FMLA Eligibility of Underserved Communities

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Executive Summary

FMLA provides eligible employees with up to 12 weeks of unpaid, job-protected leave per year. Existing evidence has documented that FMLA is associated with higher leave-taking and improved maternal and child health.[3]

Due to strict eligibility requirements, access to FMLA is not universal. Employees are eligible for leave if they have worked for their employer at least 12 months, at least 1,250 hours over the past 12 months (an average of 24 hours per week), and work at a location where the company employs 50 or more employees within 75 miles (USDOL, 2012). An estimate based on 2018 data suggests that only 56% of US employees are eligible (Brown, Herr, Roy, and Klerman 2020).

We provide estimates of current eligibility for a variety of disadvantaged groups based on large-sample, nationally representative data from the Current Population Survey (CPS) (Ruggles et al. 2021). Unlike other large-sample estimates, we account for all eligibility criteria in our estimates. We then simulate the impact of changes in the employee threshold and the working hours threshold on FMLA eligibility for these underserved communities.

We find that those with low wage income have eligibility rates that are 20 percentage points (40%) lower than the aggregate rate. Those living in poverty have lower eligibility rates by 35 percentage points (65%). Rates for workers who are non-citizens, Hispanic, single parents, foreign born, rural residents, only high school educated, or women are lower by 1 to 10 percentage points.

When we calculate eligibility under an alternative definition that has lower threshold for both firm size and working hours, we find rates of simulated eligibility that are 12 percentage points (24%) higher than current eligibility rates. Increases in eligibility rates are the highest among the most disadvantaged, with eligibility increasing as much as 59% among those living in poverty, and as much as 84% among non-citizens living in poverty.

[3] See Waldfogel 1999; Baum 2003; Han and Waldfogel 2003; Berger and Waldfogel 2004; Baker and Milligan 2005; Berger, Hill, and Waldfogel 2005; Han et al. 2009; Rossin 2011; Schott 2012; Chatterji and Markowitz 2012; Chatterji et al. 2013; Kerr 2016.

Introduction

The Family and Medical Leave Act (FMLA) plays an essential role in balancing work and personal life. FMLA provides eligible employees with up to 12 weeks of unpaid, job-protected leave per year. Employees are eligible for leave if they have worked for their employer at least 12 months, at least 1,250 hours over the past 12 months (an average of 24 hours per week), and work at a location where the company employs 50 or more employees within 75 miles (USDOL, 2012).

Existing evidence has documented that FMLA is associated with higher leave-taking and returning to work by both working mothers and fathers (Waldfogel 1999; Baum 2003; Han and Waldfogel 2003; Berger and Waldfogel 2004; Han et al. 2009; Schott 2012; Kerr 2016). FMLA also to increases fertility rates (Rossin 2011; Cannonier 2014), improves child health (Berger, Hill, and Waldfogel 2005; Rossin 2011), promotes breastfeeding (Berger et al. 2005, Baker and Milligan 2005), and improves mothers' physical and mental health (Chatterji and Markowitz 2012; Chatterji et al. 2013). As of January 2021, seven states and the District of Columbia enacted paid family leave. Three of these states do not offer job protection and the leave must therefore be combined with FMLA to achieve paid, job-protected leave. As such, FMLA access is also critical to individuals' ability to take advantage of paid family leave when it is available (Jones and Wilcher 2019).

Due to strict eligibility requirements, access to FMLA is not universal. An estimate based on 2018 data suggests that only 56% of US employees are eligible (Brown, Herr, Roy, and Klerman 2020). Single parent families and low wage workers have a higher chance of being ineligible because they either cannot work full-time or they work for smaller, ineligible employers.[4] Therefore, although FMLA has been highly effective as a policy, it may be failing to support disadvantaged groups, who need job protection the most.

We provide estimates of current eligibility for a variety of disadvantaged groups based on large-sample, nationally representative data from the Current Population Survey (CPS) (Ruggles et. al. 2021). Unlike other large-sample estimates, we account for all eligibility criteria in our estimates. We then simulate the impact of changes in the employee threshold and the working hours threshold on FMLA eligibility for these underserved communities.

[4] Smaller employers are those with less than 50 employees working within 75 miles of the physical work location

We additionally endeavor to evaluate state-based policy changes that have occurred regarding employee thresholds between 2007 to 2014. However, we find that the existing available data on leave usage is insufficient to estimate reliable trends over time for single-treated-state estimations. This is primarily because large-sample surveys, such as the CPS, measure leave poorly, for example only inquiring about leave usage in the past week rather than the past year (Callison and Pesko 2017). Further, surveys that do measure leave usage well do not have sufficient sample sizes to support state-policy evaluations. Further details on this exercise are provided in the Annex.

Existing estimates

The most accurate existing estimates of current FMLA eligibility are based on data from the 2018 Employee Perspectives of the Family and Medical Leave Act Survey (DOL 2018), henceforth EPFMLA. These data include information on all the relevant eligibility criteria for 4,470 employed adults (aged 18+).[5] The data exclude individuals who are self-employed, as FMLA requires employers to grant employees unpaid, job-protected time off work. Such protection is irrelevant for a self-employed individual who can choose to take leave at-will. Estimates of FMLA eligibility for the full population of employed individuals (who are not self-employed) and for specific sub-groups are provided by Brown, Herr, Roy and Klerman (2020). The authors estimate that FMLA eligibility among employed adults is 56%. They also present estimates for various demographic groups, finding the eligibility is only slightly lower for women, Hispanic workers, and workers with only a high school education. They find that single parents and low wage workers have eligibility rates of only 43% and 38%, respectively, and these differences are significantly different at the 5% level relative to the aggregate eligibility. The advantages of these estimates are that they are based on the full and accurate eligibility criteria: tenure with employer, working hours in the past year, and number of employees within 75 miles of one's jobsite. The primary disadvantage of these estimates is that the small sample size reduces the ability to draw inferences about sub-groups.[6] For example, based on CPS data, single parents represent only 4.8% of

[5] Employees worked for their employer at least 12 months, at least 1,250 hours over the past 12 months (an average of 24 hours per week), and work at a location where the company employs 50 or more employees within 75 miles

[6] We also note that the sample of the 2018 EPFMLA Survey excludes self-employed individuals, some of whom are eligible for FMLA. We present estimates both including and excluding this population.

working adults (authors' estimates), suggesting that the sample of single parents in the EPFMLA is approximately 214, likely too small of a sample from which to draw accurate inference.[7]

Other studies have employed larger, nationally representative data sets to estimate FMLA eligibility. These studies have alternatively employed only the Annual Social and Economic Supplement (ASEC or March supplement) of the CPS (Mayer 2013; Pihl 2016), or only the American Community Survey (ACS) (Badgett 2016), neither of which include the full set of information required to determine eligibility. Both data sources lack information on job tenure, and the ACS also lacks information on firm size, suggesting that estimates from these data will be upward biased by ignoring key criteria.

One existing study has combined the ASEC and CPS Job Tenure Supplement (JTS or January supplement) to estimate more accurate FMLA eligibility on a national scale. While methodologically similar to this study, Kerr (2016) focuses on the era surrounding the onset of FMLA (in 1993). Her work estimates how the enactment of FMLA changed leave eligibility in the 1990s. Additionally, while she does estimate separate impacts by income quartile, effects are not disaggregated by other demographic characteristics.

A key contribution of this study is to provide modern estimates of FMLA eligibility based on large-sample, nationally representative data, using the full set of eligibility criteria. In addition, we provide estimates for a larger set of disadvantaged groups than has previously been examined. The second contribution of this study is to simulate how eligibility would change for each of these groups under three potential policy changes regarding eligibility criteria.

Methods

We rely on two primary data sources. The first is the Annual Social and Economic Supplement (ASEC or March supplement) from the Current Population Survey, which is a nationally representative panel survey. These data include information on demographic characteristics, usual working hours, and firm size, which we use to partially determine FMLA eligibility. We employ ASEC data from 2011 to 2018, as during these years the categories for measuring firm size include a split at the relevant threshold of

[7] Based on the weighted analysis sample as described in the following section.

50 employees.[8] We also rely on the Job Tenure Supplement (JTS or January supplement) of the CPS, in years 2012, 2014, 2016, and 2018, for information on the individual's job tenure.

We match individual's responses across the two data sets. Given the one-year nature of the CPS panel, each individual responds to the JTS at most once.[9] We take each observation in the JTS years 2012 to 2018 and match it to the individuals' response in the ASEC in the same year. Due to the structure of the CPS panel, not all individuals in the JTS will have responded to the ASEC.[10] From the full sample across the four waves of the JTS of 519,632 individuals, we have a matched sample of 255,247. We note that survey-provided sampling weights are no longer accurate when focusing on the sub-sample of individuals present in both the January and March supplements of the same year. We follow a methodology provided by IPUMS to reconstruct accurate sampling weights based on the sub-sample that is present in both the January and the March supplements using raking (IPUMS, 2021).[11] We then further restrict the sample to employed individuals aged 18+, excluding those who are self-employed, for a final sample size of 105,043.

Once matched, we identify an individual's eligibility as follows. From the JTS we determine that an individual meets the job tenure requirement if they report that they have been with their current employer for at least one year.[12] From the ASEC we determine whether an individual meets the working hours requirement based on their report of the number of weeks they worked in the past year and the number of hours usually worked at their main job.[13] We take the product of these as our measure of the number of hours worked in the past year. Some measurement error is introduced here for individuals for whom this product is not exactly equal to the true number of hours worked in the past year. Finally, from the ASEC, we rely on an individual's self-reported firm size of their employer.[14] Additional

[8] Before 2011 and after 2018, the firm size ranges are 10-24 and 25-99 employees, which prevent identification of individuals who are currently eligible for FMLA according to the jobsite threshold of 50 employees.

[9] The CPS enrolls new households each month. Each household is interviewed each month for four consecutive months. The household is revisited one year after enrollment and is again interviewed each month for four months.

[10] Individuals interviewed in the JTS in January, would have been enrolled between October and January. If a household is enrolled in October or November, they would be interviewed during the January supplement but not during the March supplement. Thus, we expect about 50% of individuals in the JTS to appear in the ASEC.

[11] We thank Stanislav Kolenikov for his assistance with using his user-written Stata code *ipfraking* for this exercise.

[12] The variable JTYEARS is reported with an accuracy of one-hundredth of a year.

[13] WKSWORK1 includes weeks in which they worked for even a few hours and includes paid vacation and sick leave as work. UHRSWORK1 reports the number of hours usually worked in a week at the individual's main job (no time period specified).

[14] FIRMSIZE is the reported total number of persons who worked for the respondent's employer during the preceding calendar year, counting all locations where the employer operated.

measurement error is introduced here as the ASEC reports only total firm size. For individuals working for employers that have only one jobsite or that have all jobsites within 75 miles of each other, this is an accurate reflection of the number of employees within 75 miles. For individuals working for employers with multiple jobsites more than 75 miles apart, this will overestimate an individual's eligibility.

Having identified an individual's number of hours worked in the past year and firm size, we can construct simulated FMLA eligibility statuses based on potential policy changes. We focus on three potential changes: (i) reducing the requirement for hours worked from 1250 to 1000, (ii) reducing the firm size requirement from 50 to 10, and (iii) the combination of these two changes. The threshold of 10 is based on the available categories for firm size in the ASEC data: under 10, 10 to 49, 50 to 99, 100 to 499, 500 to 999, and 1000+.

We present current eligibility and simulated eligibility under each policy change for the full sample of employed adults (aged 18+) who are not self-employed and for the sub-sample of prime-working-age employed adults (aged 25 to 54). We then present estimates for employed adults within each of the following sub-groups: women, individuals with no more than high school education, low wage workers (earning less than $30,000 per year), those with family income below the poverty line, black workers, Hispanic workers, non-citizens, foreign born workers, rural residents, single parents, and individuals with a cohabiting same-sex partner or spouse.[15]

Findings

Current eligibility

Table 1 presents estimates of current eligibility for each demographic group. We estimate that 51.4% of adult workers aged 18+ are eligible for FMLA. This figure is higher when focusing on prime-working-age adults (55.3%).[16] Our estimate of overall eligibility is lower than the estimate using the EPFMLA data, 56%. Given that the EPFMLA has superior information regarding eligibility criteria (true hours worked in the past year and number of employees within 75 miles of jobsite), we conclude that the measurement error introduced by the proxies available in the CPS data create downward bias in the estimate. This is surprising given that the mismeasurement in the number of employees within 75 miles

[15] While sexual orientation is not self-reported for all individuals in the ASEC, we can identify LGBTQ individuals within the group of individuals who are married or have a cohabiting partner. This is defined as reporting a spouse or cohabiting partner with the same reported sex as the individual.

[16] Prime working age adults are those aged 25-54

of one's jobsite should result in overestimating eligibility. However, it is not possible to know the direction or magnitude of the bias introduced by the mismeasurement in hours worked in the past year. Another reason for the difference is that the EPFMLA data are from 2018 and we employ CPS data from 2012, 2014, 2016, and 2018. If FMLA eligibility is rising, this might explain the higher estimates from the EPFMLA. In fact, when using CPS data from 2018 only, we reproduce the EPFMLA estimate of 56% (55.8%). Nonetheless, we believe the estimates using the larger set of CPS data are useful for comparing relative eligibility across subgroups.

We find a number of demographic groups with FMLA eligibility that is lower than other adult workers. Groups with marginally lower eligibility include workers who are non-citizens, Hispanic, single parents, foreign born, rural residents, only high school educated, or women. These groups have eligibility rates of 41.2% to 49.9%, which are only slightly lower than the average of 51.4%, though each of these differences is statistically significant at the 0.1% level.[17] Groups with substantially lower eligibility include low wage workers (30.5%) and those below the poverty line (17.9%), differences that are also significant at the 0.1% level.[18] Groups with increased eligibility include black workers (54.9%, significant at 0.1% level) and workers with a same-sex spouse or cohabitating partner (57.1%, significant at 5% level).[19]

We also examine intersectional disadvantage by providing estimates of eligibility for women, high school educated workers, low wage workers, and those below the poverty line within sub-samples by race, ethnicity, and citizenship status. Among black workers, there is no measurable difference in eligibility for women, eligibility is slightly lower for the high school educated (52%, significant at 5%), and drops significantly for workers with low wages or living in poverty (32%, significant at 1%). Among Hispanic workers, there is no measurable difference in eligibility for women or the high school educated, but eligibility is lower for workers with low wages (30.1%, significant at the 0.1% level) and those living

[17] In most cases the CPS estimates for specific groups are lower than the estimates from EPFMLA, which excludes self-employed workers. However, for single parents this is not the case. We not that the CPS data indicate that single parents comprise only 4.8% of adult workers, suggesting that the EPFMLA data likely only includes approximately 214 single parents – a very small group on which to base eligibility estimates.

[18] Families below the poverty line are identified in the data as those with a total family income below the poverty line set for families with their demographic characteristics. This is provided in IPUMS as *poverty*. This variable compares the Census family's total income for the previous calendar year as reported in FTOTVAL to the poverty threshold as reported in CUTOFF and assigns all members of each CPS-identified family unit, not each household, the same value.

[19] We note that for workers with a same-sex spouse or cohabiting partner, we cannot separate the impact of LGBTQ status from married/cohabiting status. Married/cohabiting workers with opposite-sex partners also have higher rates of eligibility (51.1%) relative to single workers. Nonetheless, workers with same-sex spouses/partners still have slightly higher eligibility than those with opposite-sex spouses/partners.

in poverty (19.4%, significant at 0.1%). Among non-citizens, there is no measurable difference in eligibility for women, eligibility is slightly lower for the high school educated (38.4%, significant at 5%), and drops significantly for workers with low wages (28%, significant at 0.1% level) or those living in poverty (17.4%, significant at the 0.1% level). Based on these estimates, low wages and family poverty are the strongest predictors of eligibility. These factors are correlated with lack of access to FMLA more than other characteristics such as gender, race, ethnicity, nativity, citizenship, or other characteristics. In fact, among those living in poverty, eligibility is similar or higher among black workers (22.4%), Hispanic workers (19.4%), and non-citizens (17.4%) relative to eligibility in the full population living in poverty (17.9%).

Impacts of simulated policy changes

We now turn to simulations of eligibility under the three policy changes described above. Table 3 presents simulated eligibility under each policy change, with the current CPS estimate reproduced for ease of comparison. Column 5 of Table 3 presents the absolute change in eligibility under the third simulation, relative to the *status quo.*[20] Column 6 presents this as a relative change.

Our first finding is that policies that relax the firm size requirement from 50 to 10 would increase eligibility substantially (increasing overall eligibility from 51.4% to 61.1%), whereas polices that relax the required hours from 1250 to 1000 have a lesser impact (53.6%). Of course, combining the two policies has the greatest impact. We note that the simulated change in the firm size requirement is a very substantial change, however, we are unable to evaluate the impact of smaller changes in firm size given the aggregation of the firm size information into categories in the CPS data.

The combined policy would increase eligibility by 9.8 to 16.5 percentage points across all groups, with the largest absolute gains among non-citizens, followed closely by Hispanic workers, foreign born workers, and low-wage workers. In relative terms the benefits vary widely across demographic group, with the largest gains among groups with the lowest *status quo* eligibility. On average, eligibility increases by 24%. Among low wage workers and those living below the poverty line, increases are as large as 47% and 59%, respectively.

The patterns in simulated increases in eligibility among intersected groups mirror those for *status quo* eligibility. Within a race/ethnicity/citizenship group, the largest gains are seen for workers with low

[20] Eligibility under original FMLA criteria- annual work hours>=1250 and employer threshold>50

wages or below the poverty line. Within these disadvantaged groups – low wages and poverty – it does not appear that Hispanic workers or non-citizens (and certainly not black workers) are benefitted to a greater degree than other workers with low wages or living in poverty.

Conclusion

This study contributes to the understanding of current FMLA eligibility. We offer updated estimates of FMLA eligibility based on large-sample, nationally representative data, accounting for all eligibility criteria. We find that eligibility among all adult workers (age 18+) is 51.4%. While these estimates may be somewhat downward biased by focusing on a longer time period, the estimates are useful for comparing eligibility across groups.

We further provide estimates for demographic groups not previously studied with regards to FMLA eligibility. We identify several underserved communities that have low FMLA eligibility rates. We find that low income and poverty status have the strongest correlation with ineligibility, with eligibility rates in these populations as low as 18 to 30%. While we also find that low education, Hispanic ethnicity, and other characteristics are also associated with low eligibility, these factors are less salient than low income and poverty.

We find that when we define eligibility more inclusively, with a lower minimum firm size and a lower minimum number of working hours, the eligibility estimates based on data employed in this study increase by 47 to 59% among low earners and those living in poverty. We find larger changes in the estimates of eligibility when we only reduce the minimum firm size (from 50 down to 10), which increases eligibility 19%, relative to only reducing the minimum number of working hours (from 1250 to 1000), which increases eligibility 4%. While those with the lowest current eligibility stand to gain the most in relative terms, in absolute terms the biggest gains would be among non-citizen, Hispanic, foreign born, and low-wage workers.

Recommended data improvements based on this exercise include improving the measurement of firm size eligibility in the CPS, both by increasing the number and decreasing the size of the answer categories, and by separately asking firm size from number of employees with 75 miles of one's job site. This would reduce the measurement error in eligibility when using CPS data to determine eligibility status. In addition, including self-employed individuals in the EPFMLA sampling frame would improve the accuracy of the eligibility estimates based on those data.

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Tables

Table 1: FMLA eligibility of employed individuals, by subgroup

	N	Weighted share of sample	EP estimate	CPS estimate	
	(1)	(2)	(3)	(4)	
All	**105,043**		**0.56**	**0.514**	
Prime working age	69,342	66.8%		0.553	***
Women	52,126	48.4%	0.54	0.499	***
High school only	28,095	26.5%	0.50	0.483	***
Low wage	35,602	38.2%	0.38	0.305	***
Below poverty line	5,040	5.8%		0.179	***
Black	10,003	12.2%	0.57	0.549	***
Hispanic	13,790	16.4%	0.52	0.444	***
Non-citizen	6,871	8.7%		0.412	***
Foreign born	16,112	18.2%		0.476	***
Rural	19,870	13.4%		0.479	***
Single parent	4,906	5.1%	0.43	0.461	***
Same sex partner	1,005	1.1%		0.571	*

Note: Column 1 indicates the number of employed individuals in each category observed in the CPS and matched across the ASEC and JTS in 2012, 2014, 2016, and 2018. Column 2 indicates the share of the employed sample represented by each group after employing sampling weights. Column 3 reports the proportion of the group that is FMLA eligible as estimated by Brown, Roy, and Klerman (2020) using the 2018 Employee Perspectives survey (N=4,470). Column 4 reports estimates of FMLA eligibility using the CPS sample. Prime working age is defined as aged 25-54. Low wage is defined as earnings less than $30,000 a year. *** indicates that the group's eligibility is significantly different from those not in the group at the 0.1% level, or * at the 5% level. Source: authors' calculations based on CPS data from IPUMS (Ruggles et. al. 2021).

Table 2: FMLA eligibility of employed individuals, by intersected subgroup

	N	Weighted share of sub-sample	CPS estimate	
	(1)	(2)	(3)	
Black	**10,003**		**0.549**	
Women	5,637	0.541	0.549	
High school only	3,206	0.323	0.520	**
Low wage	4,072	0.463	0.380	***
Below poverty line	855	0.0972	0.224	***
Hispanic	**13,790**		**0.549**	
Women	6,274	0.432	0.446	
High school only	4,333	0.31	0.430	
Low wage	6,400	0.517	0.301	***
Below poverty line	1,309	0.108	0.194	***
Non-citizen	**6,871**		**0.412**	
Women	2,809	0.383	0.401	
High school only	1,762	0.257	0.384	*
Low wage	3,799	0.56	0.280	***
Below poverty line	879	0.134	0.174	***

Note: Column 1 indicates the number of employed individuals in each category observed in the CPS and matched across the ASEC and JTS in 2012, 2014, 2016, and 2018. Column 2 indicates the share of the sub-group represented by each group after employing sampling weights. Column 3 reports estimates of FMLA eligibility using the CPS sample. Low wage is defined as earnings less than $30,000 a year. *** indicates that the group's eligibility is significantly different from others in the same race/ethnicity/citizenship sub-group who are not in the specified gender/education/wage/poverty group at the 0.1% level, ** 1% level, * 5% level. Source: authors' calculations based on CPS data from IPUMS (Ruggles et. al. 2021).

Table 3: Simulated FMLA eligibility of employed individuals, by subgroup

	CPS estimate	Simulation Hours>=1000	Simulation Firm size>=10	Simulation Hours>=1000 & Firm size>=10	Absolute change Col (4) relative to Col (1)	Percent change Col (4) relative to Col (1)
	(1)	(2)	(3)	(4)	(5)	(6)
All	0.514	0.536	0.611	0.638	0.124	24%
Prime working age	0.553	0.571	0.657	0.679	0.126	23%
Women	0.499	0.532	0.585	0.624	0.125	25%
High school only	0.483	0.504	0.594	0.62	0.137	28%
Low wage	0.305	0.349	0.394	0.448	0.143	47%
Below poverty line	0.179	0.212	0.241	0.284	0.105	59%
Black	0.549	0.574	0.62	0.65	0.101	18%
Hispanic	0.444	0.463	0.568	0.592	0.148	33%
Non-citizen	0.412	0.429	0.554	0.577	0.165	40%
Foreign born	0.476	0.496	0.595	0.619	0.143	30%
Rural	0.479	0.497	0.585	0.608	0.129	27%
Single parent	0.461	0.485	0.551	0.58	0.119	26%
Same sex partner	0.571	0.596	0.641	0.669	0.098	17%
		0.042801556	0.188715953			

Note: Column 1 reproduces estimates from Table 1. Columns 2-4 present simulated FMLA eligibility under the specified policy change. Column 5 is the absolute change in eligibility under the policy change in Column 4, relative to the *status quo*; Column 5 is the relative change. Prime working age is defined as 15-54. Low wage is defined as earnings less than $30,000 a year. Source: authors' calculations based on CPS data from IPUMS (Ruggles et. al. 2021).

Table 4: Simulated FMLA eligibility of employed individual, by intersected sub-groups

	CPS estimate	Simulation Hours>=1000	Simulation Employees>=10	Simulation Hours>=1000 & Employees>=10	Absolute change Col (4) relative to Col (1)	Percent change Col (4) relative to Col (1)
	(1)	(2)	(3)	(4)	(5)	(6)
Black	0.549	0.574	0.62	0.65	0.101	18%
Women	0.545	0.577	0.617	0.656	0.111	20%
High school only	0.52	0.543	0.599	0.628	0.108	21%
Low wage	0.38	0.426	0.449	0.506	0.126	33%
Below poverty line	0.224	0.27	0.279	0.335	0.111	50%
Hispanic	0.444	0.463	0.568	0.592	0.148	33%
Women	0.446	0.475	0.539	0.574	0.128	29%
High school only	0.43	0.451	0.559	0.584	0.154	36%
Low wage	0.301	0.334	0.423	0.465	0.164	54%
Below poverty line	0.194	0.225	0.291	0.335	0.141	73%
Non-citizen	0.412	0.429	0.554	0.577	0.165	40%
Women	0.401	0.428	0.507	0.542	0.141	35%
High school only	0.384	0.4	0.533	0.558	0.174	45%
Low wage	0.28	0.304	0.419	0.453	0.173	62%
Below poverty line	0.174	0.193	0.29	0.321	0.147	84%

Note: Column 1 reproduces estimates from Table 2. Columns 2-4 present simulated FMLA eligibility under the specified policy change. Column 5 is the absolute change in eligibility under the policy change in Column 4, relative to the *status quo*; Column 5 is the relative change. Low wage is defined as earnings less than $30,000 a year. Source: authors' calculations based on CPS data from IPUMS (Ruggles et. al. 2021).

Annex: Policy Evaluation

Following the introduction of FMLA in 1993, seven states made changes to their own unpaid leave policy by either expanding the definition of family or reducing the employer threshold, or both. In Table 5, we describe recent changes and their effective dates. We aimed to evaluate the impact of these state-level policy changes on leave usage to verify whether the simulated changes presented above are borne out.

Recent changes in California (2021) and New Jersey (2019) are too recent to yet evaluate. In Minnesota, a change to the employee threshold was packaged together with a significant change in eligible events, making it impossible to identify the impact of the employee threshold change on its own. In Oregon, the change related to the definition of family only. We focused our analysis on Maine, Maryland, and the District of Columbia.[21]

We employ the full sample of ASEC data from 2000 to 2019, which includes 549,920 prime-working-age employed individuals. Our outcome of interest is leave usage, defined as leave taken in the past week for own illness/injury/medical problems, maternity/paternity leave, or other family/personal obligation. We note that this overestimates usage of FMLA, since it encompasses any type of leave (including paid or unpaid leave that may or may not be job-protected) and because many family or personal obligations would not be eligible for FMLA. At the same time, we note that the mean of this indicator is very low, as it only measures leave use in the past week, rather than a more comprehensive measure such as whether the individual has used any leave in the past year, for example. Only 1% of the sample reports leave usage in the past week.

To identify the impact of the changes in state-based FMLA requirements on leave usage, we propose a difference in difference estimation, conducted separately for each of the three states of interest. The estimating equation is:

$$Y_{it} = \gamma + \beta_1 T_i + \beta_2 After_t + \beta_3 (T_i \times After_t) + \upsilon_t + \varepsilon_{it}$$

where Y_{it} indicates leave usage of individual i in year t. T_i indicates that the individual resides in the treatment state. $After_t$ indicates that year t is after the year of the policy of interest. We also include

[21] We note that the change in DC was a combination of a change to the employee threshold and the definition of family, however, the change to the definition of family was minor, in that it would only affect very few individuals.

year fixed effects, υ_t, that capture the unobservable factors that vary by year. β_3 estimates the impact of the policy change under the assumption that the underlying trends in leave usage between the treatment state and the control states would be parallel if the policy change in the treatment state were not introduced.

We select as control states the states which are geographically contiguous or economically similar to the treatment states and have no state-specific FMLA changes between 2001 and 2018. The control states for DC and Maryland are Virginia, Pennsylvania, Delaware, and West Virginia and the control states for Maine are New Hampshire, Vermont, and Massachusetts.

In order to interpret difference in differences estimates as causal, it is necessary to verify that the assumption of common trends is met. That is, that in the absence of the policy change, the trend in leave usage would have been the same in the treated state as what is observed in the control states. To test this, we compare trends in leave usage across these two groups prior to the policy change.

In Figures 1 to 3, weekly leave usage rates are plotted over the eight-year period surrounding the policy change in each state. In none of the states can we verify that the trend in weekly leave usage is the same across the treatment and control states prior to the onset of the policy. This is primarily due to the non-monotonicity in the trends. That is, we observe so few individuals reporting leave usage in the past week, that there is not a smooth trend over time. Due to the very low means, there is high variability year-to-year. This prevents us from estimating reliable year-to-year trends and therefore prevents verification of the identification assumption. Even when binning observations biennially, trends are still not smooth over time.

Our conclusions from this exercise are the following. First, we cannot use a difference in differences strategy to estimate the impact of state-level policy changes in FMLA on leave usage. Second, the primary reason for this is that the available data on leave usage is poor. The CPS does not measure leave usage over the past year, only over the past week. Means of weekly leave usage are too low to estimate reliable trends over time. While other data sets have better information on leave usage, specifically, the EPFMLA survey, the sample size in this survey is too small to support state-specific analyses.

Table 5: Recent state-based changes in FMLA requirements

State	Change(s)	Year
California[22]	Firms size threshold: 5+ Worksite mileage requirement is eliminated. Definition of family (to include an adult child, a child of a domestic partner, grandparent, grandchild, or sibling)	2021
New Jersey[23]	Firm size threshold: 30+ Definition of family (to include siblings, grandparents, grandchildren, parents-in-law, any blood relative, and “any individual that the employee shows to have a close association with the employee which is the equivalent of a family relationship.”)	2019
Minnesota[24]	Definition of leave (to include leave for pregnancy, childbirth, or related health conditions) Firm size threshold: 21+	2014
Maryland[25]	Firm size threshold: 15+	2014
District of Columbia[26]	Firm size threshold: 20+ Definition of family (to include fostering)	2010
Oregon[27]	Definition of family (to include domestic partners, grandparents and grandchildren)	2008
Maine[28]	Firm size threshold: 15+	2007

Note: See footnotes for information sources

[22] “Coming Soon: Expanded family and medical leave in California” (2020) California Department of Fair Employment & Housing. https://www.dfeh.ca.gov/wp-content/uploads/sites/32/2020/12/Coming-Soon_Expanded-Family-And-Medical-Leave_ENG.pdf

[23] “The New Jersey Family Leave Act” (2019). State of New Jersey Office of the Attorney General Division on Civil Rights. https://www.nj.gov/oag/dcr/downloads/posters/8x11_flaposter.pdf

[24] “Minnesota Statutes” (2021). Minnesota Office of the Revisor of Statues. https://www.revisor.mn.gov/statutes/cite/181.940

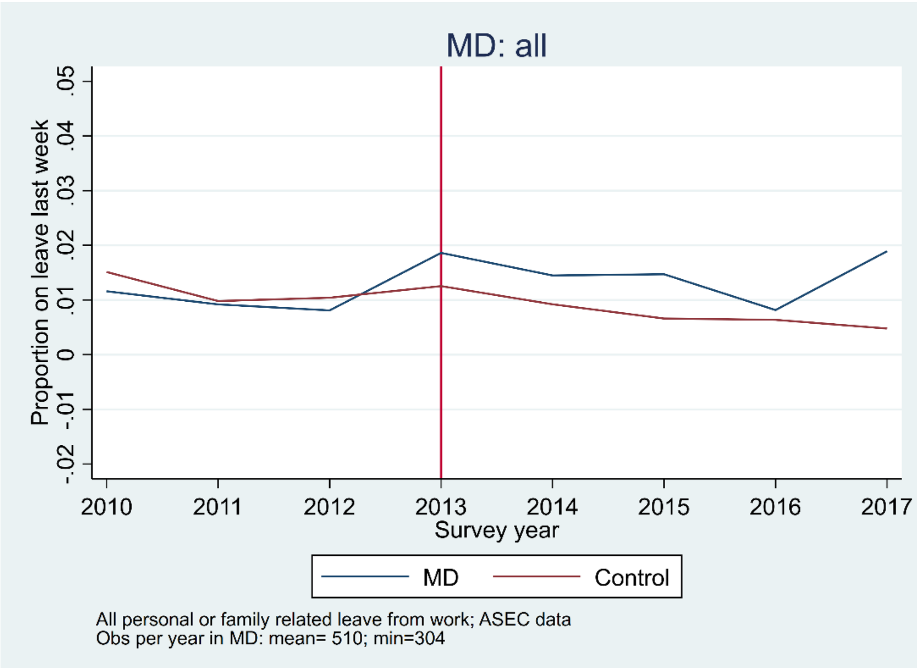
[25] “Parental Leave Act Strengthens Maryland Employee Leave Protections” (2014). JacksonLewis https://www.jacksonlewis.com/resources-publication/parental-leave-act-strengthens-maryland-employee-leave-protections

[26] “Amend Family and Medical Leave Act implementing regulations” (2010). District of Columbia Municipal Regulations. District of Columbia Register Volume No.19. https://www.dcregs.dc.gov/Common/NoticeDetail.aspx?NoticeId=N0002220

[27] “BOLI Issues Final Rules Relating to Employee Leaves Of Absence And Rest Breaks For Nursing Mothers” (200(). Bullard Law Regulatory Notebook. https://bullardlaw.com/news/alert/boli-issues-final-rules-relating-to-employee-leaves-of-absence-and-rest-breaks-for-nursing-mothers/

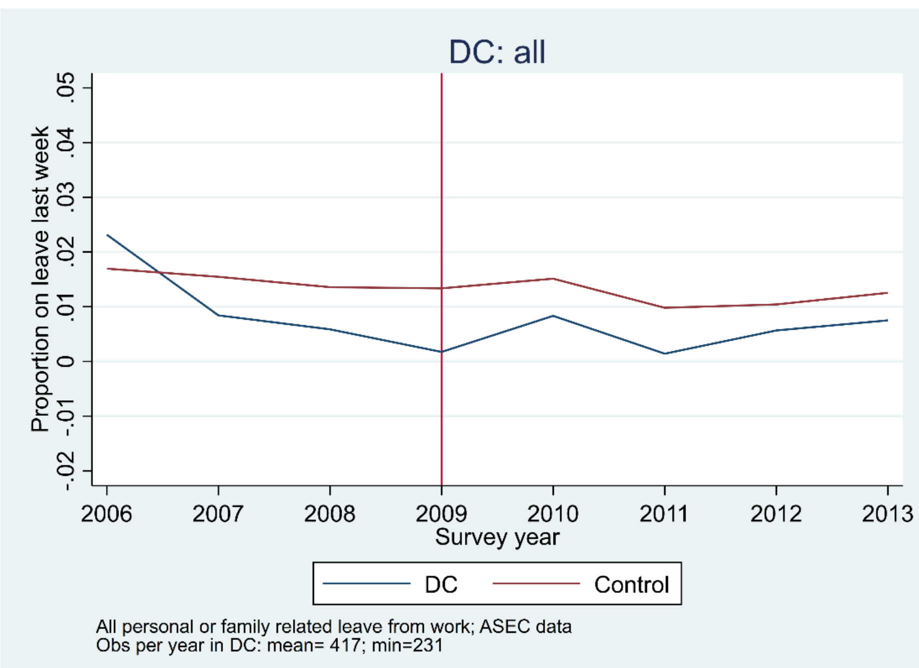
[28] “§844. Family medical leave requirement” (2007). Maine Legislature, Office of the Reviser of Statues. Title 26 Labor and Industry, Chapter 7 Employment Practices, Sub-chapter 6-A Family Medical Leave Requirement. https://www.mainelegislature.org/legis/statutes/26/title26sec844.html

Figure 1: Trends in weekly leave usage (Maryland)



Source: authors' calculations based on CPS ASEC data 2000-2019 from IPUMS (Ruggles et. al. 2021). Includes prime-working-age (25-54) employed individuals.

Figure 2: Pre trends in leave usage (District of Columbia)



Source: authors' calculations based on CPS ASEC data 2000-2019 from IPUMS (Ruggles et. al. 2021). Includes prime-working-age (25-54) employed individuals.

Figure 3: Pre trends in leave usage (Maine)

Source: authors' calculations based on CPS ASEC data 2000-2019 from IPUMS (Ruggles et. al. 2021). Includes prime-working-age (25-54) employed individuals.