	2.230	1.093
Observations	3,730		2,127		7,071		5,037	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young fathers* are defined as men between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are defined as men without children between the ages of 20-40. The post-2004 period refers to years 2005-2015.

Table 25: Summary Statistics for Sample of Young Fathers' Earnings in New Jersey and Synthetic Control States Pre-2009

	Young Fathers				Young Childless Men			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.799	0.741	10.755	0.701	10.419	0.675	10.423	0.660
Wage	65,147	63,033	60,032	55,329	42,052	36,294	41,903	36,289
Work variables								
Hours worked	44.287	6.752	44.670	6.506	42.823	6.029	43.148	5.885
Household (hh)								
Family members in hh	4.109	1.112	4.058	1.082	2.234	1.463	1.986	1.219
Children in hh	1.945	0.900	1.935	0.905	0.000	0.000	0.000	0.000
Children under 5 in hh	1.224	0.451	1.228	0.444	0.000	0.000	0.000	0.000
Metro	1.000	0.000	0.872	0.335	1.000	0.000	0.896	0.305
Demographics								
Age	34.036	3.957	34.037	3.908	31.171	4.818	31.170	4.736
White	0.823	0.382	0.912	0.283	0.795	0.404	0.880	0.325
Black	0.062	0.241	0.036	0.187	0.104	0.305	0.052	0.222
Other Race	0.115	0.320	0.051	0.221	0.101	0.302	0.068	0.252
Hispanic	0.211	0.408	0.083	0.276	0.239	0.427	0.081	0.272
Education								
High school or less	0.349	0.477	0.344	0.475	0.410	0.492	0.352	0.477
Some college	0.213	0.410	0.212	0.409	0.202	0.402	0.204	0.403
Bachelor degree or more	0.438	0.496	0.445	0.497	0.388	0.487	0.445	0.497
Marital Status								
Married	0.040	0.196	0.043	0.202	0.593	0.491	0.611	0.487
Single	0.946	0.225	0.945	0.229	0.322	0.467	0.292	0.455
Other	0.014	0.116	0.014	0.117	0.119	0.324	0.111	0.314
State								
Unemployment (%)	5.434	1.226	4.660	1.226	5.440	1.215	4.668	1.208
Population (millions)	8.435	0.242	5.389	3.776	8,421	0.245	5.793	3.630
Observations	1,604		4,758		2,877		10,545	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young fathers* are defined as men between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are defined as men without children between the ages of 20-40. The pre-2009 period refers to years 1994-2009.

Table 26: Summary Statistics for Sample of Young Fathers' Earnings in New Jersey and Synthetic Control States Post-2009

	Young Fathers				Young Childless Men			
	NJ		Control States		NJ		Control States	
	mean	sd	mean	sd	mean	sd	mean	sd
Dependent Variables								
Log wage	10.930	0.813	11.020	0.830	10.587	0.676	10.687	0.634
Wage	77,779	84,520	79,842	67,623	50,088	41,727	52,840	36,511
Work variables								
Hours worked	42.501	5.701	43.926	6.402	41.524	4.697	42.412	5.328
Household (hh)								
Family members in hh	4.040	1.106	4.077	1.085	2.428	1.555	2.052	1.249
Children in hh	1.834	0.855	1.950	0.918	0.000	0.000	0.000	0.000
Children under 5 in hh	1.208	0.419	1.275	0.490	0.000	0.000	0.000	0.000
Metro	1.000	0.000	0.840	0.366	1.000	0.000	0.865	0.342
Demographics								
Age	34.184	4.023	34.669	3.966	30.587	4.718	30.685	4.771
White	0.829	0.377	0.858	0.349	0.775	0.418	0.819	0.385
Black	0.030	0.170	0.048	0.214	0.088	0.284	0.060	0.238
Other Race	0.141	0.349	0.093	0.291	0.137	0.344	0.120	0.325
Hispanic	0.315	0.465	0.071	0.257	0.332	0.471	0.111	0.314
Education								
High school or less	0.308	0.462	0.246	0.431	0.363	0.481	0.253	0.435
Some college	0.221	0.415	0.201	0.401	0.204	0.403	0.215	0.411
Bachelor degree or more	0.471	0.500	0.554	0.497	0.433	0.496	0.532	0.499
Marital Status								
Married	0.067	0.250	0.085	0.280	0.671	0.470	0.656	0.475
Single	0.906	0.293	0.892	0.310	0.263	0.441	0.263	0.440
Other	0.030	0.170	0.023	0.151	0.102	0.303	0.108	0.310
State								
Unemployment (%)	8.037	1.502	5.991	1.240	8.063	1.511	5.941	1.286
Population (millions)	8.880	0.048	5.028	3.993	8.879	0.047	5.467	4.212
Observations	403		1661		794		3,924	

Source: IPUMS March Current Population Survey, unemployment data are from Bureau of Labor Statistics, and population data are from the United States Census Bureau. Only full-time civilian workers are included in the sample, and are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young fathers* are defined as men between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are defined as men without children between the ages of 20-40. The post-2009 period refers to years 2010-2015.

Table 27: The Effect of Paid Parental Leave on Young Father's Earnings

	Difference-in-difference				Difference-in-difference-in-difference			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.019	0.019	-0.059	-0.059	0.012	0.012	-0.055***	-0.055***
	(0.016)	(0.016)	(0.045)	(0.042)	(0.002)	(0.002)	(0.010)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	-	-	-	-	Yes	Yes	Yes	Yes
Time trend	No	Yes	No	Yes	-	-	-	-
State x Time Trend	-	-	-	-	Yes	Yes	Yes	Yes
State x Year FE	-	-	-	-	No	Yes	No	Yes
Observations	20,165	20,165	5,678	5,678	33,741	33,741	26,566	26,566
R-squared	0.432	0.432	0.452	0.452	0.420	0.421	0.426	0.426

Standard errors are in parenthesis and are robust towards heteroskedasticity for columns 1-4, while standard errors for columns 5-8 are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 24-40. *Young fathers* are defined as young individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are used as a control group. See Tables B3 and B4 in Appendix B for synthetic control states and weights used for columns 5-8. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable for columns 1-4 is defined as post-policy time period interacted with *young fathers*, while the policy variable for columns 5-8 is defined as post-policy time period interacted with the treatment state interacted with variable *young fathers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 28: Difference-in-difference-in-difference Effect of Paid Parental Leave on Young Fathers' Earnings by Education Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	CA		NJ		CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.046***	-0.044***	-0.042	-0.025	0.024	0.021	-0.128***	-0.164***	-0.039**	-0.039**	-0.030*	0.019
	(0.007)	(0.008)	(0.048)	(0.053)	(0.020)	(0.019)	(0.034)	(0.037)	(0.011)	(0.010)	(0.015)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	19,834	19,834	10,994	10,994	13,793	13,793	10,319	10,319	13,081	13,081	11,567	11,567
R-squared	0.263	0.266	0.270	0.272	0.271	0.272	0.306	0.309	0.322	0.322	0.380	0.381

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 24-40. *Young fathers* are defined as young individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are used as a control group. See Tables B3 and B4 in Appendix B for synthetic control states and weights. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young fathers*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 29: Pre-Paid Parental Leave Policy and Young Women's Employment and Earnings

	CA		NJ	
	Employment	Wages	Employment	Wages
1 Year Pre-policy	-0.000	0.012	-0.000	-0.004
	(0.003)	(0.007)	(0.017)	(0.021)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	204,710	106,750	124,564	65,429
R-squared	0.089	0.414	0.058	0.398

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 24-40. *Older women* are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. The pre-policy period for California is between 1994-2004, and the pre-policy period for New Jersey is between 1994-2009. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 30: Post-Paid Parental Leave Policy and Young Women's Employment and Earnings

	CA		NJ	
	Employment	Earnings	Employment	Earnings
1-3 Years Post-PPL	-0.022***	-0.008	0.001	-0.050***
	(0.003)	(0.008)	(0.005)	(0.006)
4 Years+ Post-PPL	-0.016***	-0.031***	-0.015	-0.060***
	(0.001)	(0.004)	(0.013)	(0.007)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	204,710	106,750	124,564	65,429
R-squared	0.089	0.414	0.058	0.398

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 24-40. *Older women* are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. The post-policy period for California is between 2005-2015, and the post-policy period for New Jersey is between 2010-2015. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 31: Pre-Paid Parental Leave Policy and Earnings of Parents

	Mothers		Fathers	
	CA	NJ	CA	NJ
1 Year Pre-policy	-0.027***	0.052***	0.002	0.058**
	(0.007)	(0.007)	(0.007)	(0.016)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	36,042	12,724	33,741	26,566
R-squared	0.407	0.395	0.421	0.426

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Parents* are defined as parents aged between 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Childless individuals* are used as a control group for mothers and are aged between 24-40. See Tables B1 and B2 in Appendix B for synthetic control states and weights. Only full-time workers are included in the sample and are defined as individuals working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as the specific year interacted with the treatment state interacted with variable *young mothers or fathers*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 32: Post-Paid Parental Leave Policy and Earnings of Parents

	Mothers		Fathers	
	CA	NJ	CA	NJ
1-3 Years Post-PPL	0.030**	-0.036	0.014	-0.014
	(0.008)	(0.017)	(0.005)	(0.027)
4 Years+ Post-PPL	0.053**	-0.020	0.011***	-0.062
	(0.014)	(0.040)	(0.001)	(0.042)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	36,042	12,724	33,741	26,566
R-squared	0.407	0.395	0.421	0.426

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Parents* are defined as individuals aged between 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Childless individuals* are used as a control group and are aged between 24-40. See Tables B1 and B2 in Appendix B for synthetic control states and weights. Only full-time workers are included in the sample and are defined as individuals working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as the specific year interacted with the treatment state interacted with variable *young mothers or fathers*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

CHAPTER EIGHT

ROBUSTNESS CHECKS

All DDD estimations are repeated with several alternative specifications to assess the robustness of the main estimates. These robustness specifications use several alternative control states, and alter definitions for *young* and *older* individuals.

Three alternative sets of control states are used as a robustness check. First, all DDD specifications, including estimations by subgroup, are estimated using neighbouring states as control states. Neighbouring states for California are Arizona, Nevada, and Oregon, while neighbouring states for New Jersey are Delaware, New York, and Pennsylvania. Recall the stark difference in the main results among Hispanic individuals in treatment and control groups was potentially a cause for concern. Using neighbouring states as alternative control states addresses this for California, and to a lesser degree for New Jersey. The variable *Hispanic* is summarized in Table E1 in Appendix E. Second, Florida, New York, and Texas are used as alternative control states. These states are used by both Rossin-Slater et al. (2013) and Byker (2016). Rossin-Slater et al. (2013) explains that they were chosen because these states were the next three largest states to California in their analysis of the CA-PFL. Using these three states as alternative control states addresses the concern for the lack of Hispanic individuals in the

main result. The variable *Hispanic* is summarized in Table E2 in Appendix E. Third, all states plus Washington D.C are used as alternative control states.[44]

All DDD specifications, including estimations by subgroup, are also estimated with narrower definitions of *young* and *older* groups. *Young* individuals are now defined as individuals between the ages of 24-33, and *older* individuals are defined as individuals between the ages of 50-65. Because using the narrower age ranges changes the individuals included in the sample, new synthetic control states are used, and their weights are displayed in Tables B3 and B4 in Appendix B.

Young Women's Employment

Table 33 presents robustness checks for young women's DDD employment results using alternative sets of control states. There are no conflicting results.[45] Results are negative for all coefficients. However, the coefficient for New Jersey when neighbouring states are being used as control states, and the coefficient for California when Florida, New York, and Texas are used as control states are not significant.

Table 34 presents robustness checks for young women's DDD employment results by education subgroup using neighbouring states as control states. The main results show that young women without a bachelor's degree in both treatment states have significant coefficients. This proves to be relatively robust because three out of the four

[44] The two PPL policies were combined as one policy while using all states plus Washington D.C for the effect of PPL on young women's employment and earnings. As expected, the magnitude of the estimators were in between the estimators presented for California and New Jersey in this paper.
[45] A conflicting result is defined as a result that is significant and whose sign is in the opposite direction as the main findings.

coefficients for women without a bachelor's degree are significant. Young women with some college experience in New Jersey is the only coefficient for young women without a bachelor's degree that is not significant.

Table 35 presents robustness checks for young women's DDD employment results using alternative definitions of young and old. Results are consistent with the main findings because the coefficients are significant and negative for both treatment states.

Table 36 presents robustness checks for young women's DDD employment results by education subgroup using alternative definitions of young and old. There are no conflicting results. All coefficients are negative, and all coefficients for young women without a bachelor's degree are significant, proving the main results are robust to the definition of age.

Summary

Estimates for the effect of PPL on young women's employment are negative and robust. Main results show that negative results are concentrated among young women in both treatment states without a bachelor's degree. This proves to be robust.

Young Women's Earnings

Table 37 presents robustness checks for young women's DDD wage results using alternative control states. There are no conflicting results. Results are both qualitatively, and quantitatively similar for California and New Jersey.

Table 38 presents robustness checks for young women's DDD wage results by education subgroup using neighbouring states as control states. The main results are

shown to be robust to using neighbouring states as a control group with the exception of earnings of young women in New Jersey with a bachelor's degree or more. This coefficient is no longer significant. All other significant coefficients remain negative, and are both qualitatively and quantitatively similar to the main DDD findings.

Table 39 presents robustness checks for young women's DDD wage results using alternative definitions of young and old. Results are significant, and larger in magnitude for both states, as expected.

Table 40 presents robustness checks for young women's DDD wage results by education subgroup using alternative definitions of young and old. All coefficients are negative and significant. Additionally, all results are larger in magnitude as expected, with the exception of young women with only some college in New Jersey. Young women with a bachelor's degree or more in New Jersey has a conflicting result with the main DDD result because it is significant, but now negative while the main DDD result is significant and positive. This suggests that this estimate is not robust, and is sensitive to the definition of age. Because all other estimates are qualitatively similar to the main DDD findings, the main DDD findings by education subgroup are robust.

Summary

Estimates for the effect of PPL on young women's earnings are negative and robust. The results are being driven by all educational subgroups with the exception of young women with a high school degree or less in California, and young women with a bachelor's degree or more in New Jersey. These two estimates are either insignificant, or not robust to the definition of age.

Young Mothers' Earnings

Table 41 presents robustness checks for young mothers' DDD wage results using alternative control states. There are no conflicting results. Results are qualitatively similar for California and New Jersey.

Table 42 presents robustness checks for young mothers' DDD wage results by education subgroup using neighbouring states as control states. The main results shows that estimates for mothers without a bachelor's degree in New Jersey, and mothers with a bachelor's degree or more in California have significant positive results. These coefficients for earnings of mothers are significant and consistent with the main results.

Table 43 presents robustness checks for young mothers' DDD wage results using alternative definitions of young and old. There are no conflicting results, and the main result for California proves to be robust both qualitatively and quantitatively.

Table 44 presents robustness checks for young mothers' DDD wage results by education subgroup using alternative definitions of young and old. There are no conflicting results, and the estimates that were significant in the main DDD findings are robust to the new definition of age with the exception of the coefficient for earnigns of mothers in California with only some college experience. The coefficient is qualitatively similar, but no longer significant.

Summary

Estimates for the effect of PPL on young mothers' earnings are positive and robust. However, estimations by subgroup that were significant in the main results are robust, and have mixed results. Young mothers in California with a bachelor's degree or

more, and young mothers in New Jersey with a high school degree experience a robust positive effect as a result of PPL. However, young mothers in New Jersey with some college experience a robust negative effect as a result of PPL.

Young Fathers' Earnings

Table 45 presents robustness checks for young fathers' DDD wage results using alternative control states. There are no conflicting results. The coefficient for earnings of fathers in California only becomes significant when using all states plus Washington D.C. Results for New Jersey are robust, but the estimate's magnitude is smaller for all alternative control state estimations.

Table 46 presents robustness checks for young fathers' DDD wage results by education subgroup using neighbouring states as control states. The main results show several significant estimates in both California and New Jersey. However, only fathers' earnings with some college in New Jersey prove to be robust because the coefficient is significant and consistent with the estimates with the main DDD by education subgroup findings. No coefficients in for fathers' earnings in California are significant when using neighbouring states as a control group.

Table 47 presents robustness checks for young fathers' DDD wage results using alternative definitions of young and old. There are no conflicting results. Results for New Jersey are robust, and the estimate's magnitude is larger which is expected due to the tighter age definition between young and older individuals in the new definition of age.

Table 48 presents robustness checks for young fathers' DDD wage results by education subgroup using alternative definitions of young and old. There are no conflicting results, and the estimates for earnings of fathers without a bachelor's degree in New Jersey proves to be robust to the new definition of age. Additionally, the estimates is larger in magnitude as expected due to the tighter age definition between young and older individuals in the new definition of age.

Summary

Estimates for the effect of PPL on young fathers' earnings are negative and robust only in New Jersey. Estimations by subgroup in California, and estimations for young fathers with a bachelor's degree or more in New Jersey are significant in the main results, but are not robust. However, estimations by subgroup in New Jersey for fathers without a bachelor's degree are robust.

Table 33: Young Women's Employment Using Alternative Control States

	Synthetic Controls		Neighbouring States		FL, NY, & TX		All States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8
Policy Estimator	-0.021**	-0.028**	-0.016**	-0.021	-0.012	-0.032*	-0.015***	-0.035***
	(0.007)	(0.006)	(0.003)	(0.009)	(0.011)	(0.012)	(0.003)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204,710	124,564	144,747	134,253	260,791	190,047	1,048,731	977,987
R-squared	0.089	0.059	0.085	0.071	0.081	0.072	0.075	0.071

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 20-40. *Older women* are used as a control group and are defined as women aged between 41-65. Columns 1 and 2 display the main results using synthetic control states in Tables B1 and B2 in Appendix B. Columns 3 and 4 display results using neighbouring states as control states. Columns 5 and 6 display results using Florida, New York, and Texas as control states. Columns 7 and 8 display results using all states plus Washington D.C as control states. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 34: Young Women's Employment Using Neighbour States by Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	Synthetic Control		Neighbour States		Synthetic Control		Neighbour States		Synthetic Control		Neighbour States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.019***	-0.058***	-0.016*	-0.048***	-0.008*	-0.028*	-0.019**	-0.012	0.003	0.005	-0.016*	0.007
	(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.012)	(0.005)	(0.016)	(0.009)	(0.011)	(0.005)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,160	68,582	62,835	59,223	62,719	32,400	42,566	32,173	69,802	48,030	39,346	42,857
R-squared	0.051	0.039	0.054	0.051	0.036	0.034	0.036	0.036	0.042	0.067	0.054	0.056

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 20-40. *Older women* are used as a control group and are defined as women aged between 41-65. Columns 1-2, 5-6, and 9-10 display the main subgroup results using synthetic control states in Table B3 and B4 in Appendix B. Columns 3-4, 7-8, and 11-12 use neighbouring states as control states. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 35: Young Women's Employment Using Alternative Age Group Definitions

	Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ
	1	2	3	4
Policy Estimator	-0.021**	-0.028**	-0.047***	-0.034***
	(0.007)	(0.006)	(0.005)	(0.004)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	204,710	124,564	99,113	62,736
R-squared	0.089	0.059	0.104	0.078

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1 and 2, *young women* are defined as women aged between 24-40, and *older women* are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states. For columns 3 and 4, *young women* are defined as women aged between 24-33, and *older women* are used as a control group and are defined as women aged between 50-65. See tables B5 and B6 in Appendix B for synthetic control states. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 36: Young Women's Employment by Subgroup Using Alternative Age Group Definition

	High School or Less Education				Some College Education				Bachelor or More Education			
	Original Age Definition		New Age Definition		Original Age Definition		New Age Definition		Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.019***	-0.058***	-0.035***	-0.035**	-0.008*	-0.028*	-0.022**	-0.029**	0.003	0.005	-0.019	-0.006
	(0.003)	(0.004)	(0.008)	(0.013)	(0.004)	(0.012)	(0.006)	(0.009)	(0.009)	(0.011)	(0.017)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,160	68,582	58,129	33,123	62,719	32,400	29,999	20,851	69,802	48,030	43,608	46,087
R-squared	0.051	0.039	0.053	0.055	0.036	0.034	0.042	0.045	0.042	0.067	0.044	0.066

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1-2, 5-6, and 9-10 *young women* are defined as women aged between 24-40, and *older women* are used as a control group and are defined as women aged between 41-65. See Tables B3 and B4 in Appendix B for synthetic control states. For columns 3-4, 7-8, and 11-12 young women are defined as women aged between 24-33, and *older women* are used as a control group and are defined as women aged between 50-65. See tables B7 and B8 in Appendix B for synthetic control states. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 37: The Effect of Young Women's Earnings Using Alternative Control States

	Synthetic Controls		Neighbour States		FL, NY, & TX		All States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8
Policy Estimator	-0.022***	-0.032***	-0.030***	-0.036***	-0.029**	-0.045***	-0.015***	-0.032***
	(0.004)	(0.003)	(0.009)	(0.002)	(0.006)	(0.005)	(0.003	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106,750	65,429	60,709	62,752	115,912	88,984	485,627	458,699
R-squared	0.414	0.398	0.400	0.384	0.408	0.400	0.387	0.384

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 20-40. *Older women* are used as a control group and are defined as women aged between 41-65. Columns 1 and 2 display the main results using synthetic control states in Tables B2 and B3 in Appendix B. Columns 3 and 4 display results using neighbouring states as control states. Columns 5 and 6 display results using Florida, New York, and Texas as control states. Columns 7 and 8 display results using all states plus Washington D.C as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 38: Effect of Paid Parental Leave on Young Women's Earnings Using Neighbour States by Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	Synthetic Control		Neighbour States		Synthetic Control		Neighbour States		Synthetic Control		Neighbour States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.009	-0.048***	-0.018	-0.041***	-0.037***	-0.161***	-0.050**	-0.141***	-0.036**	0.034***	-0.032**	0.010
	(0.007)	(0.005)	(0.010)	(0.006)	(0.002)	(0.018)	(0.014)	(0.012)	(0.008)	(0.007)	(0.012)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,134	21,522	21,229	23,143	37,705	37,997	19,280	15,900	38,052	40,108	20,200	23,709
R-squared	0.281	0.270	0.271	0.231	0.259	0.270	0.253	0.260	0.283	0.285	0.283	0.217

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 20-40. *Older women* are used as a control group and are defined as women aged between 41-65. Columns 1-2, 5-6, and 9-10 display the main subgroup results using synthetic control states in Tables B3 and B4 in Appendix B. Columns 3-4, 7-8, and 11-12 use neighbouring states as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 39: Young Women's Earnings Using Alternative Age Group Definitions

	Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ
	1	2	3	4
Policy Estimator	-0.022***	-0.039***	-0.042**	-0.069***
	(0.005)	(0.003)	(0.012)	(0.005)
Controls	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	106,750	65,429	44,824	41,980
R-squared	0.414	0.398	0.404	0.398

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1 and 2, *young women* are defined as women aged between 24-40, and *older women* are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states. For columns 3 and 4, *young women* are defined as women aged between 24-33, and *older women* are used as a control group and are defined as women aged between 50-65. See Tables B5 and B6 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women*. Variables *other race, high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ $p<0.10$,$**$ $p<0.05$,$***$ $p<0.01$.

Table 40: The Effect of Young Women's Earnings by Subgroup Using Alternative Age Group Definition

	High School or Less Education				Some College Education				Bachelor or More Education			
	Original Age Definition		New Age Definition		Original Age Definition		New Age Definition		Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.009	-0.048***	-0.037***	-0.082***	-0.037***	-0.161***	-0.066***	-0.146***	-0.036**	0.034***	-0.049**	-0.035**
	(0.007)	(0.005)	(0.010)	(0.008)	(0.002)	(0.018)	(0.005)	(0.020)	(0.008)	(0.007)	(0.018)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,134	21,522	19,478	16,039	37,705	37,997	10,954	9,279	38,052	40,108	21,787	14,606
R-squared	0.281	0.270	0.288	0.276	0.259	0.270	0.278	0.302	0.283	0.285	0.295	0.322

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1-2, 5-6, and 9-10 *young women* are defined as women aged between 24-40, and *older women* are used as a control group and are defined as women aged between 41-65. See Tables B3 and B4 in Appendix B for synthetic control states. For columns 3-4, 7-8, and 11-12 *young women* are defined as women aged between 24-33, and *older women* are used as a control group and are defined as women aged between 50-65. See Tables B7 and B8 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post policy time period interacted with the state of interest interacted with *young women*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 41: Young Mothers' Earnings Using Alternative Control States

	Synthetic Controls		Neighbour States		FL, NY, & TX		All States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8
Policy Estimator	0.049***	-0.008	0.048*	0.008	0.063***	0.028**	0.038***	0.006***
	(0.005)	(0.009)	(0.015)	(0.008)	(0.003)	(0.007)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,042	12,724	17,852	17,359	33,550	25,015	130,092	121,557
R-squared	0.407	0.395	0.403	0.399	0.406	0.398	0.398	0.396

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 20-40. *Young mothers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are used as a control group. Columns 1 and 2 display the main results using synthetic control states in Tables B2 and B3 in Appendix B. Columns 3 and 4 display results using neighbouring states as control states. Columns 5 and 6 display results using Florida, New York, and Texas as control states. Columns 7 and 8 display results using all states plus Washington D.C as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hrs the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young mothers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 42: Young Mothers' Earnings by Education Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	Synthetic Control		Neighbour States		Synthetic Control		Neighbour States		Synthetic Control		Neighbour States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	0.028*	0.162**	0.039	0.117***	0.030*	-0.285***	0.002	-0.167***	0.087**	0.005	0.115**	0.009
	(0.014)	(0.032)	(0.019)	(0.010)	(0.015)	(0.021)	(0.018)	(0.010)	(0.027)	(0.037)	(0.034)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,389	3,861	5,008	4,575	11,091	3,691	5,340	4,112	14,232	9,856	7,504	8,672
R-squared	0.298	0.260	0.278	0.227	0.237	0.256	0.239	0.253	0.305	0.319	0.303	0.315

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young individuals* are defined as individuals aged between 20-40. *Young mothers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless women* are used as a control group. Columns 1-2, 5-6, and 9-10 display the main subgroup results using synthetic control states in Tables B3 and B4 in Appendix B. Columns 3-4, 7-8, and 11-12 use neighbouring states as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post policy time period interacted with the state of interest interacted with *young mothers*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 43: Young Mothers' Earnings Using Alternative Age Group Definitions

	Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ
	1	2	3	4
Policy Estimator	0.049***	-0.008	0.041***	0.009
	(0.005)	(0.009)	(0.007)	(0.007)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes
Observations	36,042	12,724	22,684	8,985
R-squared	0.407	0.395	0.387	0.404

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1 and 2, *young* individuals are defined as individuals aged between 24-34. *Young mothers* are those whose youngest child is either one, two, three or four years old at the time of the survey, and *young childless women* are used as a control group . See Tables B1 and B2 in Appendix B for synthetic control states. For columns 3 and 4, young individuals are defined as individuals aged between 24-33. *Young mothers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey, and young childless women are used as a control group. See tables B5 and B6 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young mothers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 44: Young Mothers' Earnings by Subgroup Using Alternative Age Group Definition

	High School or Less Education				Some College Education				Bachelor or More Education			
	Original Age Definition		New Age Definition		Original Age Definition		New Age Definition		Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	0.028*	0.162**	0.051***	0.232***	0.030*	-0.285***	0.035	-0.151***	0.087**	0.005	0.119***	0.079
	(0.014)	(0.032)	(0.008)	(0.025)	(0.015)	(0.021)	(0.041)	(0.037)	(0.027)	(0.037)	(0.010)	(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,389	3,861	5,599	4,039	11,091	3,691	6,528	5,827	14,232	9,856	9,856	5,671
R-squared	0.298	0.260	0.285	0.290	0.237	0.256	0.219	0.230	0.305	0.319	0.285	0.307

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1-2, 5-6, and 9-10 young individuals are defined as individuals aged between 24-40. *Young mothers* are those whose youngest child is either one, two, three or four years old at the time of the survey, and young childless women are used as a control group. See Tables B3 and B4 in Appendix B for synthetic control states. For columns 3-4, 7-8, and 11-12 *young* individuals are defined as individuals aged between 24-33. *Young mothers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey, and *young childless women* are used as a control group. See tables B7 and B8 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young mothers*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 45: Young Fathers' Earnings Using Alternative Control States

	Synthetic Controls		Neighbour States		FL, NY, & TX		All States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8
Policy Estimator	0.012	-0.055***	0.009	-0.033*	-0.010	-0.017	-0.037***	-0.020***
	(0.002)	(0.011)	(0.004)	(0.013)	(0.009)	(0.010)	(0.007)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,741	26,566	29,196	24,354	50,624	36,137	190,165	170,678
R-squared	0.421	0.426	0.412	0.402	0.410	0.410	0.390	0.389

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 20-40. *Young fathers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are used as a control group. Columns 1 and 2 display the main results using synthetic control states in Tables B2 and B3 in Appendix B. Columns 3 and 4 display results using neighbouring states as control states. Columns 5 and 6 display results using Florida, New York, and Texas as control states. Columns 7 and 8 display results using all states plus Washington D.C as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young fathers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 46: Young Fathers' Earnings Using Neighbour States by Education Subgroup

	High School or Less Education				Some College Education				Bachelor or More Education			
	Synthetic Control		Neighbour States		Synthetic Control		Neighbour States		Synthetic Control		Neighbour States	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.046***	-0.044***	-0.008	-0.083***	0.024	0.021	0.029	-0.220***	-0.039**	-0.039**	-0.008	0.016
	(0.007)	(0.008)	(0.023)	(0.009)	(0.020)	(0.019)	(0.022)	(0.007)	(0.011)	(0.010)	(0.031)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,834	19,834	12,831	9,366	13,793	13,793	7,676	5,411	13,081	13,081	8,689	9,577
R-squared	0.263	0.266	0.266	0.218	0.271	0.272	0.260	0.285	0.322	0.322	0.327	0.350

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young* individuals are defined as individuals aged between 20-40. *Young fathers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men* are used as a control group. Columns 1-2, 5-6, and 9-10 display the main subgroup results using synthetic control states in Tables B3 and B4 in Appendix B. Columns 3-4, 7-8, and 11-12 use neighbouring states as control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post policy time period interacted with the state of interest interacted with *young fathers*. The variables *other race*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 47: Young Fathers' Earnings Using Alternative Age Group Definitions

	Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ
	1	2	3	4
Policy Estimator	0.012	-0.055***	0.007*	-0.129***
	(0.002)	(0.011)	(0.003)	(0.004)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Observations	33,741	26,566	18,081	12,632
R-squared	0.421	0.426	0.381	0.386

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1 and 2, *young* individuals are defined as individuals aged between 24-34. *Young fathers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey, and *young childless men* are used as a control group . See Tables B1 and B2 in Appendix B for synthetic control states. For columns 3 and 4, *young* individuals are defined as individuals aged between 24-33. *Young fathers* are those whose youngest child is either one, two, three or four years old at the time of the survey, and *young childless men* are used as a control group. See tables B5 and B6 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young fathers*. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table 48: Young Fathers' Earnings by Subgroup Using Alternative Age Group Definition

	High School or Less Education				Some College Education				Bachelor or More Education			
	Original Age Definition		New Age Definition		Original Age Definition		New Age Definition		Original Age Definition		New Age Definition	
	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ	CA	NJ
	1	2	3	4	5	6	7	8	9	10	11	12
Policy Estimator	-0.046***	-0.044***	-0.037	-0.102**	0.024	0.021	0.003	-0.333***	-0.039**	-0.039**	-0.023	0.055
	(0.007)	(0.008)	-0.026	(0.032)	(0.020)	(0.019)	(0.005)	(0.046)	(0.011)	(0.010)	(0.010)	(0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,834	19,834	15,694	6,569	13,793	13,793	9,077	4,258	13,081	13,081	4,216	2,006
R-squared	0.263	0.266	0.251	0.257	0.271	0.272	0.258	0.277	0.322	0.322	0.294	0.343

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. For columns 1-2, 5-6, and 9-10 *young* individuals are defined as individuals aged between 24-40. *Young fathers* are defined as individuals whose youngest child is either one, two, three or four years old at the time of the survey, and young childless men are used as a control group. See Tables B3 and B4 in Appendix B for synthetic control states. For columns 3-4, 7-8, and 11-12 *young* individuals are defined as individuals aged between 24-33. *Young fathers* are those whose youngest child is either one, two, three or four years old at the time of the survey, and *young childless men* are used as a control group. See tables B7 and B8 in Appendix B for synthetic control states. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young fathers*. The variables *other race,* and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

CHAPTER NINE

CONCLUSION

Paid parental leave (PPL) policies are becoming more popular in the United States, as eighteen states are considering implementing PPL policies (United States Department of Labor, 2015). As such, it is important to understand potential impacts of a PPL policy. One potential impact is a negative effect on young women's employment and earnings. Prior literature has found non-positive effects of PPL policies on young women's employment and earnings in Australia, Asia, Europe, and the United States. In addition to estimating the effect of PPL on young women's employment and earnings, this paper contributes to the literature by estimating the effect of PPL on the family wage gap.[46] This paper also contributes to the literature by investigating heterogeneous outcomes by education subgroup. This paper finds that PPL has a negative impact on young women's employment and earnings, and also finds weak evidence that PPL decreases the family wage gap.

Young women's employment decreases by 2.1 percentage points in California and 2.8 percentage points in New Jersey as a result of PPL. Results are concentrated among young women without a bachelor's degree. This result confirms the hypothesis of Sarin (2016) that low-skilled young women bear the greatest negative impact of PPL. This is because low-skilled young women have the most incentive to work in order to

[46] Recall that the family wage gap is the difference in earnings between a parent and non-parent. Parenthood has dichotomous wage effects for mothers and fathers. Mothers' earnings are less than childless women ceteris paribus, and that fathers' earnings are higher than childless men ceteris paribus.

qualify for benefits which increases their supply, and firms reduce their relative demand for this group because low-skilled young women have relatively more substitutes.

Young women's earnings decrease by 2.2 percent and 3.2 percent in California and New Jersey as a result of PPL, respectively. Although PPL affects all education subgroup earnings, the effects are concentrated among young women without a bachelor's degree, and particularly among young women with only some college experience.

The impact of the PPL has different effects on the earnings of mothers and fathers. As a result of PPL, young mothers' earnings relative to young childless women's earnings increase by 4.9 percent in California, but has no impact in New Jersey. This indicates that the motherhood wage penalty decreases as a result of PPL in California, which is consistent with the findings of Waldfogel (1999), and consistent with the prior literature on job continuity. Young fathers' earnings relative to young childless men's earnings decrease by 5.5 percent in New Jersey as a result of PPL, but no effect is found on young fathers' earnings in California. The estimations on the family wage gap are associated with three caveats. One, young non-parents may be a contaminated control group. Two, this paper does not control for selection into parenthood, which prior literature on the family wage gap reveals is a relevant consideration. Three, sample size is small, especially for estimations by subgroup.

This paper provides evidence that young women's employment and earnings will be negatively affected by PPL policies in the United States. Therefore, a tradeoff exists between potential benefits of PPL (child bonding, child education, child health, and

parental health), and costs to young women's employment and earnings. The effects are concentrated among young women without a bachelor's degree. It is unknown how much of the negative effect is a result of young women's labour supply increasing in order to attain for PPL benefits, or due to a relative decrease in demand for young women's labour from firms. This paper additionally provides weak suggestive evidence that PPL policies may decrease the family wage gap for mothers potentially via increased job continuity, and for fathers potentially via reducing household specialization.

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APPENDICES

APPENDIX A

DIFFERENCE-IN-DIFFERENCE FOR THE CONTROL VARIABLES OF YOUNG WOMEN'S EMPLOYMENT

Table A1: The Effect of Paid Parental Leave on Young Women's Employment Control Variables

	Difference-in-difference with Control States				Difference-in-difference without Control States			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Family Size	-0.008***	-0.008***	-0.005*	-0.005*	-0.010***	-0.010***	-0.004	-0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)
Number of Children	-0.029***	-0.029***	-0.039***	-0.039***	-0.021***	-0.021***	-0.024***	-0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Number of Children Under Five	-0.091***	-0.091***	-0.093***	-0.093***	-0.099***	-0.099***	-0.122***	-0.122***
	(0.001)	(0.001)	(0.006)	(0.006)	(0.003)	(0.003)	(0.006)	(0.006)
Metro	0.001	0.000	-0.020	-0.021	-0.003	-0.003	-	-
	(0.016)	(0.016)	(0.011)	(0.012)	(0.013)	(0.013)		
Age	0.023***	0.023***	0.013**	0.013**	0.021***	0.021***	0.010***	0.010***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
Age Squared	-0.000***	-0.000***	-0.000*	-0.000*	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.017**	0.017**	0.120***	0.120***	0.014***	0.014***	0.074***	0.074***
	(0.005)	(0.005)	(0.010)	(0.010)	(0.004)	(0.004)	(0.010)	(0.010)
Black	-0.004	-0.004	0.102***	0.102***	-0.037***	-0.037***	0.055***	0.055***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.012)	(0.012)

Table A1 (continued): The Effect of Paid Parental Leave on Young Women's Employment Control Variables

	Difference-in-difference with Control States				Difference-in-difference without Control States			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Hispanic	-0.004	-0.004	-0.027	-0.028	-0.019***	-0.019***	-0.040***	-0.040***
	(0.006)	(0.006)	(0.015)	(0.015)	(0.004)	(0.004)	(0.007)	(0.007)
Some College	0.154***	0.154***	0.105***	0.105***	0.160***	0.160***	0.100***	0.100***
	(0.007)	(0.007)	(0.002)	(0.002)	(0.004)	(0.004)	(0.007)	(0.007)
Bachelor Plus	0.218***	0.218***	0.138***	0.138***	0.222***	0.222***	0.136***	0.136***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.004)	(0.004)	(0.006)	(0.006)
Single	-0.033***	-0.033***	-0.041***	-0.041***	-0.017***	-0.017***	-0.047***	-0.047***
	(0.001)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)	(0.009)	(0.009)
Married	-0.079***	-0.079***	-0.042*	-0.043*	-0.057***	-0.057***	-0.044***	-0.044***
	(0.008)	(0.008)	(0.016)	(0.016)	(0.004)	(0.004)	(0.008)	(0.008)
Unemployment Rate	-0.000	0.004	0.004	0.014	0.002	3.920	-0.018	-0.076*
	(0.001)	(0.006)	(0.009)	(0.010)	(0.008)	(7.832)	(0.018)	(0.045)
Population	0.000	-0.000	-0.000	0.000	0.000**	0.000	0.000*	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table A1 (continued): The Effect of Paid Parental Leave on Young Women's Employment Control Variables

	Difference-in-difference with Control States				Difference-in-difference without Control States			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	-	-	-	-
Time Trend	Yes	Yes	Yes	Yes	No	Yes	No	Yes
State x Time Trend	No	Yes	No	Yes	-	-	-	-
State x Year FE	-	-	-	-	-	-	-	-
Observations	98,444	98,444	56,318	56,318	98,885	98,885	28,141	28,141
R-squared	0.106	0.106	0.079	0.080	0.092	0.092	0.056	0.056

Standard errors are in parenthesis and are clustered at the state level for columns 1-4 while standard errors for columns 5-8 are robust towards heteroskedasticity. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between the ages 24-40. *Older women* are used as a control group and are defined as women aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights used for columns 1-4. Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

APPENDIX B

SYNTHETIC CONTROL STATES AND WEIGHTS

Table B1: State Weights in Synthetic California

	Weights			
State	YW Employment	YW Earnings	YM Earnings	YF Earnings
District of Columbia	0.043	-	-	0.156
Hawaii	0.092	0.132	0.322	-
Louisiana	-	0.652	-	0.132
Michigan	0.292	0.043	-	-
Minnesota	-	-	0.040	-
Nevada	-	-	0.300	0.712
New Mexico	0.419	-	-	-
New York	0.154	-	-	-
Pennsylvania	-	0.167	0.184	-
Texas	-	-	0.134	-
Utah	-	0.006	-	-
Wisconsin	-	-	0.020	-

Note that all states, with the exception of New Jersey and Rhode Island, were candidates for synthetic control states. YW= young women; YM= young mothers; YF= young fathers.

Table B2: State Weights in Synthetic New Jersey

	Weights			
State	YW Employment	YW Earnings	YM Earnings	YF Earnings
Alabama	-	-	-	0.055
Colorado	-	0.113	-	-
Connecticut	-	0.103	-	-
Delaware	0.355	-	-	-
District of Columbia	0.128	-	0.202	-
Massachusetts	-	0.379	-	0.754
Nevada	0.033	-	-	-
New Hampshire	-	-	0.412	-
Pennsylvania	0.428	0.405	0.386	0.150
South Carolina	0.055	-	-	-
Utah	-	-	-	0.041

Note that all states, with the exception of California and Rhode Island, were candidates for synthetic control states. YW= young women; YM= young mothers; YF= young fathers.

Table B3: State Weights in Synthetic California by Education Subgroup

	Weights											
	YW Employment			YW Wages			YM Wages			YF Wages		
State	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+
Alaska	0.152	-	-	-	-	-	-	-	-	-	-	-
Arizona	0.524	0.195	-	0.668	0.323	-	-	0.085	-	0.234	-	-
Connecticut	-	-	-	-	-	-	0.037	-	-	-	-	0.147
District of Columbia	-	0.038	-	0.062	0.019	0.057	-	-	-	0.036	0.079	-
Florida	-	-	-	-	-	-	-	-	0.194	-	-	-
Hawaii	-	0.093	0.227	-	0.106	0.222	0.101	0.110	0.256	-	-	0.231
Maine	-	-	-	-	-	-	-	-	-	-	-	0.097
Massachusetts	-	0.278	0.273	-	0.244	0.132	-	0.253	-	0.096	0.169	0.492
Minnesota	-	-	-	0.034	-	-	0.046	-	-	-	-	0.034
Montana	0.033	-	-	-	-	-	-	-	-	-	-	-
Nebraska	-	-	-	0.141	-	-	-	-	-	0.125	-	-
New Hampshire	-	-	-	-	-	-	0.702	-	-	-	-	-
New Mexico	-	0.325	0.138	-	0.098	0.417	-	0.175	0.216	-	0.337	-
New York	-	0.070	0.282	0.052	0.176	0.171	0.027	0.037	0.100	-	0.188	-
Oregon	-	-	-	-	-	-	-	-	-	0.366	-	-
Pennsylvania	0.188	-	-	-	-	-	-	0.185	-	-	0.222	-
Texas	-	-	-	0.041	0.034	-	0.086	0.155	-	0.143	0.007	-
Utah	0.073	-	-	-	-	-	-	-	-	-	-	-
Washington	-	-	0.080	-	-	-	-	-	0.235	-	-	-
Wyoming	0.029	-	-	-	-	-	-	-	-	-	-	-

New Jersey, and Rhode Island were candidates for synthetic control states because those states implemented parental leave laws. Additionally, Delaware was not considered a control state for fathers with some college because missing observations prevented a balanced panel from being achieved, and a balanced panel is necessary for the synthetic controls method. YW= young women; YM= young mothers; YF= young fathers; ≤HS= high school degree or less; SC= some college experience; Bachelor+= bachelor degree or more.

Table B4: State Weights in Syntehtic New Jersey by Education Subgroup

	Weights											
	YW Employment			YW Wages			YM Wages			YF Wages		
State	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+
Colorado	0.150	-	-	-	-	-	-	-	-	-	-	-
Connecticut	-	0.008	0.300	-	0.147	0.060	-	-	0.551	0.034	0.619	0.626
District of Columbia	0.094	0.053	-	0.102	0.046	-	-	-	-	0.030	-	-
Florida	-	-	-	0.085	-	-	-	-	-	-	-	-
Hawaii	0.018	0.031	0.122	-	0.016	0.101	-	-	0.088	0.001	0.072	0.137
Illinois	0.011	-	-	-	0.014	-	-	-	-	-	-	-
Kentucky	-	-	-	-	-	-	-	-	-	-	-	0.009
Maine	-	-	-	-	-	-	-	-	0.041	-	-	-
Maryland	-	0.049	0.168	-	-	0.253	-	-	0.122	-	-	-
Massachusetts	0.154	-	-	0.710	0.001	0.206	0.334	-	0.187	0.643	0.002	-
Michigan	-	-	0.200	-	-	0.038	-	-	-	0.146	0.127	-
Minnesota	-	-	0.209	-	-	0.324	-	-	-	-	-	-
Nevada	-	-	-	-	-	-	-	-	-	0.001	-	-
New Hampshire	-	-	-	-	-	-	0.239	-	-	-	0.028	-
New York	-	-	-	-	0.340	0.019	0.427	0.274	-	-	0.092	0.019
Ohio	-	-	-	-	-	-	-	-	0.011	-	-	-
Oklahoma	-	-	-	-	-	-	-	-	-	-	-	0.015
Oregon	-	-	-	0.019	-	-	-	-	-	-	-	-
Pennsylvania	0.573	0.858	-	-	0.362	-	-	-	-	-	0.053	-
Texas	-	-	-	-	0.047	-	-	-	-	-	-	-
Utah	-	-	-	0.084	0.027	-	-	-	-	-	-	-
Vermont	-	-	-	-	-	-	-	0.160	-	-	-	-
Virginia	-	-	-	-	-	-	-	0.566	-	-	-	0.194
Washington	-	-	-	-	-	-	-	-	-	0.145	0.006	-

California, and Rhode Island were candidates for synthetic control states because those states implemented parental leave laws. Additionally, Delaware was not considered a control state for fathers with some college because missing observations prevented a balanced panel from being achieved, and a balanced panel is necessary for the synthetic controls method. YW= young women; YM= young mothers; YF= young fathers; ≤HS= high school degree or less; SC= some college experience; Bachelor+= bachelor degree or more.

Table B5: State Weights in Synthetic California for Redefined Age Groups

State	Weights			
	YW Employment	YW Earnings	YM Earnings	YF Earnings
Arizona	-	0.379	-	-
Arkansas	0.069	-	-	-
District of Columbia	0.052	-	-	0.156
Hawaii	-	0.040	0.322	-
Louisiana	0.695	-	-	0.132
Michigan	-	-	-	-
Minnesota	-	-	0.040	-
Nevada	-	-	0.300	0.712
New Mexico	-	0.214	-	-
New York	-	0.366	-	-
Pennsylvania	0.094	-	0.184	-
Texas	-	-	0.134	-
Wisconsin	-	-	0.020	-
West Virginia	0.090	-	-	-

Note that all states, with the exception of New Jersey and Rhode Island, were candidates for synthetic control states. YW= young women; YM= young mothers; YF= young fathers.

Table B6: State Weights in Synthetic New Jersey for Redefined Age Groups

	Weights			
State	YW Employment	YW Earnings	YM Earnings	YF Earnings
Alabama	-	-	-	0.055
Connecticut	-	0.019	-	-
District of Columbia	0.047	0.099	0.202	-
Maryland	0.358	-	-	-
Massachusetts	0.045	-	-	0.754
Nevada	-	0.098	-	-
New Hampshire	-	-	0.412	-
New York	-	0.105	-	-
Pennsylvania	0.550	0.680	0.386	0.150
Utah	-	-	-	0.041

Note that all states, with the exception of California and Rhode Island, were candidates for synthetic control states. YW= young women; YM= young mothers; YF= young fathers.

Table B7: State Weights in Synthetic California by Education Subgroup for Redefined Age Groups

	Weights											
	YW Employment			YW Earnings			YM Earnings			YF Earnings		
State	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+
Alaska	0.076	-	0.001	-	-	-	-	-	-	-	-	-
Arizona	0.707	-	-	0.535	-	-	0.074	0.144	-	-	-	-
District of Columbia	-	-	-	-	0.023	0.111	-	-	-	-	-	-
Hawaii	-	0.132	0.251	0.052	0.122	0.214	0.067	0.072	0.431	0.008	0.109	-
Illinois	0.113	-	0.094	0.105	-	-	-	-	-	-	-	-
Massachusetts	-	0.348	0.374	-	0.704	0.224	-	0.415	-	-	0.224	-
Minnesota	-	-	-	-	-	-	-	-	-	0.078	-	-
Nebraska	-	0.380	-	-	-	-	-	-	-	0.145	-	-
Nevada	-	-	-	-	-	-	0.148	-	-	0.389	-	-
New Hampshire	0.025	-	-	-	-	-	0.363	-	-	-	-	-
New Mexico	-	-	0.044	-	-	0.005	0.032	0.265	-	-	0.230	-
New York	-	0.140	0.196	-	-	0.129	-	-	0.015	0.051	0.208	-
North Dakota	0.061	-	-	0.154	-	-	-	-	-	-	-	-
Oregon	-	-	-	-	-	0.317	-	-	-	0.167	-	0.403
Pennsylvania	-	-	-	-	-	-	-	0.033	-	-	0.022	-
Texas	0.018	-	-	0.057	-	-	0.325	0.070	0.545	0.162	0.207	-
Utah	-	-	0.034	0.096	0.151	-	-	-	-	-	-	-
Vermont	-	-	-	-	-	-	-	-	0.003	-	-	-
Washington	-	-	-	-	-	-	-	-	0.005	-	-	-
West Virginia	-	-	0.006	-	-	-	-	-	-	-	-	0.597

New Jersey, and Rhode Island were candidates for synthetic control states because those states implemented parental leave laws. Additionally, several state were not considered a control states several categories because missing observations prevented a balanced panel from being achieved, and a balanced panel is necessary for the synthetic controls method. Delaware was not considered for a control state for mothers with some college. Colorado, Washington D.C, Kentucky, Nevada, New Mexico, Oklahoma, and South Carolina were not considered for control states for mothers with a bachelor's degree or more. Delaware, Connecticut, and Washington D.C were not considered for a control state for fathers with some college. Alaska, Washington D.C, Hawaii, Idaho, Louisiana, Mississippi, South Carolina, Tennessee, West Virginia, and Wyoming were not considered as control states for fathers with a bachelor's degree or more. YW= young women; YM= young mothers; YF= young fathers; ≤HS= high school degree or less; SC= some college experience; Bachelor+= bachelor degree or more.

Table B8: State Weights in Synthetic California by Education Subgroup for Redefined Age Groups

	Weights											
	YW Employment			YW Earnings			YM Earnings			YF Earnings		
State	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+	≤HS	SC	Bachelor+
Alaska	0.076	-	0.001	-	-	-	-	-	-	-	-	-
Arizona	0.707	-	-	0.535	-	-	0.074	0.144	-	-	-	-
District of Columbia	-	-	-	-	0.023	0.111	-	-	-	-	-	-
Hawaii	-	0.132	0.251	0.052	0.122	0.214	0.067	0.072	0.431	0.008	0.109	-
Illinois	0.113	-	0.094	0.105	-	-	-	-	-	-	-	-
Massachusetts	-	0.348	0.374	-	0.704	0.224	-	0.415	-	-	0.224	-
Minnesota	-	-	-	-	-	-	-	-	-	0.078	-	-
Nebraska	-	0.380	-	-	-	-	-	-	-	0.145	-	-
Nevada	-	-	-	-	-	-	0.148	-	-	0.389	-	-
New Hampshire	0.025	-	-	-	-	-	0.363	-	-	-	-	-
New Mexico	-	-	0.044	-	-	0.005	0.032	0.265	-	-	0.230	-
New York	-	0.140	0.196	-	-	0.129	-	-	0.015	0.051	0.208	-
North Dakota	0.061	-	-	0.154	-	-	-	-	-	-	-	-
Oregon	-	-	-	-	-	0.317	-	-	-	0.167	-	0.403
Pennsylvania	-	-	-	-	-	-	-	0.033	-	-	0.022	-
Texas	0.018	-	-	0.057	-	-	0.325	0.070	0.545	0.162	0.207	-
Utah	-	-	0.034	0.096	0.151	-	-	-	-	-	-	-
Vermont	-	-	-	-	-	-	-	-	0.003	-	-	-
Washington	-	-	-	-	-	-	-	-	0.005	-	-	-
West Virginia	-	-	0.006	-	-	-	-	-	-	-	-	0.597

California, and Rhode Island were candidates for synthetic control states because those states implemented parental leave laws. Additionally, several state were not considered a control states several categories because missing observations prevented a balanced panel from being achieved, and a balanced panel is necessary for the synthetic controls method. Delaware was not considered for a control state for mothers with some college. Colorado, Washington D.C, Kentucky, Nevada, New Mexico, Oklahoma, and South Carolina were not considered for control states for mothers with a bachelor's degree or more. Delaware, Connecticut, and Washington D.C were not considered for a control state for fathers with some college. Alaska, Washington D.C, Hawaii, Idaho, Louisiana, Mississippi, South Carolina, Tennessee, West Virginia, and Wyoming were not considered as control states for fathers with a bachelor's degree or more. YW= young women; YM= young mothers; YF= young fathers; ≤HS= high school degree or less; SC= some college experience; Bachelor+= bachelor degree or more.

APPENDIX C

ESTIMATIONS INVOLVING MEN AS CONTROL GROUPS

Table C1: Young Women's Labour Market Outcomes Using Young Men as a Control Group

	Earnings				Employment			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.030***	0.030***	0.048***	0.048***	0.005	0.005	0.000	0.000
	(0.007)	(0.007)	(0.005)	(0.005)	(0.017)	(0.017)	(0.017)	(0.018)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	114,502	114,502	65,322	65,322	187,534	187,534	106,870	106,870
R-squared	0.417	0.417	0.428	0.428	0.101	0.101	0.080	0.081

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young individuals* are defined as individuals aged between 20-40. Young men are used as a control group. See Tables B1 and 2 for synthetic control states used. Only full-time workers are included in the sample and are defined as individuals working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young women.* Variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table C2: Young Women's Labour Market Outcomes Using Older Men as a Control Group

	Earnings				Employment			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	0.024**	0.024**	-0.000	-0.001	-0.026	-0.026	-0.033*	-0.033*
	(0.007)	(0.007)	(0.005)	(0.005)	(0.015)	(0.015)	(0.015)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	119,639	119,639	72,485	72,485	199,303	199,303	120,860	120,860
R-squared	0.446	0.446	0.453	0.453	0.112	0.112	0.092	0.092

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young women* are defined as women aged between 24-40. Older men are used as a control group and are defined as men aged between 41-65. See Tables B1 and B2 in Appendix B for synthetic control states and weights. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state of interest interacted with *young women*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table C3: The Effect of Paid Parental Leave on Young Men's Wages

	Earnings				Wages			
	CA		NJ		CA		NJ	
	1	2	3	4	5	6	7	8
Policy Estimator	-0.017***	-0.018***	-0.016***	-0.016***	-0.004	-0.004	-0.036***	-0.037***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	952,437	952,437	884,923	884,923	134,977	134,977	78,983	78,983
R-squared	0.071	0.071	0.093	0.094	0.430	0.430	0.421	0.422

Standard errors are in parenthesis and are clustered at the state level. March CPS data is used from years 1994-2015. *Young men* are defined as men aged between 24-40. *Older men* are used as a control group and are defined as men aged between 41-65. See Table C4 in Appendix C for synthetic control states and weights used. Only full-time workers are included in the sample and are defined as those working 35-60 hours the previous years, and being employed at least 40 weeks in the previous year. The policy estimator variable is defined as post-policy time period interacted with the treatment state interacted with *young men*. The variables *other race*, *high school or less education*, and *marital status other* are omitted due to multicollinearity. Note: $*$ p<0.10,$**$ p<0.05,$***$ p<0.01.

Table C4: Synthetic State Weights for Young Men's Labour Market Outcomes

	Weights			
	CA		NJ	
State	Employment	Earnings	Employment	Earnings
Alabama	0.017	-	0.006	-
Alaska	0.017	-	0.005	-
Arizona	0.019	0.001	0.005	-
Arkansas	0.021	-	0.004	-
Colorado	0.011	-	0.013	-
Connecticut	0.010	-	0.022	0.298
Delaware	0.015	-	0.01	-
District of Columbia	0.007	0.104	0.378	-
Florida	0.016	-	0.008	-
Georgia	0.015	-	0.01	-
Hawaii	0.015	0.067	0.007	0.033
Idaho	0.018	-	0.006	-
Illinois	0.013	-	0.012	-
Indiana	0.02	-	0.006	-
Iowa	0.014	-	0.01	-
Kansas	0.011	-	0.01	-
Kentucky	0.017	-	0.007	-
Louisiana	0.018	-	0.006	-
Maine	0.018	-	0.007	-
Maryland	0.013		0.019	0.011
Massachusetts	0.01	-	0.031	0.299
Michigan	0.013	-	0.01	-
Minnesota	0.008	-	0.012	-
Mississippi	0.018	-	0.006	-
Missouri	0.014	-	0.009	-
Montana	0.015	-	0.007	-
Nebraska	0.013	-	0.008	-
Nevada	0.029	0.119	0.002	-
New Hampshire	0.013	-	0.014	-
New Mexico	0.02	-	0.005	-
New York	0.013	-	0.014	-
North Carolina	0.016	-	0.009	-
North Dakota	0.013		0.007	-
Ohio	0.014	-	0.01	-
Oklahoma	0.017	-	0.006	-
Oregon	0.016	-	0.008	-
Pennsylvania	0.014	-	0.016	0.347
South Carolina	0.018		0.006	-
South Dakota	0.013	-	0.007	-
Tennessee	0.017	-	0.006	-
Texas	0.019	-	0.005	-
Utah	0.014	0.709	0.006	0.011
Vermont	0.014	-	0.013	-
Virginia	0.012	-	0.017	-
Washington	0.013	-	0.009	-
West Virginia	0.287	-	0.194	-
Wisconsin	0.015	-	0.008	-
Wyoming	0.019		0.004	-

Note that all states, with the exception of New Jersey and Rhode Island, were candidates for California synthetic control states. With the exception of California and Rhode Island, all states were considered candidates for New Jersey synthetic control states.

APPENDIX D

CALCULATIONS FOR RAW MEAN DIFFERENCES

All calculations use means from summary statistics.

Young Women's Employment

Raw unconditional mean differences for young women's employment uses the following equation:

$$DDa = [employment_{Treatment\ State,\ Post\ Policy} - employment_{Treatment\ State,\ Pre\ Policy}] - [employment_{Control\ State,\ Post\ Policy} - employment_{Control\ State,\ Pre\ Policy}]$$

$$DDw = [employment_{Young\ Women,\ Post\ Policy} - employment_{Young\ Women,\ Pre\ Policy}] - [employment_{Older\ Women,\ Post\ Policy} - employment_{Older\ Women,\ Pre\ Policy}]$$

$$DDD = \{[young\ women's\ employment_{Treatment\ State,\ Post} - young\ women's\ employment_{Treatment\ State,\ Pre}] - [young\ women's\ employment_{Control\ State,\ Post} - young\ women's\ employment_{Control\ State,\ Pre}]\} - \{[older\ women's\ employment_{Treatment\ State,\ Post} - older\ women's\ employment_{Treatment\ State,\ Pre}] - [older\ women's\ employment_{Control\ State,\ Post} - older\ women's\ employment_{Control\ State,\ Pre}]\}$$

California

DDa=[0.636-0.636] – [0.693-0.702] = 0.009

DDb=[0.636-0.636] – [0.676-0.682] = 0.006

DDD={[0.636-0.636] – [0.0693-0.702]} – {[0.676-0.682] – [0.705-0.697]} = 0.023

New Jersey

DDa=[0.673-0.691] – [0.708-0.727] = 0.001

DDb=[0.673-0.691] – [0.726-0.732] = -0.012

DDD={[0.673-0.691] – [0.708-0.727]} – {[0.726-0.732] – [0.724-0.746]} = 0.005

Young Women's Earnings:

Raw unconditional mean differences for *young* women's earnings uses the following equation:

$$DDa = [\ln(wages)_{Treatment\ State,\ Post\ Policy} - \ln(wages)_{Treatment\ State,\ Pre\ Policy}] - [\ln(wages)_{Control\ State,\ Post\ Policy} - \ln(wages)_{Control\ State,\ Pre\ Policy}]$$

$$DDa = [\ln(wages)_{Young\ Women,\ Post\ Policy} - \ln(wages)_{Young\ Women,\ Pre\ Policy}] -$$

$[\ln(\text{wages})_{\text{Older Women, Post Policy}} - \ln(\text{wages})_{\text{Older Women, Pre Policy}}]$

$\text{DDD} = \{[\text{young women's } \ln(\text{wages})_{\text{Treatment State, Post}} - \text{young women's } \ln(\text{wages})_{\text{Treatment State, Pre}}] - [\text{young women's } \ln(\text{wages})_{\text{Control State, Post}} - \text{young women's } \ln(\text{wages})_{\text{Control State, Pre}}]\} - \{[\text{older women's } \ln(\text{wages})_{\text{Treatment State, Post}} - \text{older women's } \ln(\text{wages})_{\text{Treatment State, Pre}}] - [\text{older women's } \ln(\text{wages})_{\text{Control State, Post}} - \text{older women's } \ln(\text{wages})_{\text{Control State, Pre}}]\}$

California

DDa=[10.467-10.129] – [10.433-10.110] = 0.015

DDb=[10.467-10.129] – [10.615-10.280] = 0.003

DDD={[10.467-10.129] – [10.433-10.110]} – {[10.615-10.280] – [10.535-10.209]}

= 0.006

New Jersey

DDa=[10.594-10.297] – [10.526-10.244] = 0.015

DDb=[10.594-10.297] – [10.728-10.429] = -0.002

DDD={[10.594-10.297] – [10.526-10.244]} – {[10.728-10.429] – [10.643-10.328]}

= -0.001

Young Mothers' Earnings:

Raw unconditional mean differences for *young* mothers' earnings uses the following equation:

$\text{DD} = [\ln(\text{wages})_{\text{Young Mothers, Post Policy}} - \ln(\text{wages})_{\text{Young Mothers, Pre Policy}}] - [\ln(\text{wages})_{\text{Young Childless Women, Post Policy}} - \ln(\text{wages})_{\text{Young Childless Women, Pre Policy}}]$

$\text{DDD} = \{[\text{young mothers' } \ln(\text{wages})_{\text{Treatment State, Post}} - \text{young mothers' } \ln(\text{wages})_{\text{Treatment State, Pre}}] - [\text{young childless women's } \ln(\text{wages})_{\text{Control State, Post}} - \text{young childless women's } \ln(\text{wages})_{\text{Control State, Pre}}]\} - \{[\text{young mothers' } \ln(\text{wages})_{\text{Treatment State, Post}} - \text{young mothers' } \ln(\text{wages})_{\text{Treatment State, Pre}}] - [\text{young childless women's } \ln(\text{wages})_{\text{Control State, Post}} - \text{young childless women's } \ln(\text{wages})_{\text{Control State, Pre}}]\}$

California

DD=[10.506-10.086] – [10.496-10.200] = 0.124

DDD={[10.506-10.086] – [10.424-10.144]} – {[10.496-10.200] – [10.434-10.188]}

=0.090

New Jersey

DD=[10.358-10.621] – [10.309-10.561] = -0.011

DDD={[10.358-10.621] – [10.348-10.552]} – {[10.309-10.561] – [10.302-10.542]}

= -0.047

Young Fathers' Earnings:

Raw unconditional mean differences for *young* mothers' earnings uses the following equation:

$$DD=[\ln(wages)_{\text{Young Fathers, Post Policy}} - \ln(wages)_{\text{Young Fathers, Pre Policy}}] - [\ln(wages)_{\text{Young Childless Men, Post Policy}} - \ln(wages)_{\text{Young Childless Men, Pre Policy}}]$$

$$DDD=\{[\text{young fathers' } \ln(wages)_{\text{Treatment State, Post}} - \text{young fathers' } \ln(wages)_{\text{Treatment State, Pre}}] - [\text{young childless men's } \ln(wages)_{\text{Control State, Post}} - \text{young childless men's } \ln(wages)_{\text{Control State, Pre}}]\} - \{[\text{young fathers' } \ln(wages)_{\text{Treatment State, Post}} - \text{young fathers' } \ln(wages)_{\text{Treatment State, Pre}}] - [\text{young childless men's } \ln(wages)_{\text{Control State, Post}} - \text{young childless men's } \ln(wages)_{\text{Control State, Pre}}]\}$$

California

DD=[10.675-10.331] – [10.523-10.239] = 0.060

DDD={[10.675-10.331] – [10.694-10.401]} – {[10.523-10.239] – [10.476-10.258]}

= -0.015

New Jersey

DD=[10.930-10.799] – [10.587-10.419] = -0.037

DDD={[10.930-10.799] – [11.020-10.755]} – {[10.587-10.419] – [10.687-10.423]}

= -0.038

APPENDIX E

SUMMARY STATISTICS FOR CONTROL VARIABLE HISPANIC IN ALTERNATIVE CONTROL STATES

Table E1: Means for Control Variable Hispanic in Neighbouring States

	Pre-PPL		Post-PPL	
	CA	NJ	CA	NJ
Young Women's Employment				
Young Women in Treatment State	0.466	0.212	0.493	0.320
Young Women in Neighbouring States	0.270	0.161	0.309	0.177
Older Women in in Treatment State	0.325	0.154	0.368	0.201
Older Women in Neighbouring States	0.167	0.116	0.214	0.135
Young Women's Earnings				
Young Women in Treatment State	0.409	0.214	0.453	0.290
Young Women in Neighbouring States	0.237	0.136	0.282	0.149
Older Women in in Treatment State	0.278	0.142	0.327	0.205
Older Women in Neighbouring States	0.149	0.093	0.200	0.118
Young Mothers' Earnings				
Young Mothers in Treatment State	0.507	0.314	0.482	0.250
Young Mothers in Neighbouring States	0.312	0.151	0.326	0.137
Young Childless Women in Treatment State	0.315	0.108	0.375	0.163
Young Childless Women in Neighbouring States	0.161	0.113	0.214	0.140
Young Fathers' Earnings				
Young Fathers in Treatment State	0.568	0.211	0.545	0.315
Young Fathers in Neighbouring States	0.358	0.134	0.351	0.157
Young Childless Men in Treatment State	0.428	0.239	0.457	0.332
Young Childless Men in Neighbouring States	0.266	0.171	0.305	0.187

Source: IPUMS March Current Population Survey. Earnings estimations involve only full-time civilian workers that are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young individuals* are defined as individuals between the ages of 24-40, and *older individuals* are defined as individuals between the ages of 41-65. *Young mothers and fathers* are defined as individuals between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men and women* are defined as individuals without children between the ages of 20-40. For California, the pre-period refers to years 1994-2004, and the post-period refers to years 2005-2015. For New Jersey, the pre-period refers to years 1994-2009, and the post-period refers to years 2010-2015.

Table E2: Means for Control Variable Hispanic in Florida, New York, and Texas

	Pre-PPL		Post-PPL	
	CA	NJ	CA	NJ
Young Women's Employment				
Young Women in Treatment State	0.466	0.212	0.493	0.320
Young Women in FL, NY, and TX	0.322	0.335	0.372	0.377
Older Women in in Treatment State	0.325	0.154	0.368	0.201
Older Women in FL, NY, and TX	0.253	0.262	0.315	0.315
Young Women's Earnings				
Young Women in Treatment State	0.409	0.214	0.453	0.290
Young Women in FL, NY, and TX	0.285	0.304	0.347	0.349
Older Women in in Treatment State	0.278	0.142	0.327	0.205
Older Women in FL, NY, and TX	0.214	0.226	0.270	0.288
Young Mothers' Earnings				
Young Mothers in Treatment State	0.507	0.314	0.482	0.250
Young Mothers in FL, NY, and TX	0.338	0.352	0.378	0.376
Young Childless Women in Treatment State	0.315	0.108	0.375	0.163
Young Childless Women in FL, NY, and TX	0.232	0.252	0.299	0.300
Young Fathers' Earnings				
Young Fathers in Treatment State	0.568	0.211	0.545	0.315
Young Fathers in FL, NY, and TX	0.351	0.368	0.310	0.395
Young Childless Men in Treatment State	0.428	0.239	0.457	0.332
Young Childless Men in FL, NY, and TX	0.398	0.334	0.376	0.366

Source: IPUMS March Current Population Survey. Earnings estimations involve only full-time civilian workers that are defined as individuals working between 35-60 hours a week and having been employed at least 40 weeks in the previous year. *Young individuals* are defined as individuals between the ages of 24-40, and *older individuals* are defined as individuals between the ages of 41-65. *Young mothers and fathers* are defined as individuals between the ages of 24-40 whose youngest child is either one, two, three or four years old at the time of the survey. *Young childless men and women* are defined as individuals without children between the ages of 20-40. For California, the pre-period refers to years 1994-2004, and the post-period refers to years 2005-2015. For New Jersey, the pre-period refers to years 1994-2009, and the post-period refers to years 2010-2015.