Childcare Access and Female Unemployment During the Coronavirus Pandemic *

Becky Scurlock

June 7, 2020

1 Introduction

On March 13, 2020, U.S. President Donald J. Trump declared a national emergency in response to the outbreak of a highly contagious coronavirus disease, COVID-19 (Trump 2020). Almost immediately, a wave of business shutdowns, school closures, and stay-at-home orders swept the nation. Within ten days, 40 U.S. states had closed all K-12 schools, and from March to April, unemployment spiked from 4.4% to 14.4% (Education Week 2020, U.S. Department of Labor 2020). While many Americans were forced to readjust, women were hit especially hard. The unemployment rate for both men and women was 4.4% in March, yet by April, women's unemployment had increased to 16.2% while men's unemployment was only 13.5% (U.S. Department of Labor 2020). There are many possible explanations for this trend. Occupations with the highest firing rates may have been dominated by women, or men may have been more willing to take the risk of going to work. Alternatively, employers may have simply discriminated against female employees. In this paper, I examine the hypothesis that women's unemployment increased faster than men's unemployment because women needed to take care of children who were no longer in school. After K-12 schools closed in mid-March, many women may have needed child care to continue working. Those

*Thank you to Ashley Colburn and Scott Bailey for providing access to data on childcare and unemployment claims in Washington State.

who did not have access to this service may have left their jobs at a higher rate.

The relationship between access to child care and female unemployment is well-documented in the literature. Tekin (2007) found that lower child care prices led to an increase in unemployment among single mothers in the United States. Similarly, Cascio (2009) found that since 1960, about half of single mothers entered the work force after their youngest child enrolled in kindergarten. While these studies found no significant effect on employment of married women, they still suggest that the overall rate of female employment is positively correlated with access to child care. In fact, Han and Waldfogel (2001) find that reductions in child care costs could increase employment of married mothers by 3 to 14 percentage points (compared to 5 to 21 percentage points for single mothers). More recently, Gray (2019) found that working mothers in the U.S. generally quit their jobs less often where childcare subsidies are more generous. This evidence supports the hypothesis that unemployment may have increased less among women who had access to low-cost childcare during the COVID-19 pandemic.

To probe this question, I examine the effect of child care provision by school districts on female employment in Washington State. When Governor Jay Inslee ordered all public and private K-12 schools to close on March 13, many families were left without weekday child care (OSPI 2020). In response to this problem, some school districts began to provide daycare for children too young to continue their studies online (Bazzaz 2020). Since these services were funded by school districts, families could access them free of charge in the school district where their child was enrolled (Achievement Data 2020). However, some school districts did not provide child care, ostensibly due to difficulties finding staffing and protective equipment (Bazzaz 2020). In this paper, I test whether the difference between male and female unemployment increased more in areas where school districts did not provide child care.

2 Data

I obtained data on child care provision by school district from the Washington State Office of Superintendent of Public Instruction (Achievement Data 2020). This data was was collected from a weekly survey of the state's 294 school districts. Respondents answered more than 50 questions about the resources they were providing for students and families during the COVID-19 pandemic. I used responses to the following questions:

1. "Are you directly providing or funding child care for your community?"

2. "Number of child care openings available"

Summary statistics for the survey response rates by week and question ("Response Rate"), percent of school districts in each county providing child care ("Child Care," weighted by enrollment), and number of child care openings in thousands ("Openings") are reported in Table 1. On average, 83% of school districts responded each week from March 28, 2020 to May 23, 2020. All respondents answered Question 1 (providing or funding childcare), but an average of only 37% responded to Question 2. Since this response rate was so low (perhaps because it was later in the survey and required more than a "yes" or "no" answer), the analysis focuses on Question 1 but includes Question 2 as an alternative measure of child care access. Since the percent of school districts providing childcare was weighted by preschool and elementary school enrollment, the "'Child Care" statistics show that on average, 57% of students in districts responding to Question 1 were eligible for child care. Finally, the average number of recorded openings in a county and week was 146. Given that more than half of students lived in districts providing child care (according to the Question 1 responses) but only 37% of districts responded to Question 2, this is likely a significant underestimate.

I obtained data on unemployment claims by county, week, and gender from the Washington State Employment Security Department (not available online). While changes in unemployment claims do not directly measure changes in unemployment, claims may more accurately capture the number of women leaving the workforce. Women are likely to make claims soon after leaving their jobs, and their claims may be denied if child care is not deemed a valid reason for unemployment. Table 1 displays summary statistics for female and male unemployment claims. Data was missing when counts were very low, but this issue should not significantly affect total claims. Surprisingly, about 130 more men than women filed claims in the average county/week, and the average female share of unemployment claims was only 48.6%. This may reflect the fact that more men are in the labor force than women. To test this possibility, I calculate the difference in unemployment rate growth between men and women ("Growth Difference") as $\frac{C_{it}^{w}}{N_{i}^{w}} - \frac{C_{it}^{m}}{N_{i}^{m}}$, where C_{it}^{s} is the number of new claims for gender s in county i and week t and N_{i}^{s} is the labor force population for gender s in county i. While this ratio is positive on average, I fail to reject that it is significantly different from zero (Table 1). Unfortunately, this imprecision may result from the fact that the labor force data (obtained from the U.S. Census Bureau) was measured imprecisely and was aggregated from 2014-2018 (U.S. Census Bureau 2018). This measure should therefore be interpreted with caution.

Other data used in this paper includes 2019-2020 preschool and elementary school enrollment by school district, obtained from the State of Washington (State of Washington 2020), and the county where each school district is located, downloaded from the Washington Geospatial Open Data Portal (OCIO Geospatial Program 2020). Enrollment data was used to weight child care provision by school district, as previously explained, and geospatial data was used to match school districts to counties. Note that each school district is fully contained in one of the state's 39 counties, so I was able to aggregate data from school district to county level.

3 Methods

My analysis is based on the following linear model, where X_{it} is the weighted proportion of school districts providing child care and Y_{it} is the female share of unemployment claims (for county i and week t):

$$Y_{it} = \beta X_{it} + \alpha_i + \tau_t + \varepsilon_{it}$$

Here, α_i and τ_t denote county and week fixed effects, respectively, and ε_{it} is an error term with mean zero. Under the assumption that $Cov(X_{it}, \varepsilon_{it}) = 0$, this model corresponds to a linear fixed effects regression of Y_{it} on X_{it}, and we can interpret β as the causal effect of a 1-unit increase in X_{it} on Y_{it}. In this case, since X_{it} is a proportion, β represents the effect of providing childcare on Y_{it} (an increase from 0 to 1 would be an increase from no districts to all districts providing child care). In alternative specifications, I redefine X_{it} as the weighted proportion of school districts providing child care in week $t-1$ or the number of child care openings (in thousands), and Y_{it} as the unemployment growth difference defined in Section 2.

To make the assumption that $Cov(X_{it}, \varepsilon_{it}) = 0$, we must verify that there are no factors other than X_{it} that vary across both counties and weeks which could affect Y_{it}. Though we cannot prove that this is true, it seems plausible that most other factors influencing the share of female unemployment claims (or unemployment growth difference) are either time-invariant or vary consistently across counties over time. Since the data spans only two months, it seems reasonable to assume that characteristics of female workers and their employers, such as occupation, risk aversion, and tendency to discriminate against women remain constant during this period. Differences in these factors across counties should be absorbed by county fixed effects. Furthermore, changes in coronavirus conditions or policies at the state (or national) level should vary consistently across counties, such that they are absorbed by week fixed effects.

However, one can imagine factors varying across both counties and weeks that may have affected the female unemployment claim share. For example, the rate of increase or decrease in coronavirus cases may have varied drastically across counties over time. If women are more risk-averse than men, then female unemployment claims may have increased more in counties with more coronavirus cases. It is also possible that the decision to provide child care was endogenous: women may have already been more likely to stay employed in districts that provided child care. Thus, while county and week fixed effects control for many possible determinants of the female share of unemployment claims, we cannot guarantee that $Cov(X_{it}, \varepsilon_{it}) = 0$, and thus that the fixed effects regression has a causal interpretation.

4 Results

The results of the regression of female unemployment claim share on child care (the percentage of districts providing child care weighted by enrollment) are displayed in columns 1 and 2 of Table 2. While the estimated coefficients are negative, as expected (a negative coefficient implies that an increase in child care provision corresponds to a decrease in the female share of unemployment), it is insignificant at any conventional confidence level with both robust and clustered standard errors. In fact, replacing child care with child care in the previous week (columns 3 and 4), the coefficients are similar in magnitude but opposite in sign (the standard errors are also similar). Were these estimates significant, they would suggest that if all districts in a county started providing child care in the same week, then the female unemployment claim share would decrease by about 1%, but the following week, it would increase by 1%. Thus, the results of these regressions provide no conclusive causal insights, and we fail to reject the hypothesis that child care had no effect on the female share of unemployment claims.

For the reasons described in Section 2, the other regressions (which use number of child care openings as the independent variable and/or unemployment growth difference as the dependent variable) must be interpreted with caution, due to data limitations. In columns 5 and 6 of Table 2, I use female unemployment claim share as the dependent variable and child care openings as the independent variable. While the (negative) coefficient is insignificant with robust standard errors, it becomes significant at the 5% level when clustering standard errors by county and week. Since openings are measured in thousands, this estimate provides some evidence that 1,000 new child care openings could result in a 1% decrease in the female unemployment claim share.

Table 3 displays the results from regressions of the unemployment growth difference (the difference in the ratios of female claims to female labor force and male claims to male labor force) on child care, child care in the previous week, and openings. While all coefficients are negative, they are very small and imprecisely estimated (only the coefficient from the regression on openings with clustered standard errors (column 6) is significant at the 10% level). Given that the mean growth difference is only 0.003 with standard deviation 0.007 (Table 1), the magnitudes of these coefficients could be economically significant (they imply a 0.1% or 0.2% decrease in the difference between the share of women and men in the labor force making unemployment claims for a 1-unit increase in the independent variable; these numbers are small because the labor force is much larger than the number of people making unemployment claims). However, since the coefficients are not statistically significant, we cannot reject the null hypothesis that child care and openings have no effect on the growth difference (only column 6 provides very tentative evidence that openings may reduce the growth difference). The combination of incomplete data and low statistical signficance make the results of the regressions in Table 3 inconclusive.

While there are few results to check for robustness, Table 4 displays the results of regressions that test the effect of potential issues in the data (with female unemployment claim share as the dependent variable). In column 1, I replace all "missing" unemployment claims with 0, since we know the count for these claims is small. This adjustment provides a "lower bound" on the effect of the missing data. The results show that under this specification, the coefficient on child care nearly triples in magnitude and changes sign, while remaining insignificant. This test provides further evidence that the true coefficient on child care may not be negative.

Next, I make the child care variable constant across school districts over time (I take the most common response, “Yes” or “No,” and extend it to the whole period). Some school districts alternated between “Yes” and “No,” so this test controls for potential error in survey responses. This adjustment should make childcare constant in each county over time, reducing the number of observations to 39. In reality, the calculated child care shares vary because different numbers of districts responded to the survey each week. I therefore kept only the calculated share for each county when the maximum number of school districts responded, and extended this value to all time periods. The resulting coefficient (column 2) is still negative, but it is much lower in magnitude and has nearly double the standard error as the estimate in Table 2, column 1. According to this test, the true coefficient on child care is likely to be zero.

I then address the low (and highly variable) response rate for the number of child care openings by weighting each observation by the inverse of the proportion of students in the county enrolled in responding districts (column 3). This adjustment effectively extends the number of openings to the entire county such that the ratio of openings to enrollment remains constant. Again, while the coefficient remains negative, it decreases in magnitude and is statistically insignificant with clustered standard errors. This result suggests that the significant estimate in column 6, Table 2 may be biased by the low response rate.

Finally, I test whether the female share of unemployment claims was already increasing faster before schools closed in districts that did not provide child care. In columns 4 and 5, I regress the difference in female claim share between the weeks ending on March 14 and March 7 on the independent variable in the end period (either child care or openings). Though the estimates are insignificant, they are both negative, suggesting that the female unemployment claim share may have already been increasing more slowly before the pandemic in districts that provided more child care. Compared to the other regressions, these estimates are quite large in magnitude. If significant, column 4 would suggest that an increase in child care from 0 to 1 in the end period corresponds to an 8.4% decrease in the change in female unemployment claim share in the pre-period, and column 5 would imply that this share increased by 4.6% less before the pandemic in counties with 100 more openings in the end period (recall that openings are measured in thousands). Though these estimates are not reliable (due to missing data, observations in nearly half of counties were dropped), they show that we cannot reject the possibility that endogeneity in child care provision tainted the results.

5 Conclusion

While the estimated regression coefficients mostly have the correct sign, the lack of significance and failure of robustness checks prevent us from rejecting the hypothesis that child care provision has no effect on the female unemployment claim share. In fact, the possibility that this share was increasing faster pre-COVID-19 in districts that did not provide child care suggests that the true coefficient may not have a causal interpretation (since the assumption that $Cov(X_{it}, \varepsilon_{it}) = 0$ may not hold). However, the lack of significant results may have been caused by poor data quality. Much of the survey data was missing (and possibly inaccurate), unemployment claim data was only available at the county level, and labor force data was aggregated across a 5-year period ending two years ago. These issues significantly reduced the number of observations in the analyzed data, and may have amplified estimation error.

Given more time, I would try to address these issues by finding the number of unemployment claims by school district. With this data, I would be able to run a difference-in-differences regression where the "treatment" was child care provision (I would make child care provision consistent across time in each district, as in column 2 of Table 4). This would allow me to avoid issues of endogeneity and greatly increase the number of observations in my dataset (from 39 counties to 294 school districts across 9 weeks). However, as suggested by columns 4 and 5 of Table 4, parallel trends may not hold, so I would need to check this assumption carefully to make any causal inference. Alternatively, I could search for an instrument that was correlated with child care provision but uncorrelated with any other factor affecting the female unemployment share (and that only affected this share through child care provision). While it is difficult to imagine a variable that meets these criteria, detailed research on how school districts decided to provide child care may reveal a potential instrument. Finally, better labor force data may allow for a more reliable estimate of the difference in the unemployment growth rate between men and women. While the results may remain insignificant, more fine-grained and accurate data would increase my confidence in the estimated effect of child care provision on female unemployment.

In conclusion, this paper provides no evidence that lack of child care contributed to the increase in female unemployment during the coronavirus pandemic, yet we cannot conclude that this effect was null. Given the large standard errors, potential endogeneity, and low data quality, the results of these regressions are provisional at best. Further research using better data, more plausible assumptions, and more convincing robustness checks may succeed in identifying a causal effect.

Bibliography

Achievement Data (2020, May). Data: All Responses. *Tableau Public*. https://public.tableau.com/profile/achievement.data.hidden#!/vizhome/ServicesProvidedDuringSchoolClosures/Notes?publish=yes.

Bazzaz, D. (2020, May). How Washington school districts are succeeding and struggling since coronavirus shut them down. *The Seattle Times*. https://www.seattletimes.com/education-lab/everything-we-know-about-what-washington-school-districts-have-been-doing-since-coronavirus-shut-them-down/.

Cascio, E. U. (2009). Maternal Labor Supply and the Introduction of Kindergartens into American Public Schools. *Journal of Human Resources 44*(1), 140–170. https://muse.jhu.edu/article/466691/pdf.

Education Week (2020, May). Map: Coronavirus and School Closures. *Editorial Projects in Education*. https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html.

Gray, A. (2019). *Female Unemployment and Statistical Discrimination: The Revealing Effects of Child Care Subsidies*. Ph. D. thesis, Johns Hopkins University. http://www.econ2.jhu.edu/jobmarket/2018/GrayA/JobPaper/JobPaperGrayA.pdf.

Han, W. and J. Waldfogel (2001). Child Care Costs and Women's Employment: A Comparison of Single and Married Mothers With Pre-School-Aged Children. *Social Science Quarterly 82*(3), 552–568. https://www.jstor.org/stable/42955741.

OCIO Geospatial Program (2020, April). School Districts - Washington State. *Washington Geospatial Open Data Portal*. https://geo.wa.gov/datasets/OSPI::school-districts-washington-state/data.

OSPI (2020, May). Novel Coronavirus (COVID-19) Guidance and Resources. *Washington Office of Superintendent of Public Instruction*. https://www.k12.wa.us/about-ospi/press-releases/novel-coronavirus-covid-19-guidance-resources.

State of Washington (2020, May). Report Card Enrollment 2019-20 School Year. *Data.WA.gov*. https://data.wa.gov/Education/Report-Card-Enrollment-2019-20-School-Year/gtd3-scga.

Tekin, E. (2007). Childcare Subsidies, Wages, and Employment of Single Mothers. *The Journal of Human Resources 42*(2), 453–87. https://www.jstor.org/stable/40057313.

Trump, D. J. (2020, March). Proclamation on Declaring a National Emergency Concerning the Novel Coronavirus Disease (COVID-19) Outbreak. https://www.whitehouse.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/.

U.S. Census Bureau (2018). 2018: ACS 5-Year Estimates Subject Tables. *United States Census Bureau*. https://data.census.gov/cedsci/table?q=S2301&tid=ACSST1Y2018.S2301.

U.S. Department of Labor (2020, May). Labor Force Statistics from the Current Population Survey. *U.S. Bureau of Labor Statistics*. https://www.bls.gov/web/empsit/cpseea10.htm.

Tables

Table 1: Summary Statistics

	N	Mean	SD	Min	Max
Response Rate (C)	9	0.830	0.057	0.697	0.888
Response Rate (O)	9	0.367	0.029	0.306	0.391
Child Care	346	0.571	0.350	0	1
Openings (1,000)	346	0.146	0.443	0	3.306
Female Claims	346	1304	3238	0	33198
Male Claims	346	1435	3585	0	30751
Female Share	238	0.486	0.070	0	0.659
Growth Difference	238	0.003	0.007	-0.032	0.030

NOTES: Response Rate (C) is the proportion of school districts that reported whether they were providing child care, and Response Rate (O) is the proportion that reported the current number of child care openings. All districts that reported the number of child care openings also reported whether they were providing child care. Other variables are described in the main text.

Table 2: Regressions with Female Unemployment Claim Share as Dependent Variable

VARIABLES	(1) Robust SEs	(2) Clustered SEs	(3) Robust SEs	(4) Clustered SEs	(5) Robust SEs	(6) Clustered SEs
Child Care	-0.007	-0.007				
	(0.022)	(0.023)				
Child Care (Lagged)			0.010	0.010		
			(0.026)	(0.025)		
Openings					-0.010	-0.010**
					(0.009)	(0.004)
Observations	237	237	208	208	237	237
R-squared	0.352	0.352	0.426	0.426	0.353	0.353

NOTES: Standard errors in columns 2, 4, and 6 are clustered by county and week. Those in columns 1, 3, and 5 are heteroskedastic robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Regressions with Difference in Unemployment Rate Growth as Dependent Variable

VARIABLES	(1) Robust SEs	(2) Clustered SEs	(3) Robust SEs	(4) Clustered SEs	(5) Robust SEs	(6) Clustered SEs
Child Care	-0.002	-0.002				
	(0.002)	(0.001)				
Child Care (Lagged)			-0.001	-0.001		
			(0.002)	(0.001)		
Openings					-0.001	-0.001*
					(0.001)	(0.000)
Observations	237	237	208	208	237	237
R-squared	0.607	0.607	0.632	0.632	0.607	0.607

Notes: Standard errors in columns 2, 4, and 6 are clustered by county and week. Those in columns 1, 3, and 5 are heteroskedastic robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Robustness Checks

VARIABLES	(1) Missing = 0	(2) Child Care Constant	(3) Weighted Openings	(4) Pre-Period	(5) Pre-Period
Child Care	0.020	-0.002		-0.084	
	(0.065)	(0.047)		(0.068)	
Openings			-0.002		-0.459
			(0.006)		(0.407)
Observations	346	39	208	20	20
R-squared	0.342	0.000	0.429	0.061	0.062

Notes: The standard errors in columns 1 and 3 are clustered by county and week. Those in columns 2, 4, and 5 are heteroskedastic robust. In columns 1-3, the dependent variable is the proportion of unemployment claims made by women. In columns 2-4, it is the pre-period difference in this proportion. *** p<0.01, ** p<0.05, * p<0.1.