

Attending Preschool at Ages 3 and 4: Impact on Wages in Adulthood



**Kayla Turk
University of Akron
Department of Economics
Senior Project
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Abstract

With years of existing research on the short- and long-term effects of early childhood education, this paper aims to build on how adult wages are dependent on early childhood education while capturing the importance of attending preschool by the ages of 3 and 4. My research is founded on human capital theory and utilizes the Mincer earnings function to analyze whether children with preschool education at the ages of 3 and 4 work at higher-paying jobs as adults than children without preschool education at these ages. While appropriately significant results in wages are yielded regarding total years of education and work experience amongst other variables that capture disadvantages within the labor market, there are limitations within the data that make it difficult to conclude that the age in which a child begins their education has a significant impact.

Table of Contents

I. Introduction.....	5
II. Literature Review.....	9
III. Theoretical Model and Testable Hypothesis.....	15
IV. Empirical Examination.....	18
<i>Data.....</i>	18
<i>Regression Analysis.....</i>	19
<i>Results.....</i>	22
V. Conclusions.....	25
References.....	27
Appendix.....	29

I. Introduction

“By age 3, inequality is clear: Rich kids attend school. Poor kids stay with a grandparent.” At least that is what author Heather Long claims in her 2017 article titled as such in the Washington Post. Reading this article made me wonder, does a child who attends preschool at a young age end up all-around more successful than their non-attending peers? Turns out, there are several years of research and studies done on the costs and benefits of early childhood education. The benefits in many writings seem plentiful: development of cognitive skills, such as reading, writing, and mathematics; greater academic achievement, such as higher test scores and overall GPA; development of non-cognitive skills, such as social interaction, self-discipline, and motivation; higher earnings during adulthood; lower rates of crime; and the list goes on. Even in Long’s article, she makes the case that children without formal pre-schooling are indefinitely a year behind in verbal and mathematical skills, while they also end up in lower-paying jobs. However, there are trade-offs in every decision.

One cost can be the lack of one-on-one time with the child. With the number of children in one class that a teacher must account for, there is much less individualized time per child than they have the chance of receiving at home. Another immediate- and constant-felt cost of enrolling a child in preschool is of course the dollar amount itself, which according to the National Association of Child Care Resource and Referral Agencies (NACCRRA) ranges on average from \$4,460 to \$13,158 per year depending on the quality and location of the school, which would equate to \$372 to \$1,100 a month—a cost that many families in America struggle to afford. In fact, to take a deeper look at what this cost really feels like for a median-income family, or even worse a single parent on a full-time minimum wage income, I gathered some

2019 data from the Economic Policy Institute (EPI) on what the average annual child care cost is for a 4-year-old in each state, and what percentage this accounts for out of these types of income. Let's take a look at Wisconsin as an example. The average cost of child care for a 4-year-old in the state of Wisconsin is \$12,567. The average median income of a family in Wisconsin is \$67,786, which results in 18.5% of their income being wiped out by child care. If that isn't enough, let's look at the single parent living on a full-time minimum wage income, which in Wisconsin would amount out to \$15,080 per year. This results in 83.3% of this parent's income being expensed to child care, which doesn't leave much for anything else. Figures for each state are shown in the following maps (data tables are provided in the appendix section).

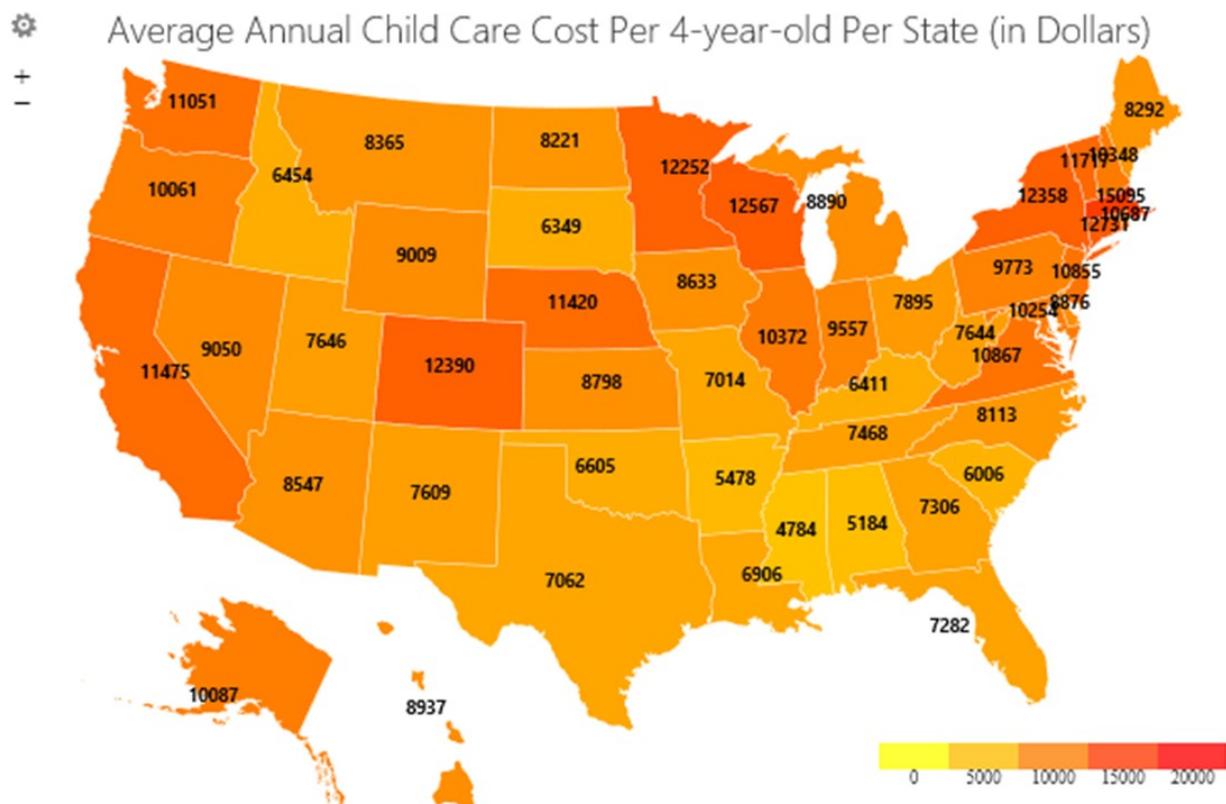


Figure 1.1. Data from EPI (map excludes Washington, D.C. value of \$19,112).

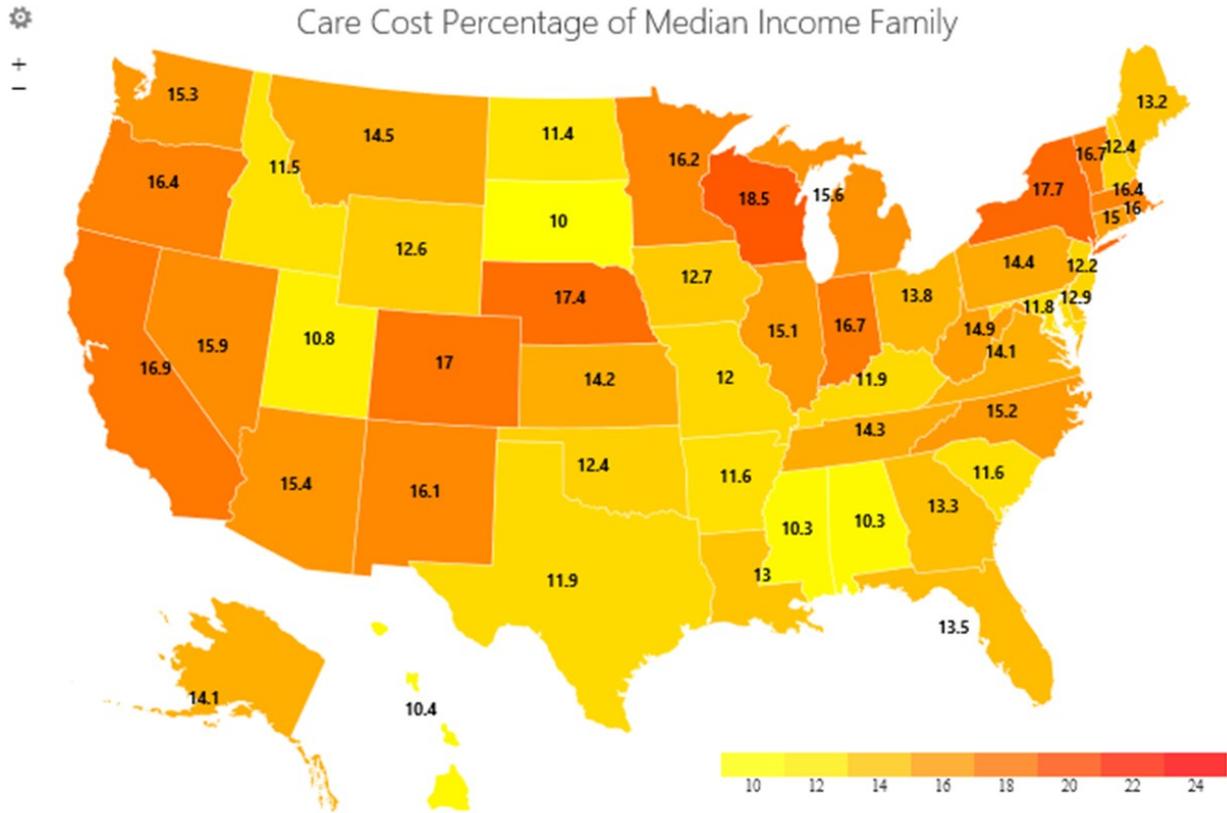


Figure 1.2. Data from EPI (map excludes Washington, D.C. value of 22.5%).

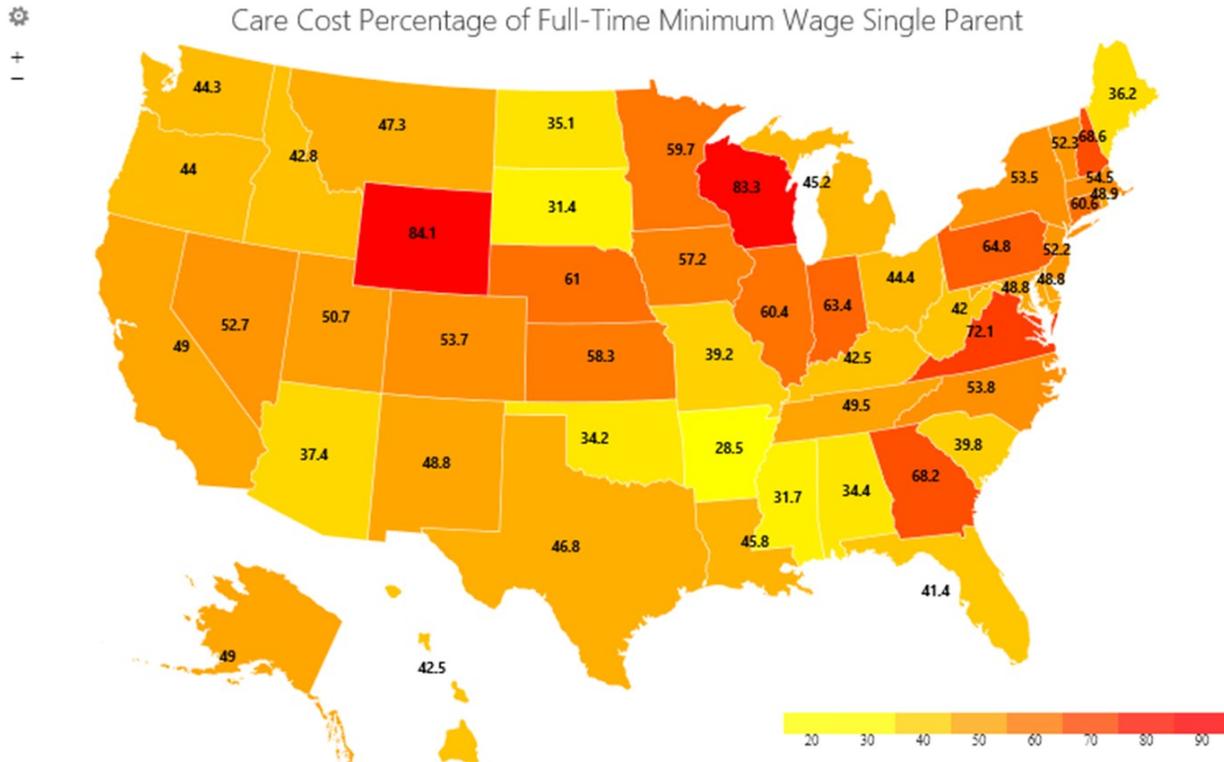


Figure 1.3. Data from EPI (map excludes Washington, D.C. value of 65.6%).

So how does this affect enrollment rates? According to the data referenced in the National Institute for Early Education Research's (NIEER) *The State of Preschool 2019: State Preschool Yearbook*, only 5.9% of 3-year-olds and 34% of 4-year-olds were enrolled in state-funded preschool in 2018-2019 nationwide, and total enrollment continues to grow at a “snail’s pace” with 3-year-old enrollment growing at a 0.3 percentage point increase over the previous year, and 4-year-old enrollment growing at a 0.9 percentage point increase (Friedman-Krauss, Barnett, Garver, Hodges, Weisenfeld, Gardiner, 2020, p.14). With the above figures of how much child care costs on average for parents, it is understandable why many parents have a difficult time fitting this into their budget. The issue is, these early years are the most important for brain and skill development, and the United States as a whole is not investing enough into

early childhood education. The United States currently spends \$30 billion a year in government money on early-childhood education (Long, 2017) with federal, state, and local funds being allocated to programs such as Head Start, Early Head Start, Universal Pre-K, Childcare and Development Block Grants, IDEA Part C Grants for Infants and Families, and IDEA Part B Preschool Grants (Afton, 2019). Yet the authors of *Cradle to Kindergarten: A New Plan to Combat Inequality*, make the argument that this investment should be raised to \$100 billion per year, which would amount to approximately 0.6 percent of GDP in order to be on track with what other developed nations are spending that have much higher rates of enrollment (as high as 100% of 3- and 4-year-olds [Long, 2017]). This would imply that preschool education in the United States is currently underfunded by about \$70 billion—a pretty astounding figure. So why is this happening? And why does this matter?

The aim of this paper is to help make the case whether universal preschool should be further invested into, and I will do this by researching and interpreting whether children with preschool education at the ages of 3 and 4 end up working at higher-paying jobs as adults than children without preschool education at these ages. I have chosen to focus on salary and wages as my dependent variable since I seem to have found a lot more research on the cognitive benefits of preschool, especially in the short-term, and stopping there rather than how it ties in or effects salary and wages in adulthood. Policy recommendations will be made depending on the robustness of the final results from the data.

II. Literature Review

The following literature has helped provide guidance for my research. The research within these papers has covered both the short- and long-term effects of preschool education

examining both cognitive and non-cognitive effects. They have studied a wide variety of program types, from less expensive state- and federally-funded programs such as universal pre-k or Head Start, to more expensive, higher-quality programs such as the Carolina Abecedarian Project.

Longer-Term Effects of Head Start

Garces, Thomas, and Currie (2002) provide a unique strategy in studying the long-term effectiveness of public preschool program Head Start, a program started for disadvantaged children as part of the “War on Poverty.” They drew their focus on the long-term effects of Head Start because it was clear to them that short- and medium-term benefits of attending this early education program had been discovered, such as higher test scores; however, critics insisted that these benefits eventually faded out and that in the long-term, Head Start children were no better off than non-Head Start children.

The authors used questions from a supplement to the Panel Survey of Income Dynamics (PSID). In the 1995 data, there are questions that specifically inquire about Head Start participation, as well as other preschools. The individuals being interviewed were between the ages of 18- and 30-years-old. The advantage to using the PSID is that it has been gathering data from a set of 4,802 households, and they have been continually interviewed annually from 1968 to 1996, and bi-annually since 1997. Over time, not only have the original 18,000 individuals from these households been interviewed, but so have their children, grandchildren, etc. Using this data, Garces, Thomas, and Currie were able to compare outcomes between individuals who had attended Head Start as children versus their siblings who did not. They tested whether the siblings who participated in Head Start were more likely to have completed high school, attend

college, obtain higher earnings in their twenties, and/or were less likely to have been charged for a crime than their siblings who had not participated in Head Start. In their methodology, they controlled for the effects of other preschools, as well as for unobserved family characteristics that would also have impact on the child's eventual outcome as an adult. In their results for white individuals, the sibling who attended Head Start was more likely than their non-Head Start sibling to have completed high school and to attend college. The same was not true for black individuals. There was little evidence for either whites or blacks that Head Start attendees obtained higher earnings in their twenties. Lastly for blacks, Head Start-attending siblings were less likely to be booked or charged with a crime than their non-Head Start siblings.

Effects of Texas's Targeted Pre-Kindergarten Program on Academic Performance

Andrews, Jargowsky, and Kuhne (2012) analyze Texas's targeted pre-kindergarten program to assess how a large-scale public program affects math and reading achievement tests, the probability to be held back in a grade, and the likelihood that a student will receive special education services. Data is utilized from Texas Schools Microdata Panel (TSMP) by the Texas Schools Project (TSP), University of Texas at Dallas, which contains 13 years of individual data for more than 10 million students enrolled in Texas public schools between 1990 and 2002. Data is available for grades pre-K-12, including enrollment, attendance, test scores, amongst other useful information such as age, ethnicity, language, and economic status. It is found that even basic pre-k programs that lack the features recommended in pre-k literature can have a positive impact on math and reading test scores, especially for economically disadvantaged and/or Limited English proficient students, as well as the reducing the probability of retention in grade and assignment to education.

Early Childhood Education

Elango, García, Heckman, and Hojman (EGHH) (2015) discuss the model of the technology of skill formation in their paper *Early Childhood Education* (2015), inspired from the previous works of Cunha and Heckman (2007, 2009). There are different stages of the life cycle, in this case broken down into prenatal, birth, early childhood, later childhood, adolescence, and adulthood. Throughout this cycle, the skills within each stage have been determined by the previous cycle's level of parental skills, investment, and child skills (EGHH, 2015, p. 12). It is a common thread in previous research, when determining the effectiveness of early childhood programs—especially for disadvantaged children—that most get wrapped up in focusing most or all of their efforts in solely looking into the income of the parents as part of the backstory. Although this is important to consider, EGHH discuss that this is only part of the big picture. Environment plays a considerable role in the success of a child later in adulthood, which would fall into the realm of parental skills. Families with low income may still care for, nurture, and give substantially more time and attention to their child(ren) than a family with high income; however, the family with high income can invest more money into their child(ren)'s pre-kindergarten program than the low income family, falling into the investment realm. Thus, the two should not be discussed without each other.

This leads into the further discussion of how both cognitive and non-cognitive skills matter. Again, going back to what is typically highlighted in research discussing the benefits of early childhood programs, they tend to focus on cognitive skills measured via higher test scores, IQ, and a variety of other academic achievements. Not enough research focuses on the non-cognitive skills of self-discipline, motivation, interpersonal interaction, or overall physical and

mental health, which are essential building blocks to a child's success later in life. EGHH explain that these skills all complement each other, and that fostering both cognitive and non-cognitive skills early in a pre-k program is necessary, or it becomes increasingly difficult to assess later in life.

Long-term Effects of Preschool on School Performance, Earnings and Social Mobility

Raut (2018) addresses how the income gap between the rich and the poor has been widening over the last 30 years, as well as the wage gap between college-educated and non-college-educated workers. Many workers in the United States have not completed college, most of which are from disadvantaged families. Raut ultimately researches if poverty and income disparity can be conquered through school, particularly through preschool investment. Many professionals and researchers find that children of poor socioeconomic status are not prepared for college because they were never prepared for school from the beginning. Raut shows empirically that the investment in preschool results in children acquiring motivational and socialization skills, especially in children of poor socioeconomic status, and these skills improve the lifetime earnings of children. Raut gathered data from the NLSY dataset and used 2 different skill sets: (1) cognitive skills, such as IQ and schooling level; (2) non-cognitive skills, such as socialization skill, motivational skills measured in terms of job aspiration and educational aspiration, and self-control skills measured in Rotter's locus of control scale. When estimating an augmented Mincer earnings function with the non-cognitive skills together with other traditional Mincer earnings function variables as regressors, the author finds positive effects on schooling level and earnings that are statistically significant. Ultimately, Raut concluded that society will earn back \$1.16 per each \$1.00 invested into the public preschool program.

Starting School at Four: The Effect of Universal Pre-Kindergarten on Children's Academic Achievement

Fitzpatrick (2008) focuses her research on studying universal pre-kindergarten programs in Georgia and the long-term educational effects of children within a difference-in-difference framework. Policymakers tend to face a trade-off on whether it is better to invest the money in intensive early childhood intervention programs similar to the Carolina Abecedarian Project, or to institute less expensive, smaller-scale education-based universal pre-k programs. Data was collected on gender, race, English proficiency, whether the child had any special learning needs, school size, math and reading scores, and whether the student qualified for free or reduced lunches. Statistically significant gains were found for some groups of children, but not enough to make a strong conclusion for the best design of pre-k.

Public Funding and Enrollment in Formal Child Care in the 1990s

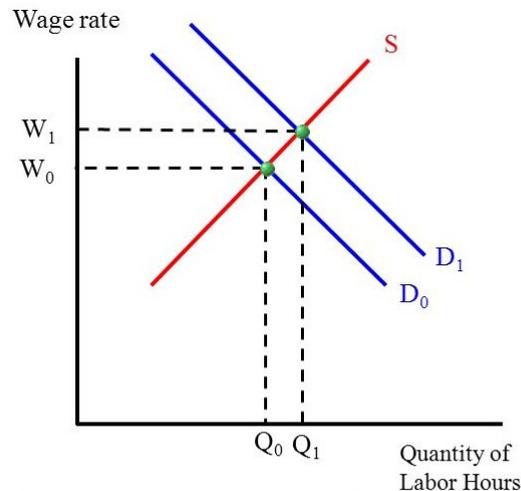
Magnuson, Meyers, and Waldfogel (2007) focus on formal care enrollment for 3- and 4-year-olds in low-income families versus higher-income families, and how increases in state expenditures for early education and child care are associated with these children's enrollment in formal child care. They conduct analyses separately for low- and higher-income earning samples because the effects of child-care policies may differ between the two groups. The results showed that the probability that a child would be enrolled in "formal care" (any program that the respondent identifies as a school) and early education programs increased with more public funding for low-income young children. This result suggests that gaps in formal care, without public investment, would have widened between low- and higher-income families.

Literature Review Conclusion

The authors of these papers have indicated that there is indeed a pressing issue for low-income families and their ability to invest into enrolling their child(ren) into preschool programs, and have highlighted positive outcomes from the children who are invested into at a young age. They have equally suggested that further research is necessary in order to create the best policy framework revolving around early childhood education.

III. Theoretical Model and Testable Hypothesis

George J. Borjas (2013) defines human capital as the unique set of abilities and acquired skills that we bring into the labor market, most of which is acquired in school and in formal and informal on-the-job training programs (Borjas, 2013, p. 235). Human capital theory (HCT) emphasizes that by increasing the level of cognitive stock of economically productive human capability through education, the productivity and efficiency of workers will increase as a result (Almendarez, 2011). As the productivity of worker (marginal product of labor) increases due to higher human capital, it causes a rightward shift in the labor demand curve, increasing the wage rate as a result.



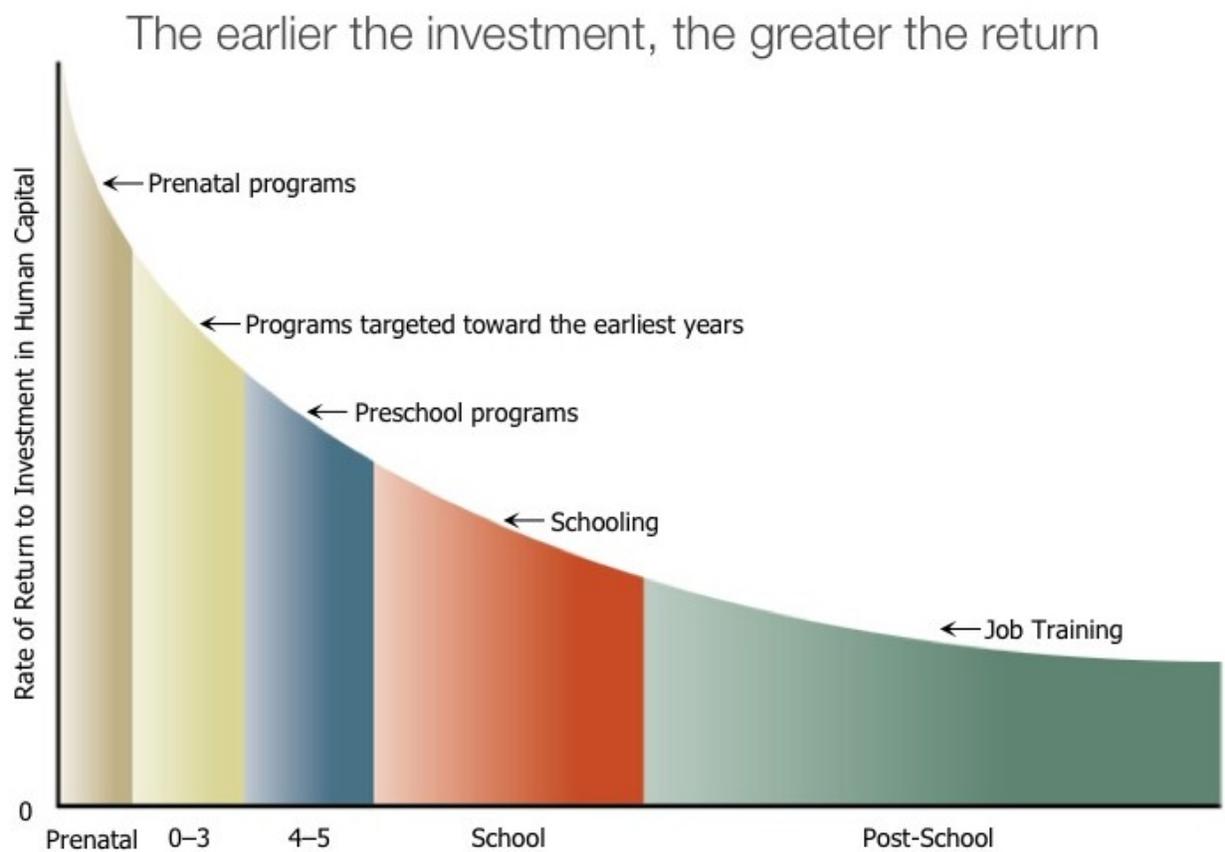
Source: Contemporary Labor Economics - 11th Edition (McConnell, Brue, Macpherson, 2017).
Chapter 6: Wage Determination and the Allocation of Labor.

To further build upon HCT, James Heckman has created the Heckman Equation as an argument for investing in early childhood education for disadvantaged children:

<p>+ Invest</p>	Invest in educational and developmental resources for disadvantaged families to provide equal access to successful early human development.
<p>+ Develop</p>	Nurture early development of cognitive and social skills in children from birth to age five.
<p>+ Sustain</p>	Sustain early development with effective education through to adulthood.
<p>= Gain</p>	Gain a more capable, productive and valuable workforce that pays dividends to America for generations to come.

Heckman explains that early investment produces the greatest returns in human capital, and is also much easier and more cost-effective than remediation later in life (2020). This is because the architecture of the brain forms from the prenatal period to age 5, making this an important stage

for developing cognitive and sociobehavioral skills. During this period, the brain's ability to learn from experience is at its highest level, making experiences and learning during this period directly affect achievement in adulthood. Building skills becomes harder if this window is missed (2019, World Bank Group, p. 75). The Heckman curve displays this higher rate of return in earlier ages:



This ultimately leads to my testable hypothesis that the age in which the respondent began attending school will have had a significant impact on the wages or salary that they earned

in 2016 (since I will be using 2017 data), with a null hypothesis that the age they began school will have had no or minimal effect on their 2016 earned wages or salary.

IV. Empirical Examination

Data

For this research, the most recent data (year 2017) was pulled from the Panel Study of Income Dynamics (PSID). Data was retrieved from the PSID Family-level category; however, it is important to note that the data under this category is still separated into different individuals within the household. I have collected data for the Reference Person (head of household). In order to create an econometric model based on the mincer earnings function, I gathered data for several variables. The dependent variable is built on the Reference's wages or salary in 2016. The independent variables include the Reference's total years of completed education, total years of work experience, age, sex, race (white, black, or other [including American Indian/Alaska Native, Asian, Native Hawaiian or Pacific Islander, or other]), if they are of Spanish descent, what age they started school between the ages of 0-6, if they received a high school diploma or GED, if they received any type of degree from college or elsewhere, if their parents were poor or not, and if their parents were separated at any age between 0-6. The original sample size included 9,607 respondents. Certain respondents were filtered out of my data for the reasons listed in the following table (refer to the next section "*Regression Analysis*" on p. 20 for variable definitions).

Variable	Samples Filtered Out	Reason
In_Ref_WoS	60	Listed as "Don't know" or "Refused to give."
Ref_CompEduc	140	Listed as 0 years completed; listed as "Don't know."

Ref_WkExp_Total	332	Listed as "Don't know" or "Refused to give." 1 sample claimed to have 57 years of work experience and was 46 years old.
Ref_Age	1347	Anyone over age 65 since this is a general age for retirement and may skew data (remaining samples were 18+); anyone listed as "Don't know."
Ref_Race_Bl/Ref_Race_O	35	Listed as "Don't know" or "Refused to give."
Ref_SHL	3	Listed as "Don't know" or "Refused to give."
Ref_SS_ZOT/Ref_SS_TF/ Ref_SS_FS	5917	Listed as "Don't know," "Refused to give," "Reference never started nor changed schools during childhood," or "Inappropriate: respondent is not Reference Person."
Ref_AA/Ref_BA/Ref_MA/ Ref_PHD/Ref_OD	1	Listed as "Don't know" or "Refused to give."
Ref_VTAM	1	Listed as "Don't know" or "Refused to give."
Ref_Par_Poor	22	Listed as "Don't know" or "Refused to give."
Note: 1748/9607 (18.2%) of original sample size remaining.		

Age, sex, and race were utilized in order to capture disadvantages within the labor market. Information on the Reference's parents was utilized to capture any advantages or disadvantages the Reference may have had growing up that may have changed whether they attended preschool by a certain age and the quality of the school they may have attended.

Regression Analysis

The econometric model used for my regression analysis is based on the mincer earnings function:

$$\log w = as + bt - ct^2 + \text{Other variables}$$

where w is the worker's wage rate, s is the number of years of schooling, t gives the number of years of labor market experience, and t^2 is a quadratic on experience that captures the concavity of the age-earnings profile (Borjas, 2013, p. 277).

The regressors I use are labeled as follows:

ln_Ref_WoS = natural log of the Reference's wages or salary in 2016
 Ref_CompEduc = Reference's total years of completed education
 Ref_WkExp_Total = Reference's total years of work experience since 18 years old
 Ref_WkExpSq_Total = Reference's total squared years of work experience since 18 years old
 Ref_Age = age of Reference
 Ref_Sex = sex of Reference; if Reference is male or not
 Ref_Race_Black = dummy variable for if Reference is black or not
 Ref_Race_O = dummy variable for if Reference is any of the above-mentioned other races
 Ref_Race_SHL = dummy variable for if Reference is of Spanish descent
 Ref_SS_ZOT = dummy variable for if Reference started school between the ages of 0-2 or not
 Ref_SS_TF = dummy variable for if Reference started school between the ages of 3-4 or not
 Ref_SS_FS = dummy variable for if Reference started school between the ages of 5-6 or not
 Ref_HSGED = dummy variable for if Reference received a high school diploma/GED or not
 Ref_AA = dummy variable for if Reference received an Associate's degree or not
 Ref_BA = dummy variable for if Reference received a Bachelor's (B.A./B.S.) degree or not
 Ref_MA = dummy variable for if Reference received a Master's (M.A./M.S./M.B.A.) degree
 Ref_PHD = dummy variable for if Reference received a Doctorate (Ph.D.)/Law (L.L.B./J.D.)/Medical (M.D./D.D.S./D.V.M./D.O.) degree or not
 Ref_OD = dummy variable for if Reference received a degree listed as "other"
 Ref_VTAM = dummy variable for if Reference received a degree or certificate through a vocational school, training school, or apprenticeship program or not, including military occupational specialties
 Ref_Par_Poor = dummy variable for if Reference's parents were poor growing up or not
 Ref_Par_SepZO = dummy variable for if Reference's parents were separated between the ages of 0-1 or not

Ref_Par_SepOn = dummy variable for if Reference's parents were separated at the age of 1 or not

Ref_Par_SepTw = dummy variable for if Reference's parents were separated at the age of 2 or not

Ref_Par_SepTh = dummy variable for if Reference's parents were separated at the age of 3 or not

Ref_Par_SepFo = dummy variable for if Reference's parents were separated at the age of 4 or not

Ref_Par_SepFi = dummy variable for if Reference's parents were separated at the age of 5 or not

Ref_Par_SepSi = dummy variable for if Reference's parents were separated at the age of 6 or not

These are arranged and ran as an OLS model in Excel as follows:

$$\log w = a_0 + as + bt - ct^2 + \text{Other variables}$$

$\ln_Ref_WoS = \text{Intercept} + \text{Ref_CompEduc} + \text{Ref_WkExp_Total} - \text{Ref_WkExpSq_Total} + \text{Remaining Regressors}$

I expect when running this regression that variables for the Reference's education, work experience, age, sex (male), and starting school between ages 0-2 or 3-4 will yield positive signs for their coefficients. Reason being as years of education, work experience, and age increase, I also expect their income to increase alongside these, as well as when diplomas, certificates, or degrees are attained. Additionally, being a male in the labor market is historically advantageous over being a female in regards to income. Lastly, I am expecting that starting school by or before 4 years old will result in a higher future income because of the skills developed during these ages, as well as it allows the chance of more overall years of education to be completed.

On the flip side, I expect when running this regression that variables for the Reference's race (non-white), ethnicity (Spanish/Hispanic/Latino), parents being poor or separated growing up, and starting school between the ages of 5-6 will yield negative signs for their coefficients. Reason being that being non-white and/or being Hispanic in the labor market is historically disadvantageous. Additionally, having poor and/or separated parents could also be disadvantageous in the sense of the quality of school a child ends up in, if they are able to attend school by a certain age at all, and/or the type of home environment they grow up in. Lastly, I am expecting that starting school after 4 years old will result in a lower future income for opposite reasons of starting by age 4.

Results

When running my regression in Excel with all of the above-mentioned variables factored in, I received the following results:

Regression Statistics for ln_Ref_WoS			
No. of obs.	1456	SSR	1204.8948 7
No. of missing obs.	292	TSS	1641.9691 3
Mean of Dep Var	10.3348 7	R ²	0.2661890 8
RMSE	0.91824 5	F stat.	19.937236 1

Variable	Estimate	SE	Robust SE (HC3)
Intercept	8.56644 1	0.70814 4	0.3186827 4
Ref_CompEduc	0.10166 3	0.01746 9	0.0174581 6
Ref_WkExp_Total	0.03211 1	0.01019 1	0.0121561 5
Ref_WkExpSq_To	0.00117	0.00030	0.0004483

tal	6	5	6
Ref_Age	0.01357 3	0.00281	0.0029185 5
Ref_Sex	0.43322 9	0.05036 4	0.0534829 8
Ref_Race_BlK	- 0.19649	0.05479 5	0.0568696 1
Ref_Race_O	- 0.04745	0.12950 5	0.1354646 7
Ref_SHL	0.06559 8	0.10020 1	0.0954679 4
Ref_SS_ZOT	- 1.24238	0.65838 3	0.1646337 1
Ref_SS_TF	- 0.66192	0.65831 1	0.1653637 2
Ref_SS_FS	-0.7279	0.65881 1	0.1673537 6
Ref_HSGED	0.16238 2	0.10179 4	0.1146036 7
Ref_AA	0.09777 9	0.09493 8	0.0987912 3
Ref_BA	0.30395	0.08399 2	0.0780062 4
Ref_MA	0.43569 1	0.12146 2	0.1057395 9
Ref_PHD	0.93863 8	0.17600 3	0.1966381
Ref_OD	- 0.29459	0.22226 8	0.1978316 6
Ref_VTAM	- 0.00454	0.05733 5	0.0609784 3
Ref_Par_Poor	0.04207 2	0.05792 3	0.0558405 1
Ref_Par_SepZO	- 0.01493	0.11879 9	0.127909
Ref_Par_SepOn	-0.0027	0.11050 4	0.1084191 8
Ref_Par_SepTw	- 0.06071	0.09932 8	0.1137673 7
Ref_Par_SepTh	- 0.07877	0.08696 8	0.0964850 6
Ref_Par_SepFo	- 0.05447	0.07985 3	0.0897371 5
Ref_Par_SepFi	0.02532 8	0.07160 5	0.0774826 8
Ref_Par_SepSi	- 0.03822	0.07204 7	0.0722388 3

19 of my variables came out with the signs I expected them to. The 7 variables that came out different than I expected were Ref_SHL, Ref_SS_ZOT, Ref_SS_TF, Ref_OD, Ref_VTAM, Ref_Par_Poor, and Ref_Par_SepFi. The 292 missing observations are due to individuals that reported \$0 as their 2016 income. Since I am using the natural log of the respondents' wages, $\ln(0) = \text{undefined}$, thus generating a #NUM error in Excel. For my R^2 , I would consider in many other cases a result of .26 low; however, since I am dealing with the mincer earnings function, and evidence suggests that differences in education and labor market experience among workers usually account for about a third of the variation in wage rates in the population (Borjas, 2013, p. 278), I consider .26 to be an appropriate result. My F statistic is also a strong number, supporting the big picture of the mincer equation. However, none of this strongly supports that the difference in age that the respondent started school made a significant impact in their wages.

If I rerun this regression in Excel in a way that will generate p-values for my variables (which unfortunately I can only run 16 variables at a time to do so), they tell an important part of the story. Since I can only run a limited number of variables, I kept in the necessary variables to run a mincer equation and added only the age in which the respondent started school, which generates the following:

<i>Regression Statistics</i>	
Multiple R	0.496401916
R Square	0.246414862
Adjusted R Square	0.23999682
Standard Error	0.924390486
Observations	1422

	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	12	393.6919184	32.8076598	38.3940848	3.77553E-78

			7	4	
Residual	1409	1203.987358	0.85449777		
Total	1421	1597.679276			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	7.72603 5155	0.69571 8813	11.1051 1173	1.58309 E-27	6.36127 8997	9.09079 1314	6.36127 8997	9.09079 1314
Ref_CompEduc	0.16814 5736	0.01174 9227	14.3112 1711	1.77486 E-43	0.14509 7876	0.19119 3595	0.14509 7876	0.19119 3595
Ref_WkExp_Total	0.03062 6792	0.01035 126	2.95875 0227	0.00314 044	0.01032 1253	0.05093 2331	0.01032 1253	0.05093 2331
Ref_WkExpSq_Total	0.00114 2525	0.00030 8679	3.70133 8319	0.00022 2731	0.00053 7005	0.00174 8045	0.00053 7005	0.00174 8045
Ref_Age	0.01459 2139	0.00281 3049	5.18730 3479	2.44487 E-07	0.00907 3924	0.02011 0355	0.00907 3924	0.02011 0355
Ref_Sex	0.42868 7082	0.05091 2734	8.42003 6557	9.14114 E-17	0.32881 4165	0.52855 9999	0.32881 4165	0.52855 9999
Ref_Race_Black	- 0.19956 7857	- 0.05448 7229	- 3.66265 3798	- 0.00025 8858	- 0.30645 2679	- 0.09268 3035	- 0.30645 2679	- 0.09268 3035
Ref_Race_White	- 0.05142 1576	- 0.14085 5522	- 0.36506 6102	- 0.71511 6853	- 0.32773 0679	- 0.22488 7526	- 0.32773 0679	- 0.22488 7526
Ref_SHL	- 0.00209 3435	- 0.10556 8903	- 0.01983 0031	- 0.98418 1769	- 0.20499 5705	- 0.20918 2574	- 0.20499 5705	- 0.20918 2574
Ref_SS_ZOT	- 1.16749 0743	- 0.66265 8031	- 1.76182 9917	- 0.07831 487	- 2.46739 3248	- 0.13241 1762	- 2.46739 3248	- 0.13241 1762
Ref_SS_TF	- 0.52588 3004	- 0.66275 1682	- 0.79348 4225	- 0.42762 9358	- 1.82596 922	- 0.77420 3212	- 1.82596 922	- 0.77420 3212
Ref_SS_FS	- 0.58150 2543	- 0.66324 4381	- 0.87675 4571	- 0.38076 9414	- 1.88255 5262	- 0.71955 0176	- 1.88255 5262	- 0.71955 0176
Ref_Poor	- 0.01304 7317	- 0.05854 6836	- 0.22285 2638	- 0.82368 25	- 0.10180 1028	- 0.12789 5662	- 0.10180 1028	- 0.12789 5662

As expected, my R^2 drops here since I am controlling for less factors. Focusing mostly on the highlighted p-values however completes the story of the results. None of these have a p-value <

0.05, and thus we cannot reject the null hypothesis. This leaves it inconclusive that the age in which these respondents began school had any major impact on their salary or wages in 2016.

V. Conclusions

As essentially stated at the end of my results section, I cannot conclude based on my data and results that starting preschool by 3 or 4 years old has a substantial impact on adulthood wages. However, it is important for me to state that there are a number of limitations in my data:

- 1) The number of respondents I had to filter out was a major disadvantage. It may have skewed the randomness and quality of my sample.
- 2) Due to the current state of Covid-19 and the university being shut down, I was unable to use a program like SAS to run my regression as I had issues getting it to work properly at home, and had to resort to using Excel. Although Excel is a great program, it was not realistic for me in the available time frame to include variables such as the respondent's occupation/industry, the state they reside in, or other variables that would have been helpful in telling the overall story.
- 3) If I were to do this project again, I would choose a different database than PSID. I was inspired to use this database, as one of my papers that I studied in my literature review used it. However, the year they studied had information on the respondents attending Head Start. They have not revisited the subject of Head Start since 1995, and I wanted to use the most recent data available. There were other variables that were also unavailable in this database, such as ones focusing on any cognitive/non-cognitive skills, further information on the school or daycare they attended, and easily-locatable information on their parents.

Unfortunately, it is unrealistic for me to recommend any policy based on my results. As a recommendation for future research, I would use a database that contained the information that

PSID was missing, maybe such as NLSY or another fit database. I would also study the programs and funding of the states that have higher enrollment rates and compare them to the states with the lowest enrollment rates—what are they doing that is better? In general, there is much more research to be done on this subject, especially when it comes to the long-term effects of early childhood education.

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Appendix

State	Total State Pre-K Spending	State Head Start Spending	Per Child Enrolled	
			State Spending	All Reported Spending
Alabama	\$95,962,050	\$0	\$5,116	\$6,257
Alaska	\$7,200,000	N/R	\$5,521	\$5,521
Arizona	\$21,712,929	\$0	\$4,013	\$4,013
Arkansas	\$113,276,553	\$0	\$5,612	\$9,332
California	\$2,027,027,473	\$0	\$8,253	\$8,427

Colorado	\$61,161,584	\$0	\$2,787	\$4,525
Connecticut	\$131,864,893	\$5,083,238	\$8,786	\$8,786
Delaware	\$6,149,300	N/R	\$7,277	\$7,277
District of Columbia	\$256,938,561	\$0	\$18,669	\$19,710
Florida	\$391,215,901	\$0	\$2,253	\$2,253
Georgia	\$365,326,541	\$0	\$4,539	\$4,539
Hawaii	\$2,991,420	\$0	\$7,208	\$7,208
Idaho	\$0	\$0	\$0	\$0
Illinois	\$385,174,818	\$0	\$4,746	\$5,811
Indiana	\$0	\$0	\$0	\$0
Iowa	\$89,752,273	\$0	\$3,375	\$3,516
Kansas	\$23,930,010	\$0	\$2,164	\$2,164
Kentucky	\$105,163,876	\$0	\$4,925	\$8,453
Louisiana	\$88,579,785	\$0	\$4,701	\$4,793
Maine	\$22,220,882	\$3,124,038	\$3,634	\$8,414
Maryland	\$134,159,629	\$1,800,000	\$4,184	\$8,432
Massachusetts	\$101,170,969	\$9,600,000	\$2,716	\$3,430
Michigan	\$244,600,000	N/R	\$6,586	\$6,586
Minnesota	\$54,114,602	\$11,112,490	\$6,570	\$6,570
Mississippi	\$4,490,818	\$0	\$2,298	\$9,457
Missouri	\$19,274,567	\$0	\$3,330	\$3,330
Montana	\$2,887,242	\$0	\$8,492	\$9,633
Nebraska	\$25,506,522	\$0	\$1,828	\$8,585
Nevada	\$7,848,995	\$0	\$3,669	\$6,832
New Hampshire	\$0	\$0	\$0	\$0
New Jersey	\$692,241,537	\$0	\$13,172	\$13,502
New Mexico	\$68,184,800	\$0	\$6,060	\$6,060
New York	\$842,225,288	\$0	\$6,668	\$6,912
North Carolina	\$160,828,280	\$0	\$5,450	\$9,162
North Dakota	\$564,009	\$0	\$531	\$531
Ohio	\$71,480,000	\$0	\$4,000	\$4,000
Oklahoma	\$181,685,479	\$0	\$4,294	\$9,096
Oregon	\$91,917,617	\$74,436,226	\$9,820	\$9,820
Pennsylvania	\$293,749,908	\$59,177,799	\$6,563	\$6,563
Rhode Island	\$7,209,482	\$1,190,000	\$6,675	\$11,784
South Carolina	\$82,651,532	\$0	\$2,888	\$3,138
South Dakota	\$0	\$0	\$0	\$0
Tennessee	\$86,552,900	\$0	\$4,841	\$6,266
Texas	\$854,984,186	\$0	\$3,579	\$3,640
Utah	\$0	\$0	\$0	\$0
Vermont	N/R	\$0	N/R	N/R
Virginia	\$70,049,572	\$0	\$3,967	\$6,299

Washington	\$121,004,051	\$0	\$8,969	\$8,969
West Virginia	\$99,009,024	\$0	\$7,316	\$11,052
Wisconsin	\$175,620,801	\$6,264,100	\$3,402	\$6,110
Wyoming	\$0	\$0	\$0	\$0
Resource:	NIEER The State of Preschool 2019: State Preschool Yearbook (2018-2019 school year)			

State	State Pre-K and Head Start Enrollment as % of Total Population			
	Pre-Kindergarten		Head Start	
	3-Years-Old	4-Years-Old	3-Years-Old	4-Years-Old
Alabama	0%	32%	9%	7%
Alaska	2%	10%	11%	13%
Arizona	2%	4%	7%	9%
Arkansas	18%	32%	10%	7%
California	12%	7%	38%	7%
Colorado	9%	23%	5%	7%
Connecticut	9%	31%	5%	4%
Delaware	2%	5%	6%	9%
District of Columbia	71%	87%	0%	0%
Florida	0%	75%	6%	8%
Georgia	0%	60%	9%	3%
Hawaii	0%	2%	6%	7%
Idaho	0%	0%	5%	8%
Illinois	22%	31%	7%	7%
Indiana	0%	0%	6%	8%
Iowa	3%	66%	6%	3%
Kansas	2%	26%	6%	8%
Kentucky	9%	29%	10%	11%
Louisiana	0%	30%	17%	11%
Maine	0%	44%	8%	4%
Maryland	5%	38%	6%	4%
Massachusetts	16%	30%	6%	3.8%
Michigan	0%	32%	11%	5%
Minnesota	1%	10.5%	7%	6%
Mississippi	0%	5%	25%	24%
Missouri	1.5%	6%	8%	7%
Montana	0.02%	2%	14%	17%
Nebraska	15%	34%	3%	3%
Nevada	0%	6%	3%	3%
New Hampshire	0%	0%	4%	5%
New Jersey	20%	30%	4%	3%

New Mexico	5%	38%	14%	14%
New York	2%	54%	8%	4%
North Carolina	0%	24%	6%	4%
North Dakota	0%	10%	9%	12%
Ohio	1%	11%	10%	10%
Oklahoma	3%	76%	16%	10%
Oregon	8%	12%	7%	8%
Pennsylvania	10%	20%	7%	9%
Rhode Island	0%	10%	8%	10%
South Carolina	0.50%	47%	10%	6%
South Dakota	0%	0%	13%	16%
Tennessee	0.10%	22%	8%	5%
Texas	9%	49%	7.6%	7%
Utah	0%	0%	4%	5%
Vermont	65%	78%	7%	9%
Virginia	0%	17%	6%	6%
Washington	5%	9%	6%	6%
West Virginia	6%	59%	10%	2%
Wisconsin	1%	72%	10%	7%
Wyoming	0%	0%	8%	11%
Resource:	NIEER The State of Preschool 2019: State Preschool Yearbook (2018-2019 school year)			

State	4-year-old Annual Child Care Cost	Median Family Income	Care Cost % of Median Income
Alabama	\$5,184	\$50,335	10.3%
Alaska	\$10,087	\$71,746	14.1%
Arizona	\$8,547	\$55,386	15.4%
Arkansas	\$5,478	\$47,126	11.6%
California	\$11,475	\$68,034	16.9%
Colorado	\$12,390	\$73,048	17.0%
Connecticut	\$12,731	\$84,824	15.0%
Delaware	\$8,876	\$68,827	12.9%
District of Columbia	\$19,112	\$84,892	22.5%
Florida	\$7,282	\$53,859	13.5%
Georgia	\$7,306	\$55,117	13.3%
Hawaii	\$8,937	\$85,854	10.4%
Idaho	\$6,454	\$56,056	11.5%
Illinois	\$10,372	\$68,751	15.1%
Indiana	\$9,557	\$57,254	16.7%
Iowa	\$8,633	\$67,854	12.7%

Kansas	\$8,798	\$61,914	14.2%
Kentucky	\$6,411	\$53,944	11.9%
Louisiana	\$6,906	\$53,042	13.0%
Maine	\$8,292	\$62,744	13.2%
Maryland	\$10,254	\$87,119	11.8%
Massachusetts	\$15,095	\$92,108	16.4%
Michigan	\$8,890	\$57,054	15.6%
Minnesota	\$12,252	\$75,756	16.2%
Mississippi	\$4,784	\$46,656	10.3%
Missouri	\$7,014	\$58,329	12.0%
Montana	\$8,365	\$57,815	14.5%
Nebraska	\$11,420	\$65,534	17.4%
Nevada	\$9,050	\$57,057	15.9%
New Hampshire	\$10,348	\$83,565	12.4%
New Jersey	\$10,855	\$88,898	12.2%
New Mexico	\$7,609	\$47,115	16.1%
New York	\$12,358	\$69,651	17.7%
North Carolina	\$8,113	\$53,249	15.2%
North Dakota	\$8,221	\$72,213	11.4%
Ohio	\$7,895	\$57,283	13.8%
Oklahoma	\$6,605	\$53,061	12.4%
Oregon	\$10,061	\$61,447	16.4%
Pennsylvania	\$9,773	\$67,828	14.4%
Rhode Island	\$10,687	\$66,928	16.0%
South Carolina	\$6,006	\$51,996	11.6%
South Dakota	\$6,349	\$63,730	10.0%
Tennessee	\$7,468	\$52,325	14.3%
Texas	\$7,062	\$59,440	11.9%
Utah	\$7,646	\$71,094	10.8%
Vermont	\$11,717	\$69,962	16.7%
Virginia	\$10,867	\$77,325	14.1%
Washington	\$11,051	\$72,124	15.3%
West Virginia	\$7,644	\$51,210	14.9%
Wisconsin	\$12,567	\$67,786	18.5%
Wyoming	\$9,009	\$71,611	12.6%
Resource:	Economic Policy Institute (July 2019)		

State	4-year-old Annual Child Care Cost	Full-time Minimum Wage Salary	Care Cost % of Min Wage Salary
Alabama	\$5,184	\$15,080	34.4%
Alaska	\$10,087	\$20,571	49.0%

Arizona	\$8,547	\$22,880	37.4%
Arkansas	\$5,478	\$19,240	28.5%
California	\$11,475	\$24,960	46.0%
Colorado	\$12,390	\$23,088	53.7%
Connecticut	\$12,731	\$21,008	60.6%
Delaware	\$8,876	\$18,200	48.8%
District of Columbia	\$19,112	\$29,120	65.6%
Florida	\$7,282	\$17,597	41.4%
Georgia	\$7,306	\$10,712	68.2%
Hawaii	\$8,937	\$21,008	42.5%
Idaho	\$6,454	\$15,080	42.8%
Illinois	\$10,372	\$17,160	60.4%
Indiana	\$9,557	\$15,080	63.4%
Iowa	\$8,633	\$15,080	57.2%
Kansas	\$8,798	\$15,080	58.3%
Kentucky	\$6,411	\$15,080	42.5%
Louisiana	\$6,906	\$15,080	45.8%
Maine	\$8,292	\$22,880	36.2%
Maryland	\$10,254	\$21,008	48.8%
Massachusetts	\$15,095	\$27,680	54.5%
Michigan	\$8,890	\$19,656	45.2%
Minnesota	\$12,252	\$20,509	59.7%
Mississippi	\$4,784	\$15,080	31.7%
Missouri	\$7,014	\$17,888	39.2%
Montana	\$8,365	\$17,680	47.3%
Nebraska	\$11,420	\$18,720	61.0%
Nevada	\$9,050	\$17,160	52.7%
New Hampshire	\$10,348	\$15,080	68.6%
New Jersey	\$10,855	\$20,800	52.2%
New Mexico	\$7,609	\$15,600	48.8%
New York	\$12,358	\$23,088	53.5%
North Carolina	\$8,113	\$15,080	53.8%
North Dakota	\$8,221	\$23,450	35.1%
Ohio	\$7,895	\$17,784	44.4%
Oklahoma	\$6,605	\$19,290	34.2%
Oregon	\$10,061	\$22,880	44.0%
Pennsylvania	\$9,773	\$15,080	64.8%
Rhode Island	\$10,687	\$21,840	48.9%
South Carolina	\$6,006	\$15,080	39.8%
South Dakota	\$6,349	\$20,230	31.4%
Tennessee	\$7,468	\$15,080	49.5%
Texas	\$7,062	\$15,080	46.8%

Utah	\$7,646	\$15,080	50.7%
Vermont	\$11,717	\$22,402	52.3%
Virginia	\$10,867	\$15,080	72.1%
Washington	\$11,051	\$24,960	44.3%
West Virginia	\$7,644	\$18,200	42.0%
Wisconsin	\$12,567	\$15,080	83.3%
Wyoming	\$9,009	\$10,712	84.1%
Resource:	Economic Policy Institute (July 2019)		