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The Impact of Leave Length on After Leave Experience under Family and Medical Leave Policy in the U.S.

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Abstract: This research examines employee experiences under the Family and Medical Leave Policy in the United States and to what extent the length of leave affects the post-leave employment experience. The data source comes from the Family Medical Leave Act Employee Survey, which was conducted by the U.S. Department of Labor in 2018. This research further investigates whether females are more likely to be discriminated against than males and whether the eligibility of FMLA would decrease the possibility of being treated differently. Three hypotheses were 1) the longer leave one takes, the higher the possibility of being treated differently; 2) females have a higher possibility than males of being treated differently; and 3) FMLA-eligible employees have less possibility than their counterparts of being treated differently. This study found that longer leave length is associated with a higher possibility of being treated differently. Another important finding is that females have a higher possibility than males of being treated differently after controlling for other factors. Also, this study suggests that there is no significant difference between FMLA eligible groups and non-FMLA eligible groups. This study discussed policy implications regarding the length of most recent leave and gender, including the need to expand the length and types of family leave coverage, the need for government-mandated paid leave, and approaches for increasing employee knowledge of leave rights.

Keywords: Family and Medical Leave Act, FMLA, Paid maternity leave, Paternity leave

1. Introduction

As family and work patterns have changed in recent decades, the demand for time off to care for family needs has grown rapidly. Women, and increasingly men as well, are often caught between the conflicting demands of paid work and family responsibilities, especially when they become parents or when a family member suffers from a serious illness. Because of high labor force participation rates among mothers and the caregiving needs of an aging population, “work-family balance” has become an urgent but elusive challenge for millions of Americans.

However, public policies in the United States lack support workers who need time off to care for family members. Longstanding government-sponsored programs provide mothers and fathers with income replacement and job protection for extended periods prior to and after the birth of a new child. Paid sick leave and vacation plans are widespread, and some governments provide for eldercare.

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The 1993 Family and Medical Leave Act (FMLA), on the other hand, is the only major U.S. legislation that addresses these concerns, guaranteeing up to twelve weeks of job-protected leave with continuing fringe benefits for both men and women who need time off from work to attend to their own medical conditions or for family care. FMLA covers all public-sector workers, and private-sector workers who work for organizations with fifty or more employees on the payroll at or within seventy-five miles of the worksite. In addition, to be eligible for FMLA leave, one must have been with the same employer for at least 12 months and have worked 1,250 hours or more in the year preceding the leave. However, the FMLA only covers about half of all employees and less than a quarter of all new mothers [1]. Since FMLA leaves are unpaid, even those who are eligible usually cannot afford to take advantage of it.

Many U.S. employees depend on a patchwork of employer-provided benefits to make ends meet, such as paid sick days, holidays, disability insurance, and/ or parental and family leave, since there is no government provision for wage replacement during family leave. However, employer-provided incentives are not widely available. Most managers and professionals, as well as public-sector employees and others protected by collective bargaining agreements, have benefits that include salary replacement during a family leave. However, a large portion of the American workforce does not have access to paid sick days or vacation, and paid parental or family leave is even rarer. Low-wage jobs, as well as the numbers of independent contractors, freelancers, and others who lack a secure connection to an employer, are especially vulnerable.

This research report presents findings from the employee survey conducted by the U.S. Department of Labor in 2018 of 4,470 individuals about their leaving experiences with FMLA in the 12 months prior to the survey. This dataset is the cross-sectional data, and the desired sample size is 1592 after roughly cleaning off all the unqualified data rows. The central research question is if a significant relationship is identified, to what extent the length of leave affects the post-leave employment experience.

2. Literature Review

The FMLA (1993) allows employees to take time off while they are sick, giving birth, or caring for a sick child, spouse, or parent. When it comes to work leaves, there is little discussion of employees' perceived need for job leaves to care for family members; however, there is more research on the use of such leaves, especially maternity leaves. After the passage of FMLA, little research has been done on the impact of gender on either the tendency to take leave or the length of leave. Furthermore, the literature to data has almost entirely focused on maternity or parental leave, usually for newborns, while examining who takes leave.

According to most surveys, women are much more likely than men to take parental leave [2,3]. Women took an average of 9 weeks of maternity leave, and most women returned to work earlier than they wanted for two reasons: they needed the money, and the leaves allowed by their employers were too short [4]. A few reports showed that men do take parental leave on a regular basis, but only for a few days to a week [5,6].

A few studies examined how the use of maternity leaves has changed since the introduction of state leave policies, but the results are mixed. Using census data from 1980 and 1990, researchers discovered that maternity leave laws resulted in fewer mothers quitting work after childbirth compared to states [7]. They also found that mothers with young children were more likely to take time off where leave statutes were in place. The scientist compares national data from the pre-FMLA (1992-1993) and post-FMLA (1994-1995) periods, and he suggests that, although changes in employment continuity were negligible, there was an increase in leave-taking among mothers [1,8]. However, these effects were primarily among mothers with newborn children who worked in medium-size firms (100 to 499 employees). Another research uses national data both before and after

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the passage of the FMLA to reach a different conclusion: she claims that while the legislation had no impact on jobs, it did substantially extend the average length of maternity leave. As a result, she concludes that the primary impact of the FMLA on maternity leave taking could have been to extend the length of available leave for women who already had some job-protected leave options [9].

While these researchers have begun to examine the effects of leave legislation on actual leave use, there are limits on their ability to specify such effects. While these researchers implement some important controls, they are unable to adequately monitor all of the potentially confounding effects. As a result, measures of change can exaggerate the impact of legislation. Furthermore, all of these change analyses are limited to maternity leave; while there are obvious advantages to focusing on those particular types of leave, none evaluates the general need for or uses of work leaves to care for the wide range of family members covered by the FMLA. A study notes that the most substantial effects of the FMLA on labor market behaviors will be among the population of employed caregivers, not just recent mothers [9]. Moreover, none of the studies use clear questions that directly ask respondents whether they took time off from work to care for family members. Finally, these analyses of change over time do not compare essential social characteristics -- such as gender or race -- of those who need or take leaves with those who do not.

Studies have found that an estimated 65% of Black parents and 75% of Hispanic parents are ineligible or unable to afford paid leave under the FMLA [10]. Following the reality that Black and Hispanic women earn far less than white women, they're more likely to leave or lose their jobs after having a child, which increases the risk of perpetual cycles of poverty, social deprivation, and social hardship for the children [11,12].

Given that previous research has ignored racial disparities in family leave use, none has gone further to investigate the intersection of the primary reason for leave and gender. This research is a step in that direction. Moreover, this research goes beyond prior studies by examining the wide variety of family leaves protected by the FMLA and determining if race and gender inequalities in leave-taking and length of leave differ across the various types of family leave.

3. Data and Methods

The data source of this research comes from the Family Medical Leave Act (FMLA) Employee Survey, which was conducted by the U.S. Department of Labor in 2018. This dataset is cross-sectional data, and the unit of analysis is individual. The 4,470 employees surveyed by phone and online were working-age adults employed in the public or private sector in the 12 months prior to the survey. The dataset originally contained 400 variables and 1540 observations.

After removing all the missing data and unqualified data rows, the number of observations that apply to this research drops to 1,439. One notable issue of this dataset is the skewed race distribution. The number of white respondents is 1,214, making up 80.34 percent, while the black respondents just account for 10.68 percent. This issue may increase the omitted bias on race of our following regression model.

The dependent variable, post-leave experience, is measured by a single question-- "Were you treated differently after taking leave?". The answer "Yes" to this question was coded as 1, and "No" was coded as 0. The major explanatory variable, the length of most recent leave, was recorded in an uneven scale on the dataset. It was coded with a daily interval between 1 to 5 days, but it changed to 5-day interval between 5 to 50 days, and 10-day interval between 50 to 70 days, and 20-day interval between 70 to 120 days and above 120 days for the rest. Considering the uneven scale, this variable cannot be treated numerically on the regression model. Therefore, the data was regrouped into four categories based on frequency distribution, and each quintile is one category. The first quartile contains observations between 1 to 5 days, the second quartile contains observations between 5 to 15 days, the third quartile contains observations between 15 to 45 days, and the last quartile contains any

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observations above 45 days.

To operationalize another important variable, reasons accounting for taking leave, 13 reasons were regrouped into 3 categories. The first category is a personal illness, disability and other serious health conditions, which make up 56.13 percent; the second category is taking care of health issues of others other than yourself, accounting for 25.09 percent; the third one is any reasons related to newbabys making up 18.80 percent. The other variable that was regrouped is the race. As mentioned above, the distribution of race is very skewed, so these variables were divided into three categories. White-only is one category, with total observations making up 80.34 percent, and the black-only respondents are the other category, making up 10.68 percent; all others belong to the third category. The other two variables, gender and FMLA eligibility, were treated as dummy variables. For the gender variable, the female was coded as 1, and the male was coded as 0. For the FMLA eligibility, the eligible individuals were coded as 1, and ineligible individuals were coded as 0.

4. Results and Discussion

Table 1: The characteristics of variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
exp_new	1439	.1556637	.3626622	0	1
gen_new	1439	.580959	.4935736	0	1
reason_new	1439	1.629604	.7829809	1	3
length_new	1439	2.485059	1.092212	1	4
race_new	1439	1.271716	.6029361	1	3
fmla_eligible	1439	.628909	.4832647	0	1

To better prove the hypothesis, this section explores the characteristics of a single variable in Table 1, the correlation between two or three related variables. All the findings would be explored in the order of hypothesis.

Hypothesis 1: The longer leave one takes, the higher the possibility of being treated differently.

Hypothesis 2: Females have a higher possibility than males of being treated differently.

Hypothesis 3: FMLA-eligible employees have less possibility than their counterparts of being treated differently.

4.1. Hypothesis 1: The longer leave one takes, the higher the possibility of being treated differently

4.1.1. The correlation between experience and their leave_length

Table 2: The correlation between experience and leave_length

As a result of taking leave, were you treated differently?	Most recent leave: total time taken off work				Total
	Quantile 1	Quantile 2	Quantile 3	Quantile 4	
No	303	323	333	256	1215
	86.82	86.83	85.60	77.81	84.43
Yes	46	49	56	73	224
	13.18	13.17	14.40	22.19	15.57
Total	349	372	389	329	1439
	100.00	100.00	100.00	100.00	100.00

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Table 2 shows that almost 80% of people in any quantile of leave_length who return to work are not treated differently. The longer one takes, the higher percent of possibility that people would be treated differently.

Table 3: The characteristics of experience and leave_length

Experience if leave_length is at quantile 1					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	349	.1318052	.3387645	0	1
Experience if leave_length is at quantile 2					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	372	.1317204	.338642	0	1
Experience if leave_length is at quantile 3					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	389	.1439589	.3515001	0	1
Experience if leave_length is at quantile 4					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	329	.2218845	.4161468	0	1

Quantile 1: The odds of being treated differently when at quantile 1(1,5) =0.13/0.87 =0.15;
Quantile 2: The odds of being treated differently when at quantile 2(6,15) =0.13/0.87=0.15;
Quantile 3: The odds of being treated differently when at quantile 3(16,25)=0.14/0.86=0.16;
Quantile 4: The odds of being treated differently when at quantile 4(26+)=0.22/0.78=0.28;

1)Odds ratio of being treated differently = 0.15/0.15= 1; for the leave length between 1 to 5 days, the odds that Y=1(being treated differently) for a female is the same as the odds that Y=1(being treated differently) for a male.

2)Odds ratio of being treated differently = 0.16/0.15= 1.07; for the leave length between 16 to 25 days, the odds that Y=1(being treated differently) for a female is 1.07 times greater than the odds that Y=1(being treated differently) for a male.

3)Odds ratio of being treated differently = 0.28/0.16= 1.75; for the leave length more than 26 days, the odds that Y=1(being treated differently) for a female is 1.75 times greater than the odds that Y=1(being treated differently) for a male.

Table 4: The logistic regression for the hypothesis 1

Logistic regression					Number of observations	1439
Log likelihood = -617.24308						
Experience	Coefficient	Standard error	Z value	P>|z|	Lower 95% confidence interval	Higher 95% confidence interval
Length	.2118797	.0675124	3.14	0.002	.0795579	.3442015
_cons	-2.23575	.1937013	-11.54	0.000	-2.615397	-1.856102

Table 3 and Table 4 prove hypothesis 1: The longer leave one takes, the higher the possibility of being treated differently.

4.2. Hypothesis 2: Females have a higher possibility than males of being treated differently

There are 603 males and 836 females in our observable dataset.

4.2.1. The correlation between gender and after-leave experience

Table 5: The correlation between gender and after-leave experience

As a result of taking leave, were you treated differently?	Gender of respondent		Total
	Males	Female	
No	532	683	1215
	88.23	81.70	84.43
Yes	71	153	224
	11.77	18.30	15.57
Total	603	836	1439
	100.00	100.00	100.00

From Table 5, it is obvious to see that 18.30% of females surveyed reported that they have been treated differently while 11.77% of man have been treated differently. To further explore the possibility of being treated differently, the odds ratio of both genders as followed:

Table 6: The characteristics of experience and gender

Experience if gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	603	.1177446	.3225731	0	1
Experience if gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	836	.1830144	.3869098	0	1

Based on the results from Table 6, the odds of being treated differently when gender_new == 0 (male) =0.118/0.882= 0.134; the odds of being treated differently when gender_new == 1 (female) = 0.183/0.817=0.224. Odds ratio of being treated differently = 0.224/0.134 =1.67. The odds that Y=1(being treated differently) for a female is 1.67 times greater than the odds that Y=1(being treated differently) for a male.

Table 7: The logistic regress for the hypothesis 2.

Logistic regression					Number of observations	1439
Log likelihood = -616.41199						
Experience	Coefficient	Standard error	Z value	P>|z|	Lower 95% confidence interval	Higher 95% confidence interval
Gender	1.67851	.2598401	3.35	0.001	1.239238	2.273492
_cons	.1334587	.0168624	-15.94	0.000	.1041832	.1709605

As shown in Table 7, on average, the females are 1.68% more likely to be treated differently than males when holding other variables constant. So, this study explores other factors that is related with gender difference such as difference in leave-length and leave reason.

4.2.2. Correlation between gender and leave_length

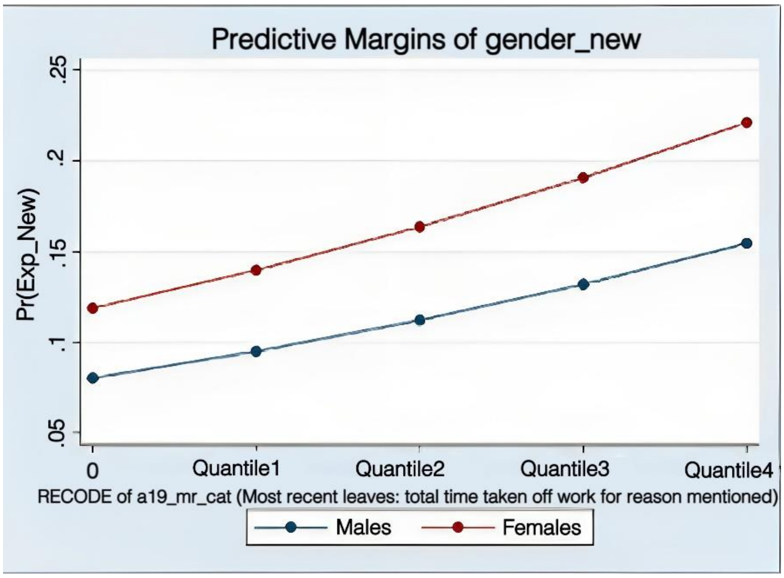

Figure 1: Correlation between gender and leave_length.

In Figure 1, on average, the leave length the women take is longer than men do with women on average taking 2.62 days while men 2.29 days. In addition, the quantile of leave length of women is mainly distributed in quantile three and four while man is in quantile one and two.

Table 8: The characteristics of experience and gender at the leave_length is at quantile 1.

Experience if leave_length is at quantile 1 and gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	182	.1208791	.326886	0	1
Experience if leave_length is at quantile 1 and gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	167	.1437126	.3518531	0	1

From Table 8, the odds of being treated differently when gender_new == 0 (male) at quantile 1(1,5)= 0.12/0.88= 0.14; the odds of being treated differently when gender_new == 1 (female) at quantile 1(1,5) =0.14/0.86 =0.16. Odds ratio of being treated differently = 0.16/0.14= 1.14. For the leave length between 1 to 5 days, the odds that Y=1 (being treated differently) for a female is 1.14 times greater than the odds that Y=1(being treated differently) for a male.

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Table 9: The characteristics of experience and gender at the leave_length is at quantile 2.

Experience if leave_length is at quantile 2 and gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	168	.0952381	.2944211	0	1
Experience if leave_length is at quantile 2 and gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	204	.1617647	.3691407	0	1

As shown in Table 9, the odds of being treated differently when gender_new == 0 (male) at quantile 2(6,15)= 0.095/0.905 = 0.1; the odds of being treated differently when gender_new == 1 (female) at quantile 2(6,15) = 0.16/0.84 = 0.19. Odds ratio of being treated differently = 0.19/0.1= 1.9. For the leave length between 6 to 15 days, the odds that Y=1(being treated differently) for a female is 1.9 times greater than the odds that Y=1(being treated differently) for a male.

Table 10: The characteristics of experience and gender at the leave_length is at quantile 3.

Experience if leave_length is at quantile 3 and gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	148	.1148649	.3199415	0	1
Experience if leave_length is at quantile 3 and gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	241	.1618257	.3690573	0	1

From Table 10, the odds of being treated differently when gender_new == 0 (male) at quantile 3(15,45)= 0.11/0.89= 0.12; the odds of being treated differently when gender_new == 1 (female) at quantile 3(15,45) = 0.16/0.84 = 0.19. Odds ratio of being treated differently = 0.19/0.12= 1.58. For the leave length between 15 to 45 days, the odds that Y=1(being treated differently) for a female is 1.58 times greater than the odds that Y=1(being treated differently) for a male.

Table 11: The characteristics of experience and gender at the leave_length is at quantile 4.

Experience if leave_length is at quantile 4 and gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	105	.152381	.3611135	0	1
Experience if leave_length is at quantile 4 and gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	224	.2544643	.4365352	0	1

As show in Table 11, the odds of being treated differently when gender_new == 0 (male) at quantile 4(46,125)= 0.15/0.85= 0.17; the odds of being treated differently when gender_new == 1 (female) at quantile 3(46,125) = 0.25/0.75 = 0.33. Odd ratio of being treated differently = 0.33/0.17 = 1.94. For the leave length between 46 to 125 days, the odds that Y=1(being treated differently) for

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a female is 1.94 times greater than the odds that Y=1(being treated differently) for a male. All of these results suggest that women are likely treated differently in any quantile on average.

4.2.3. Correlation between After-leave experience and gender for different reasons

Table 12: The characteristics of experience and gender at reason 1 (illness).

Experience if gender is 0 (Male) and reason is 1 (illness)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	338	.1301775	.3369975	0	1
Experience if gender is 1 (Female) and reason is 1 (illness)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	468	.2179487	.4132942	0	1

From Table 12, the odds of being treated differently when gender_new == 0 (male) at reason 1: for her own illness = 0.13/0.817=0.149; the odds of being treated differently when gender_new == 1 (female) at reason 1: for her own illness =0.218/0.782= 0.279. Odds ratio of being treated differently = 0.279/0.149 =1.56. For the reason of taking a leave due to her own illness, the odds that Y=1(being treated differently) for a female is 1.56 times greater than the odds that Y=1(being treated differently) for a male.

Table 13: The characteristics of experience and gender at reason 2 (for new-born).

Experience if gender is 0 (Male) and reason is 2 (for new-born)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	147	.1156463	.3208936	0	1
Experience if gender is 1 (Female) and reason is 2 (for new-born)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	213	.1267606	.3334883	0	1

As shown in Table 13, the odds of being treated differently when gender_new == 0 (male) at reason 2: for new-born or related = 0.116/0.884 = 0.13; the odds of being treated differently when gender_new == 1 (female) at reason 2: for new-born or related =0.127/0.873= 0.145. Odds ratio of being treated differently = 0.145/0.13 = 1.12. For the reason of taking a leave due to care for new-born or related, the odds that Y=1(being treated differently) for a female is 1.12 times greater than the odds that Y=1(being treated differently) for a male.

Table 14: The characteristics of experience and gender at reason 3 (care for others).

Experience if gender is 0 (Male) and reason is 3 (care for others)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	118	.0847458	.2796906	0	1
Experience if gender is 1 (Female) and reason is 3 (care for others)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	155	.1548387	.3629235	0	1

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Table 14 shows the odds of being treated differently when gender_new == 0 (male) at reason 3: care for others = 0.085/0.915 = 0.093; the odds of being treated differently when gender_new == 1 (female) at reason 3: care for others =0.155/0.845= 0.18. Odds ratio of being treated differently = 0.18/0.093 = 1.94. For the reason of taking a leave due to care for others, the odds that Y=1(being treated differently) for a female is 1.94 times greater than the odds that Y=1(being treated differently) for a male.

All of these results indicate that women are more likely to be treated differently no matter what reason is used for the leave. After all of these interpretations, it can be conducted that females are more likely to be treated differently no matter what other variables are held constants, which can verify our second hypothesis: females are more likely to be treated differently than males when holding other factors constant.

4.3. Hypothesis 3: FMLA-eligible employees have less possibility than their counterparts of being treated differently

4.3.1. Correlation between FMLA_eligible and after-leave experience

Table 15: The correlation between FMLA eligible and after-leave experience.

As a result of taking leave, were you treated differently?	Respondent was eligible for FMLA at start of reference period		Total
	Not FMLA	FMLA Elig	
No	441	774	1215
	82.58	85.52	84.43
Yes	93	131	224
	17.42	14.48	15.57
Total	543	905	1439
	37.11	62.89	100.00

Table 15 indicates that more than 80% of people surveyed reported no difference when coming back to work no matter whether they are eligible or not. 17.42% of people who are not eligible for FMLA reported they are being treated differently, while the percent for people who are eligible for FMLA is 14.48%. 37.11% of people surveyed are not eligible for FMLA and 62.89% of people are eligible for FMLA. And this study further explores the difference caused by gender.

4.3.2. Correlation between leave experience and gender and FMLA_eligible

Table 16: The characteristics of experience and gender if FMLA_eligible.

Experience if gender is 0 (Male) and FMLA_eligible					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	395	.1113924	.3150165	0	1
Experience if gender is 1 (Female) and FMLA_eligible					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	510	.1705882	.3765181	0	1

From Table 16, the odds of being treated differently when gender_new == 0 (male) when they are FMLA_eligible = 0.111/0.889=0.125; The odds of being treated differently when gender_new == 1

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(female) when they are FMLA_eligible =0.171/0.829=0.206. Odds ratio of being treated differently = 0.206/0.125 = 1.648. When the people surveyed are FMLA_eligible, the odds that Y=1(being treated differently) for a female is 1.648 times greater than the odds that Y=1(being treated differently) for a male.

Table 17: The characteristics of experience and FMLA_eligible for male.

Experience and FMLA_eligible if gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	395	.1113924	.3150165	0	1
Experience and not FMLA_eligible if gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	208	.1298077	.3369026	0	1

As shown in Table 17, the odds of being treated differently when gender_new == 0 (male) when they are FMLA_eligible = 0.11/0.89=0.12; The odds of being treated differently when gender_new == 0 (male) when they are not FMLA_eligible =0.13/0.87=0.15. Odds ratio of being treated differently = 0.15/0.12=1.25. For male, the odds that Y=1(being treated differently) when not FMLA_eligible is 1.25 times greater than the odds that Y=1(being treated differently) when FMLA_eligible.

Table 18: The characteristics of experience and gender if not FMLA_eligible.

Experience and not FMLA_eligible if gender is 0 (Male)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	208	.1298077	.3369026	0	1
Experience and not FMLA_eligible if gender is 1 (Female)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	326	.175976	.3740256	0	1

From Table 18, the odds of being treated differently when gender_new == 0 (male) when they are not FMLA_eligible = 0.13/0.87=0.15; the odds of being treated differently when gender_new == 1 (female) when they are not FMLA_eligible =0.17/0.85=0.2. Odds ratio of being treated differently = 0.2/0.15= 1.3. When the people surveyed are not eligible for FMLA, the odds that Y=1(being treated differently) for a female is 1.3 times greater than the odds that Y=1(being treated differently) for a male. In conclusion, FMLA eligibility would influence the possibility of being treated differently, but the influence is not as significant. After all of the correlation analysis between different variables and a single variable, this is an overall model for our analysis.

Table 19: Taking family leave: logistic regression model (N=1436)

Variables	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)
2. reason_new	-0.67	-0.66	-0.63	-0.64
	(0.37)	(0.37)	(0.37)	(0.37)
3. reason_new	0.43	0.39	0.54	0.53

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Table 19: (continued).

	(0.48)	(0.48)	(0.48)	(0.48)
2. length_new	-0.19	-0.20	-0.24	-0.21
	(0.30)	(0.30)	(0.30)	(0.30)
3. length_new	0.14	0.15	0.11	0.13
	(0.27)	(0.27)	(0.27)	(0.27)
4. length_new	0.70**	0.71**	0.69**	0.71**
	(0.27)	(0.27)	(0.27)	(0.27)
2. reason_new#1. length_new	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
2. reason_new#2. length_new	1.00*	1.04*	0.96	0.95
	(0.50)	(0.50)	(0.50)	(0.50)
2. reason_new#3. length_new	-0.22	-0.24	-0.29	-0.30
	(0.59)	(0.59)	(0.59)	(0.59)
2. reason_new#4. length_new	0.25	0.22	0.17	0.13
	(0.56)	(0.56)	(0.57)	(0.57)
3. reason_new#1. length_new	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
3. reason_new#2. length_new	-1.07	-1.01	-0.95	-0.96
	(0.70)	(0.70)	(0.70)	(0.70)
3. reason_new#3. length_new	-0.95	-0.92	-1.07	-1.08
	(0.63)	(0.63)	(0.64)	(0.64)
3. reason_new#4. length_new	-1.22*	-1.77*	-1.49*	-1.52*
	(0.58)	(0.58)	(0.59)	(0.59)
Fmla_eligible		-0.24	-0.22	-0.22
		(0.15)	(0.15)	(0.15)
Gender_new			0.51**	0.50**
			(0.16)	(0.16)
2. race_new				0.20
				(0.23)
3. race_new				0.41
				(0.25)
Constant	-1.70***	-1.56***	-1.87***	-1.92***
	(0.21)	(0.23)	(0.25)	(0.25)

Observation: 1436
Standard errors in parentheses: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Table 19 indicates that the p-value of most categories in length and reason for taking leave is

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insignificant at the significance level of 5%. However, the p-value of quartile 4 (above 45 days) is below 0.01, showing great significance, so it failed to fully reject the null hypothesis 1 and 3. All the tables in this section exploring their separate relationship can strongly prove our three hypotheses. The p-value of gender is smaller than 0.01, showing the statistical significance of rejecting the null hypothesis 3.

5. Limitations

Limitation 1: uneven distribution in race: Around 80% of our survey respondents are Whites. Although a significant relationship was found between people of other races and after-leave job discrimination (see race in appendices), the small sample size may lead to a biased result of our research.

Limitation 2: The leave length variable is a categorical variable. Our leave length is a categorical variable that contains four quantiles of length. After the data was cleaned, there was a significant relationship between quantile four and discrimination, but it cannot be determined as a specific relationship between leave length and discrimination. It is possible that some specific data in one quantile contradicts the conclusion. Only if the leave length is a quantitative variable can this study conclude an accurate relationship between length of leave and discrimination.

Limitation 3: difference in number of females and males. Our data has 200 more female respondents than the male. This may cause a biased result for our race conclusion. Given the large number of females responding, they took a long leave, and previous results already identified a positive relationship between leave length and discrimination. It is uncertain whether it is the length of leave, rather than gender, that causes more females to feel discriminated against as a result of leave.

Limitation 4: there may exist the problem of multicollinearity. This research runs separate regressions that start with two explanatory variables and adds one new explanatory variable each time for a new regression until it reaches the final regression that contains all the variables. The coefficient of some variables will change each time a new variable is added. This is an indication that more than one explanatory variable is correlated. While the multicollinearity problem does not reduce the overall predictive power of our model, it affects the calculations regarding the individual predictors. Moreover, the predictor, despite changing the coefficient value after a new variable is introduced, does not change the sign. Therefore, our conclusion about leave discrimination still holds.

6. Conclusion

The result shows that medical leaves above 26 days have a statistically significant effect on after-leave discrimination. A higher length of leave will cause job discrimination. Therefore, this research report recommends policymakers impose more FMLA care protection on the long time leave and remove some overstretching policies on short leave. Current FMLA protection enforces 12 work weeks of unpaid FMLA leave (60 days) every year. One recommended policy would be extending this enforcement to more than 60 days.

The result also shows that females are more likely to feel discriminated against after taking a leave. Therefore, this research recommends policymakers impose some special enforcement for females. For example, policymakers can protect females by setting a floor for their after-leave salary, which should not be less than 80% of their salary before-leave.

Another finding is that FMLA-eligible employees find they are less likely to get discriminated against after taking a leave. This is a good sign that the FMLA Care Act has a substantial effect on leave protection. Therefore, this research recommends policymakers continue expanding the coverage of the FMLA act, forcing more employers to follow this act. Furthermore, improving the minimum requirement of the FMLA act and employers with more than 20 workers, not 50, should follow this act. This can significantly expand the coverage of the FMLA act.

Our finding shows that people that is not White or Black may suffer discrimination after leaving. Despite the limited sample size, it is obvious to find a statistically significant relation between people of other races and after-leave discrimination. Therefore, policymakers can also improve the anti-discrimination law not only for the Black people but also for the minority races, like Asians.

The interaction effect of people taking a long time left due to new-born-related issues reduces the long-leave discrimination to none. Leaving due to other reasons does not have this effect. Therefore, policymakers should support long-time medical leave for reasons other than newborn caring. For example, the FMLA care act should force employers to grant unpaid 60 days and above leave for workers due to family members' health issues.

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Appendices

Race

What race do you consider yourself to be? Based on D6 (ROD)	As a result of taking leave, were you treated differently?		Total
	No	Yes	
Whites	995	172	1167
	85.26	14.74	81.10
Blacks	124	29	153
	81.05	18.95	10.63
Others	96	23	119
	80.67	19.33	8.27
Total	1215	224	1439
	84.43	15.57	100.00

Experience if race is 1 (White)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	1167	.1473865	.3546427	0	1
Experience if race is 2 (Black)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	153	.1895425	.3932261	0	1
Experience if race is 3 (Others)					
Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Experience	119	.1932773	.3965382	0	1

The odds of being treated differently when you are a white (1)= 0.15/0.85= 0.17; the odds of being treated differently when you are a black (2)= 0.1895/0.81= 0.234; the odds of being treated differently when you are other (3) = 0.19/0.81= 0.23. Odds ratio of being treated differently = 0.23/0.17= 1.35. When holding all else constant, the odds that Y=1(being treated differently) for a black and others is 1.35 times greater than the odds that Y=1(being treated differently) for a white.