CHARLES UNIVERSITY FACULTY OF SOCIAL SCIENCES

Institute of Economic Studies



Do Current Childcare Costs Cause Women to Leave their Jobs? A Workforce Retention Regression Analysis

Bachelor's thesis

Author: Magdalena Anne Zucek Study program: Economics and Finance Supervisor: PhDr. Mgr. Jana Votápková, Ph.D. Year of defense: 2024

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Prague, July 31, 2024

Magdalena Anne Zucek

Abstract

This thesis investigates the impact of childcare costs and other determinants on the employment of mothers of young children across various years, using data from the IPUMS USA database. The study employs logistic regression and Tobit models to analyze employment status and hours worked for mothers in 2008, 2013, and 2018, as well as in a combined full dataset. Results highlight that rising childcare costs reduce maternal employment but not as significantly as other factors are able to affect maternal employment, with variations observed over time. Additionally, factors such as the number of children, age, marital status, and education level play crucial roles. The findings underscore the importance of addressing not only work flexibility but also childcare affordability and its influence on maternal workforce participation.

Keywords	Childcare costs, USA, labor market
Title	Do Current Childcare Costs Cause Women to
	Leave their Jobs? A Workforce Retention Re-
	gression Analysis
Author's e-mail	magdalena.zucek@gmail.com
Supervisor's e-mail	jana.votapkova@fsv.cuni.cz
Author's e-mail Supervisor's e-mail	Leave their Jobs? A Workforce Retention R gression Analysis magdalena.zucek@gmail.com jana.votapkova@fsv.cuni.cz

Abstrakt

Tato práce zkoumá vliv nákladů na péči o děti a dalších determinantů na zaměstnanost matek malých dětí v rózných letech s využitím dat z databáze IPUMS USA. Studie používá logistickou regresi a Tobitovy modely k analýze zaměstnaneckého statusu a odpracovaných hodin matek v letech 2008, 2013 a 2018, stejně jako v kombinovaném celkovém datasetu. Výsledky ukazují, že rostoucí náklady na péči o děti snižují zaměstnanost matek, avšak ne tak výrazně jako jiné faktory, které mohou ovlivnit zaměstnanost matek, přičemž se v průběhu času pozorují variace. Kromě toho hrají klíčové role faktory jako počet dětí, věk, rodinný stav a člínek vzdělání. Závěry zdárazníjí důležitost zaměření se nejen na flexibilitu práce, ale i na dostupnost péče o děti a její vliv na část matek na pracovním trhu.

Náklady na péči o dítě, USA, pracovní trh
Jsou náklady na institucionalizovanou péči
o dítě rozhodujícím faktorem pro ženy zů-
stat v domácnosti?
magdalena.zucek@gmail.com
jana.votapkova@fsv.cuni.cz

Acknowledgments

The author is grateful to PhDr. Mgr. Jana Votápková, Ph.D.for her guidance throughout the thesis writing process. Also, great appreciation goes out to the author's family, who has helped her throughout her entire academic career with unwavered support and encouragement: Thank you Petr & Petra.

Typeset in FSV IATEX template with great thanks to prof. Zuzana Havrankova and prof. Tomas Havranek of Institute of Economic Studies, Faculty of Social Sciences, Charles University.

Bibliographic Record

Zucek, Magdalena Anne: Do Current Childcare Costs Cause Women to Leave their Jobs? A Workforce Retention Regression Analysis. Bachelor's thesis. Charles University, Faculty of Social Sciences, Institute of Economic Studies, Prague. 2024, pages 50. Advisor: PhDr. Mgr. Jana Votápková, Ph.D.

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Acronyms

IPUMS Integrated Public Use Microdata Series

NDCP National Database of Childcare Prices

- AIC Akaike Information Criterion
- MLE Maximum Likelihood Estimation
- $\mathbf{AME} \ \ \mathbf{Average} \ \ \mathbf{Marginal} \ \ \mathbf{Effect}$
- **LR** Likelihood Ratio
- **FIPS** Federal Information Processing Standards

Chapter 1

Introduction: 2-3 Pages Long

Modern mothers continue to spend two to three times more time with their children daily compared to fathers, despite slight increases in the involvement of fathers in housework and childcare (Craig and Powell 2012). This persistence of traditional gender norms forces women to balance professional and household responsibilities, particularly childrearing (Conroy 2019). Women often face stress and guilt from trying to manage both work and family life (Guendouzi 2006), and those prioritizing childrearing may sacrifice career opportunities and financial independence (Conroy 2019).

The modern workforce and family dynamics have seen significant shifts over recent decades, yet traditional expectations continue to heavily influence maternal responsibilities. Women today are navigating an evolving work environment, where balancing a career with childcare duties remains a substantial challenge. The dual pressure of maintaining professional success while fulfilling parental roles underscores a complex intersection of gender expectations and economic necessities. The expectation for women to prioritize their role as caregivers, even as they pursue their own careers, reflects deep-seated societal norms that can often lead to emotional and practical difficulties (Guendouzi 2006). As a result, many women experience stress and guilt associated with their inability to meet both professional and familial expectations (Guendouzi 2006).

Childcare availability and costs are critical factors impacting maternal employment decisions. Over the last two decades, the landscape of childcare has become increasingly challenging for working mothers. Finding affordable, high-quality childcare has grown more difficult, with costs varying significantly across regions (Yavorsky and Ruppanner 2022). For instance, the disparity in childcare expenses between counties can reach nearly \$20,000 annually, illustrating the financial burden on families (Yavorsky and Ruppanner 2022). This variability in costs not only affects family budgets but also influences mothers' decisions to either enter or remain in the workforce.

This thesis aims to explore how childcare costs and other determinants affect maternal employment. Using data from the IPUMS USA database, the study employs logistic regression and Tobit models to analyze employment status and working hours for mothers in the years 2008, 2013, and 2018. This data is complemented by accessible information from the Women's Bureau on median childcare prices across counties. The analysis reveals that rising childcare costs negatively impact maternal employment, though not as significantly as other factors. Variations over time and crucial influences such as the number of children, age, marital status, and education level are examined. The findings highlight the need to address both work flexibility and childcare affordability to enhance maternal workforce participation.

Furthermore, this research delves into how changes in childcare costs over time affect maternal employment differently across various socio-economic backgrounds. It also considers the broader implications of these findings for policy and practice, emphasizing the importance of creating supportive work environments and accessible childcare options. The study aims to contribute to a deeper understanding of the complex relationship between childcare costs, maternal employment, and the broader socio-economic factors at play.

The thesis is organized as follows: Chapter 2 reviews existing literature on maternal employment and childcare, discussing the influence of childcare costs and availability. This review will highlight key findings from prior research and set the context for the current study. Chapter 3 details the dataset, variables used, and any necessary data cleaning and adjustments that were needed to be made. Chapter 4 outlines the methodological approaches employed, including the logistic regression and Tobit models utilized in the analysis. Results and discussion of these results are presented in Chapter 5, offering insights into how childcare costs and other determinants impact maternal employment. Finally, Chapter 6 concludes the thesis and suggests potential areas for further research, providing recommendations for policy and future studies based on the findings.

Chapter 2

Literature Review

2.1 Childcare Availability

Maternal employment decisions in the United States are influenced by the availability of daycare, as without accessible daycare they must sacrifice work and other priorities impacting both their well-being and financial independence. The country grapples with a "care crisis," characterized by a great disparity between the demand and supply of early childhood education and care (ECEC) (Yavorsky and Ruppanner 2022). Even before the COVID-19 pandemic, "childcare deserts" were widespread, affecting one in two families, particularly lowincome mothers. Only 33% of children under six can be accommodated in licensed daycare centers nationwide (Yavorsky and Ruppanner 2022). Nationwide polls consistently reveal challenges in locating suitable childcare options across various income levels (Conroy 2019). The available research lacks evidence and discussion about the direct impact this has on the mothers. The accommodation must be a burden, but the percentages of influence were not determined in these studies.

Conroy (2019) analyzes the US Decennial Census, showing how improved childcare access mitigates the long-term negative impact of young children on female labor force participation, facilitating women's retention or re-entry into the workforce emphasizing the positive impact of childcare availability on employment. Mothers with access to affordable, high-quality daycare have enhanced job prospects, as they can allocate less time to household chores and are more likely to participate in the workforce. Ruppanner et al. (2019) found from the American Time Use Survey between 2005 to 2014 that even minor daily variations in childcare responsibilities significantly affect maternal workforce participation (Ruppanner et al. 2019).

An equal amount of importance is attributed to quality childcare, impacting both the social and cognitive development of children. In order to help their child's development, a mother must compromise on her duties and even employment. Nevertheless, as highlighted by Yavorsky and Ruppanner (2022), affordability is still a major problem, especially for low-income families, which puts kids in poverty traps.

2.2 High Childcare Costs

Center-based median childcare costs in the U.S. exhibit great variability, especially across different states. For instance, annual expenses in Arkansas may amount to \$5,000, whereas in Washington, DC, they can be about \$24,000 (Yavorsky and Ruppanner 2022). Unbelievably, in many states, these costs surpass the average in-state college tuition fees.

An upward trend in childcare expenses is notable, with weekly expenditures for working families with children aged 0 to 14 increasing by a substantial 71% between 1985 and 2011 (Herbst 2018). Depending on geographic location and family structure, childcare expenses can consume up to 70% of household income (Miller et al. 2020), but Yavorsky and Ruppanner (2022) highlighted that a majority of American families allocate between nine to eighteen percent of their earnings to child care. The U.S. Department of Health and Human Services identifies affordable child care as constituting no more than 7% of a family's income (Miller et al. 2020) which means that some childcare expenses can be beyond possibility.

The affordability challenge significantly influences maternal employment decisions, intensified by regional disparities in childcare expenses. In states like Mississippi, where daycare costs are comparatively lower, mothers are more inclined to pursue full-time employment to combat the daycare payments compared to their counterparts in areas with higher childcare expenditures such as New York where childcare costs are one of the highest in the U.S. (Ruppanner et al. 2019). It is more economically efficient for some mothers to stay at work and pay for the childcare if it is affordable enough. But generally, Ruppanner et al. (2019) note that mothers tend to reduce their employment when facing expensive childcare whether it be at a national level or even county level.

Subsidized or low-cost childcare options hold the promise of alleviating

the overall burden of employment expenses for these underprivileged economic groups, thereby potentially boosting parental workforce participation and fostering greater utilization of ECEC services (Morrissey 2017). Unfortunately, subsidies on childcare are quite scarce and hard to access as some regions of the U.S. do not have such availability. To alleviate this financial strain, many middle-class and lower-income families must resort to more economical alternatives, such as assistance from relatives or friends (Yavorsky and Ruppanner 2022). Non-parental care is a key work-family balance strategy, which is evident in studies such as one made in 2006 where it was apparent that 69% of households with children aged 0-4 use formal care and 56% of households use informal care (Craig and Powell 2012). Over time, the dynamics around childcare options have changed. Families with preschool-aged children are more likely to rely on parents, stepparents, other relatives, and school-based providers (not likely to charge) allowing them to feel comfortable with the care for their children and them being able to provide for the family at the same time (Herbst 2018).

2.3 Child Age

Marco et al. (2009) noted that in 2005, nearly 63% of mothers with children under 6 were employed. In 2015, the labor force participation rate for mothers with children under one was 58.1%, increasing to 64.2% for those with children under six, and reaching 74.4% for mothers with children aged six to seventeen (of Labor Statistics 2016). By 2022, these rates rose to 67.9% for mothers with children under six and 76.7% for those with children aged six to seventeen (of Labor Statistics 2023), indicating a gradual increase in participation rates over seven years.

According to Yavorsky and Ruppanner (2022) research, families are more likely to use childcare for preschool-age children (0–5), highlighting the significance of ensuring access to high-quality childcare. However, the needs of childcare vary greatly depending on the age of children. Morrissey (2017) noted that roughly 61% of American children under five in regions with quality childcare regularly attended an ECEC program in 2011, spending an average of 33 hours per week in care. Women without access to high-quality childcare options for young children are more likely to leave the workforce, especially from private sector positions (Conroy 2019).

As children reach kindergarten age, typically around five or six, mothers

are compelled to rejoin the workforce due to their children going to a school with a full-day schedule. This structural impact of the school day length on maternal employment is well-documented, with many women adjusting their work schedules during their children's early years and resuming full-time employment when their children start school (Ruppanner et al. 2019).

2.4 Work-Time Flexibility

A supportive work environment has a big impact on moms' capacity to manage work and childcare. Marco et al. (2009) found that parents in less flexible work situations had trouble scheduling daycare and didn't have enough time to spend with their kids. Businesses that implement family-friendly practices frequently see improvements in employee commitment and lower absenteeism (Marco et al. 2009).

An additional factor that affects the time use of the mother is the commute to and from work. Conroy (2019) highlights that in line with moms' preference for more time spent with their kids, commute time plays a significant role in explaining the differences in women's labor market participation.

2.5 Marital Status

A mother's choice of employment is influenced by her marital status, particularly in terms of her ability to balance childcare, household chores, and work obligations. of Labor Statistics (2016) highlighted differences in the labor force participation rates between married and nonmarried women with newborns in 2015. Married moms had a lower rate of 57.6 percent, while mothers in other marital statuses had a higher rate of 59.1 percent. Compared to mothers in other marital situations, married moms continued to show a lower labor force participation rate throughout 2022 (of Labor Statistics 2023).

With less time to go to childcare facilities and work, single mothers frequently have unique problems when trying to find inexpensive daycare compared to their married counterparts. Since single moms are twice as likely as married mothers to rely on relatives for care, they then primarily rely on unofficial care arrangements and family members for childrearing (Han and Waldfogel 2001). Additionally, the lack of a spouse who could provide care adds to the higher average cost of childcare for single mothers per hour worked, even reaching the level of costs (Han and Waldfogel 2001). Generally, families with small children still follow the model described by Craig and Mullan (2011), in which the woman takes care of the home and the father works as the principal earner. Compared to these households, single mothers have to deal with the difficult challenge of juggling two jobs; they frequently have to provide both care and income.

2.6 Education

A mother's educational background influences her abilities and willingness to work. The higher the education attained, the higher likelihood of finding a suitable job that is time-flexible. Zamarro and Prados (2021) show that female employment with college level education is at least 25 percentage points higher than that of non-college educated women. Morrissey (2017) similarly highlights that the women with children with higher education were more likely to be employed and specifically said that an increase in child care by 10% increased female less-educated employment rate to 67% and college-educated employment rate to 86%. Other factors that affect maternal employment in tandem with college education could be analyzed, where most tackle merely child age and/or childcare availability.

2.7 Czech Republic vs. the United States

Maternity and family leave laws differ between the Czech Republic and the United States with more emphasis on going right to work after birth of a child for the mother. Therefore, it seemed more compelling and time-sensitive to look into the U.S. situation.

In the Czech Republic, introduced in 1990 and remains unchanged, parents are entitled to job-protected leave until their child is two, three, or even four. Based on that they are entitled to different allowance and even the speed in which they cash the fixed amount. Due to these helpful regulations, less than 6% of Czech women work while receiving parental stipend, indicating low labor force participation (Bičáková and Kalíšková 2019).

In contrast, family leave laws in the US, notably the 1993 Family and Medical Leave Act (FMLA), provide 12 weeks of unpaid, job-protected leave for qualifying workers, with limited access to paid leave, as of 2015, only 12% of private-sector employees had this benefit (Rossin-Slater 2017). While some states offer paid family leave programs, the American family support system tends to discourage mothers from staying at home with their children too long after birth opposite of the Czech Republic, prompting the study to explore the influences on women's employment decisions in the United States. The research of the United States needed more specificity in terms of individuals and prices of accessible daycare in their respective counties as well as more varied factors of the amount and age of children. Therefore the following research does just that.

Chapter 3

Data

The source of our data is the Integrated Public Use Microdata Series (IPUMS) database, which provides access to integrated, high-precision samples of the American population. These samples are drawn from sixteen federal censuses, from the American Community Surveys of 2000-present, and from the Puerto Rican Community Surveys of 2005-present. Collectively, they constitute a rich array of quantitative information on long-term changes in the American population.

IPUMS USA assigns uniform codes across all samples and consolidates relevant documentation into a coherent form to facilitate the analysis of social and economic change.

For this analysis, we use data from the years 2008, 2013, and 2018. These years were specifically chosen because of the available data on median childcare prices per county provided by the Women's Bureau. The National Database of Childcare Prices (NDCP) is the most comprehensive federal source of childcare prices at the county level. The database offers childcare price data by childcare provider type, age of children, and county characteristics. This childcare data is available only from 2008 to 2018, allowing us to incorporate this crucial variable into this analysis.

To assign a median childcare cost to each individual in the survey, we aligned the Federal Information Processing Standards (FIPS) codes from the IPUMS USA survey with the FIPS codes for the childcare costs. This alignment ensures that each respondent is associated with the appropriate median childcare cost based on their county of residence.

3.1 Dependent Variables

In this analysis, we use two different dependent variables:

Employment Status (*empstat*): This binary dummy variable was made from the original employment status category to indicate whether the responding mother was employed (1) or out of the labor force (0). For the purposes of the analysis, categories including employed and unemployed were combined as unemployed was still considered looking and seeking a job in the next several weeks.

Hours Worked (uhrswork): This continuous variable represents the number of hours worked by the respondent in a week, capped at 60 hours to account for realistic working limits. Researchers like Kajitani et al. (2016) hold the belief that individuals, specifically women, have lower cognitive scores and no longer work well and efficiently above 60 hours, therefore the cap was set, otherwise outlier values spanned until 99 hours.

3.2 Independent Variables

The independent variables being used describe sociodemographic characteristics, education level, and mostly family composition to see direct effects on the *empstat* and *uhrswork* variables.

Average Childcare Price (*avg_childcare_price*): This continuous variable measures the average cost of childcare in the respondent's respective county. This variable was assigned by aligning FIPS codes from the IPUMS USA survey with those from the NDCP to assign relevant costs to respondents.

Number of Children (nchild): This continuous variable counts the number of children in the respondent's household.

Number of Young Children under 5 Years old (nchlt5): This continuous variable specifically counts the number of children under the age of 5 in the household. At the age of 5 children are prepared to go to kindergarten (elementary school), so the need for institutional childcare is no longer at as high demand as before.

Youngest Child Age (yngch): This continuous variable represents the age of the youngest child in the household.

Age (age): This continuous variable indicates the age of the respondent at the time of the survey. age has also been manipulated with. As the legal adult age is 18, the lower threshold has been bounded at 18 years old, and due to menopause and less likelihood of baring children at an older age, the higher threshold was bounded at 55 years old.

Marital Status (marst): This binary dummy variable indicates the respondent's marital status of either married or not.

Education (*educ*): This categorical variable represents the highest level of education attained by the respondent, ranging from no formal education to advanced degrees.

Total Family Income (*ftotinc*): This continuous variable measures the total income of the respondent's family, providing insight into their economic status and stability.

Travel Time to Work (*trantime*): This continuous variable indicates the amount of time the respondent spends traveling to work, affecting their available working hours.

3.3 Cleaning the Data

Appendix A includes the descriptive statistics of all necessary variables for all individual years as well as the full dataset, meaning all of the years evaluated together. There it is possible to see the bounds of variables and their frequencies. Any values that did not represent real values or simply said N/A were all represented as N/A and were therefore left out from any analyses. A robustness check was performed and is specified in Appendix C. A check on the dependent variable *avg_childcare_price* was made changing the combination of original survey answers into the binary values. To verify that the combination of survey answers employed and unemployed was robust and valid, a check was made combining unemployed and out of the work force versus employed. A recoded model with this new combination was made and tested against the original model. The Log-Likelihood values are slightly lower for the recoded model compared to the original model suggesting that the re-coded model might fit the data slightly worse, keeping the original model relatively stable. Also, in terms of the the Akaike Information Criterion (AIC) values, they are higher for the re-coded model, indicating that the original model has a better balance between fit and model complexity, as lower AIC values generally indicate a better model fit.

Chapter 4

Methodology

This chapter outlines the methodological approaches employed to analyze the dataset that was all done in R Studio. The first model is a logistic regression for the binary variable *empstat*. The second model is the Tobit regression for the bounded variable *uhrswork*.

4.1 Logistic Regression

Logistic regression is a widely-used statistical method for modeling binary outcome variables. In this study, it is used to examine the factors influencing employment status (*empstat*), which is coded as 1 for employed and 0 for not employed.

The logistic regression model predicts the log-odds of the binary outcome as a linear combination of the predictor variables:

$$\ln\left(\frac{P(y=1 \mid x_1, x_2, \dots, x_k)}{1 - P(y=1 \mid x_1, x_2, \dots, x_k)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k \quad (4.1)$$

Here, y is the binary dependent variable, x_1, x_2, \ldots, x_k are the independent variables, and $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients to be estimated. This formulation ensures a linear relationship between the predictors and the log-odds of the outcome.

To express this relationship in terms of probability, we transform the logodds back to the probability scale using the logistic function:

$$P(y=1 \mid x_1, x_2, \dots, x_k) = \frac{1}{1 + \exp(-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k))} \quad (4.2)$$

This equation ensures that the predicted probabilities lie within the [0, 1] interval, a key characteristic of probabilities.

The estimation of the coefficients $\beta_0, \beta_1, \ldots, \beta_k$ is carried out using Maximum Likelihood Estimation (MLE). This method identifies the parameter values that maximize the likelihood of observing the given sample data, resulting in consistent, asymptotically normal, and efficient estimators under general conditions.

To interpret the effect of each predictor on the probability of the outcome, we calculate the marginal effects. The marginal effect of an independent variable x_j on the probability P(y = 1 | x) is given by:

$$\frac{\partial P(y=1 \mid x)}{\partial x_j} = P(y=1 \mid x) \left(1 - P(y=1 \mid x)\right) \beta_j$$
(4.3)

To provide a summary measure, the Average Marginal Effect (AME) is computed by averaging these marginal effects across all observations:

$$AME = \frac{1}{N} \sum_{i=1}^{N} \left(P(y_i = 1 \mid x_i) \left(1 - P(y_i = 1 \mid x_i) \right) \beta_j \right)$$
(4.4)

Evaluating the goodness-of-fit of the logistic regression model is crucial. McFadden's pseudo R^2 is one such measure, defined as:

$$R_{\rm McFadden}^2 = 1 - \frac{\log(L_{\rm full})}{\log(L_{\rm null})}$$

$$\tag{4.5}$$

In this formula, L_{full} is the log-likelihood of the fitted model, while L_{null} is the log-likelihood of a model that includes only the intercept.

The significance of the predictors is tested using the Likelihood Ratio (LR) test, which compares the fit of the full model to a restricted model excluding one or more predictors. The LR test statistic is calculated as:

$$LR = 2\left(\log(L_{\rm ur}) - \log(L_{\rm r})\right) \tag{4.6}$$

where $L_{\rm ur}$ is the log-likelihood of the unrestricted model, and $L_{\rm r}$ is the log-likelihood of the restricted model. This statistic follows a chi-squared distribution with degrees of freedom equal to the number of restrictions.

By employing logistic regression, this analysis aims to uncover the key fac-

tors that significantly impact the likelihood of being employed, providing a comprehensive understanding of the determinants of employment status.

4.2 Tobit Regression

The Tobit model, also known as Tobin's regression model, is designed for situations where the dependent variable is censored. Censoring occurs when the value of the dependent variable is only partially observed due to constraints or thresholds. In this study, *uhrswork* is bounded at 0 and 60 hours per week, reflecting realistic working conditions and outlier control.

The Tobit model combines elements of both linear regression and survival analysis. It models the latent (unobserved) variable that represents the actual number of hours worked and assumes that this latent variable is observed only within certain bounds. The model can be expressed as:

$$y_{i}^{*} = \beta_{0} + \beta_{1}x_{i1} + \beta_{2}x_{i2} + \dots + \beta_{k}x_{ik} + \epsilon_{i}$$
(4.7)

where y_i^* is the latent variable representing the number of hours worked, $x_{i1}, x_{i2}, \ldots, x_{ik}$ are the independent variables, $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients, and ϵ_i is the error term. The error term ϵ_i is assumed to follow a normal distribution with mean zero and constant variance σ^2 .

The observed variable y_i is defined by the following censoring mechanism:

$$y_{i} = \begin{cases} y_{i}^{*} & \text{if } y_{i}^{*} > 0 \text{ and } y_{i}^{*} < 60 \\ 0 & \text{if } y_{i}^{*} \le 0 \\ 60 & \text{if } y_{i}^{*} \ge 60 \end{cases}$$
(4.8)

This formulation captures the constraints imposed on the dependent variable: values below 0 are set to 0, and values above 60 are capped at 60. The Tobit model estimates both the coefficients of the independent variables and the variance of the error term.

The estimation of the Tobit model is performed using MLE. The likelihood function for the Tobit model is derived from the combination of the normal distribution of the latent variable and the probability mass at the censoring points. The log-likelihood function is:

$$\log L = \sum_{0 < y_i < 60} \log \left(\frac{1}{\sigma} \phi \left(\frac{y_i^* - \beta_0 - \beta_1 x_{i1} - \dots - \beta_k x_{ik}}{\sigma} \right) \right)$$
(4.9)

$$+\sum_{y_i=0}\log\Phi\left(\frac{-\beta_0-\beta_1x_{i1}-\cdots-\beta_kx_{ik}}{\sigma}\right)$$
(4.10)

$$+\sum_{y_i=60} \log\left(1 - \Phi\left(\frac{60 - \beta_0 - \beta_1 x_{i1} - \dots - \beta_k x_{ik}}{\sigma}\right)\right)$$
(4.11)

where ϕ is the probability density function and Φ is the cumulative distribution function of the standard normal distribution.

The marginal effects in the Tobit model can be computed to understand the impact of each independent variable on the observed dependent variable. The marginal effect of x_j on the expected value of the censored variable is given by:

$$\frac{\partial E(y_i \mid x)}{\partial x_j} = \beta_j \cdot \phi \left(\frac{y_i^* - \beta_0 - \beta_1 x_{i1} - \dots - \beta_k x_{ik}}{\sigma} \right) \cdot \left[\frac{1}{\sigma} \frac{\partial \left(\frac{y_i^* - \beta_0 - \beta_1 x_{i1} - \dots - \beta_k x_{ik}}{\sigma} \right)}{\partial x_j} \right]$$
(4.12)

where $\phi(\cdot)$ denotes the normal density function.

To evaluate the model's fit, the log-likelihood function is used to gauge how well the model explains the variation in the data. This is complemented by assessing the significance of the model's predictors through Wald tests or likelihood ratio tests.

By employing the Tobit model, this analysis aims to account for the censored nature of the hours worked data and to provide insights into how various factors influence the observed number of working hours, taking into consideration the bounds imposed by realistic working conditions.

Chapter 5

Results & Discussion: 10-12 Pages Long

5.1 Results of Regressions

5.1.1 Logistic Regressions

Individual Years

Table 5.1 presents the logistic regression results for maternal employment in the years 2008, 2013, and 2018, including estimated coefficients, standard errors, and average marginal effects (AME).

The average childcare price shows a small but statistically significant negative effect on maternal employment in 2008, with each dollar increase in childcare price reducing the probability of employment by approximately -0.01% This effect is not statistically significant in 2013. By 2018, the effect becomes positive but remains small, with each additional dollar in childcare price increasing the probability of employment by approximately 0.04%. This variability suggests that the impact of childcare costs on employment decisions may differ over time.

The number of children consistently has a strong negative effect on the likelihood of maternal employment across all years. Each additional child reduces the probability of employment by about 4% in 2008, 4.5% in 2013, and 3.9% in 2018. This indicates that as the number of children increases, the probability of a mother being employed decreases significantly.

Similarly, having more children under the age of 5 significantly decreases the probability of maternal employment, with the probability decreasing by

	Dependent variable: empstat						
		Logistic Regression			AME		
	2008	2013	2018	2008	2013	2018	
avg_childcare_price	-0.001^{***} (0.0003)	-0.0001 (0.0002)	0.0004^{**} (0.0002)	-0.000	-0.000	0.000	
nchild	-0.203^{***} (0.011)	-0.221^{***} (0.010)	-0.202^{***} (0.010)	-0.042	-0.045	-0.039	
nchlt5	$-0.275^{***}(0.024)$	-0.199^{***} (0.022)	-0.203^{***} (0.022)	-0.058	-0.040	-0.039	
yngch	0.033^{***} (0.009)	0.039*** (0.008)	0.010 (0.008)	0.007	0.008	0.002	
age	0.004^{**} (0.002)	0.010^{***} (0.002)	0.006^{***} (0.002)	0.001	0.002	0.001	
marst	-1.082^{***} (0.034)	$-1.314^{***}(0.030)$	$-1.285^{***}(0.033)$	-0.226	-0.267	-0.245	
educ	0.129*** (0.005)	0.149*** (0.005)	0.177*** (0.005)	0.027	0.030	0.034	
ftotinc	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)	0.00000^{***} (0.00000)	0.000	0.000	0.000	
Constant	1.217*** (0.088)	0.698^{***} (0.078)	0.598^{***} (0.082)	1.217	0.698	0.598	
Observations	39,311	50,487	52,021				
Log Likelihood	-23,823.790	-29,964.280	-29,350.060				
Akaike Inf. Crit.	47,665.570	59,946.550	58,718.120				
Note:				*p<0.1; *	*p<0.05; *	**p<0.01	

p<0.1; **p<0.05; p < 0.01

5.8% in 2008, 4.0% in 2013, and 3.9% in 2018 per additional young child. This reflects the greater care demands of young children, which may limit the mother's ability to work.

The age of the youngest child shows a positive effect on maternal employment in 2008 and 2013, with each additional year of the child's age increasing the likelihood of the mother being employed by 0.7% in 2008 and 0.8% in 2013. In 2018, this effect is not statistically significant, suggesting that as children reach school age, the impact on employment may diminish. This is consistent with the notion that mothers may prioritize employment less as their children reach an age where they require less intensive care (Conroy 2019).

Maternal age shows a small but positive effect on employment, with each additional year of age increasing the probability of being employed by approximately 0.1% across the years. This suggests that older mothers are slightly more likely to participate in the workforce.

Marital status has a substantial negative impact on employment, significantly reducing the likelihood of employment by approximately 22.6% in 2008, 26.7% in 2013, and 24.5% in 2018 for married women compared to those who are not married. This indicates that married mothers are less likely to be employed, likely due to increased caregiving responsibilities at home. Han and Waldfogel (2001) clearly argues that married mothers have a larger likelihood of working less than single mothers because of family flexibility.

Higher levels of education consistently have a positive effect on employment, with each additional level of education increasing the probability of employment by approximately 2.7% in 2008, 3.0% in 2013, and 3.4% in 2018. This suggests that more education enhances the likelihood of maternal employment.

Total family income has a very small but significant positive effect on employment, with each additional dollar in family income increasing the probability of maternal employment by 0.000% across all years. This indicates that higher family income is associated with a slightly increased likelihood of the mother being employed, which is consistent with the idea that higher income may correlate with increased maternal labor force participation.

Full Dataset

Table 5.2 presents the logistic regression results for maternal employment using the full dataset, including estimated coefficients, standard errors, and average marginal effects (AME).

The average childcare price shows a very small positive effect on maternal employment, though this effect is not statistically significant (p > 0.10). Each additional dollar in childcare price increases the probability of employment by approximately 0.00%. This suggests that changes in childcare costs do not meaningfully impact employment probability in the full dataset.

	Logistic Re	AME	
avg_childcare_price	0.0001	(0.0001)	0.000
nchild	-0.208^{***}	(0.006)	-0.011
nchlt5	-0.223^{***}	(0.013)	-0.013
yngch	0.027^{***}	(0.005)	-0.010
age	0.006***	(0.001)	0.001
marst	-1.236^{***}	(0.019)	-0.105
educ	0.152^{***}	(0.003)	0.011
ftotinc	0.00000^{***}	(0.00000)	0.000
Constant	0.778^{***}	(0.047)	
Observations	141,819		
Log Likelihood	-83,261.800		
Akaike Inf. Crit.	166,541.600		
Note:	*p<	(0.1; **p<0.0)5; ***p<0.01

 Table 5.2: Logistic Regression for Employment in Full Dataset

The number of children has a significant negative effect on maternal employment, with each additional child decreasing the probability of employment by approximately 1.1% (p < 0.01). This substantial effect highlights that as the number of children increases, the likelihood of a mother being employed significantly declines. Similarly, having more children under the age of 5 significantly decreases the probability of maternal employment, with each additional young child reducing the probability of employment by about 1.3% (p < 0.01). This result emphasizes the increased caregiving responsibilities associated with young children, which can limit the mother's ability to work.

The age of the youngest child has a positive and statistically significant effect on maternal employment (p < 0.01). Each additional year of the child's age increases the probability of employment by approximately 0.1%. This effect indicates that as the youngest child grows older, the likelihood of maternal employment slightly increases, reflecting reduced childcare demands.

Maternal age also shows a small but statistically significant positive effect on employment, with each additional year of age increasing the probability of being employed by about 0.1% (p < 0.01). This suggests that older mothers are slightly more likely to participate in the workforce, though the effect is modest.

Marital status has a strong negative impact on employment, significantly reducing the probability of employment by approximately 10.5% for married women compared to those who are not married (p < 0.01). This substantial effect indicates that married mothers are less likely to be employed, likely due to increased domestic and caregiving responsibilities.

Higher levels of education consistently have a positive and statistically significant effect on employment, with each additional level of education increasing the probability of employment by approximately 1.1% (p < 0.01). This result underscores the importance of education in enhancing the likelihood of maternal employment.

Total family income has a very small but statistically significant positive effect on employment, with each additional dollar in family income increasing the probability of maternal employment by 0.000% (p < 0.01). Although the effect of income on employment is minimal, higher family income is associated with a slightly increased likelihood of maternal labor force participation.

5.1.2 Tobit Regressions

Individual Years

Table 5.3 presents the Tobit regression results for hours worked (uhrswork) in the individual years 2008, 2013, and 2018, including estimated coefficients and standard errors.

The average childcare price has a statistically significant negative effect on hours worked across all years (p < 0.01). Specifically, each additional dollar in childcare price decreases the number of hours worked by approximately 2.3 hours in 2008, 2.1 hours in 2013, and 1.7 hours in 2018. This consistent negative effect suggests that higher childcare costs significantly reduce the number of hours worked, reflecting increased financial burden associated with childcare.

	Dependent variable:				
		uhrswork			
	(2008)	(2013)	(2018)		
avg_childcare_price	-0.023^{***} (0.003)	-0.021^{***} (0.002)	-0.017^{***} (0.002)		
nchild	-1.928^{***} (0.128)	-2.374^{***} (0.113)	-1.919^{***} (0.103)		
nchlt5	-3.906^{***} (0.277)	-2.787^{***} (0.246)	-2.558^{***} (0.229)		
yngch	-0.638^{***} (0.096)	-0.471^{***} (0.084)	-0.603^{***} (0.079)		
age	-0.054^{**} (0.023)	0.018(0.021)	-0.033(0.021)		
marst	-9.356^{***} (0.331)	-9.831^{***} (0.288)	-10.480^{***} (0.284)		
educ	1.378*** (0.058)	1.474^{***} (0.051)	1.684*** (0.049)		
ftotinc	0.00002^{***} (0.00000)	0.00003^{***} (0.00000)	0.00002^{***} (0.00000)		
trantime	0.595^{***} (0.006)	0.598^{***} (0.005)	0.499^{***} (0.005)		
Constant	21.843*** (0.933)	16.990*** (0.829)	$19.065^{***}(0.791)$		
Observations	39,311	50,487	52,021		
Log Likelihood	-129,462.200	$-165,\!966.600$	$-177,\!590.400$		

 Table 5.3: Tobit Regression for Hours Worked in Individual Years

Note:

*p<0.1; **p<0.05; ***p<0.01

The number of children also has a substantial negative effect on hours worked, with each additional child reducing hours worked by about 1.9 hours in 2008, 2.4 hours in 2013, and 1.9 hours in 2018 (p < 0.01). This significant reduction underscores the impact of additional children on the ability to work more hours, likely due to increased caregiving demands.

The presence of more children under the age of 5 significantly decreases hours worked. Each additional young child decreases hours worked by approximately 3.9 hours in 2008, 2.8 hours in 2013, and 2.6 hours in 2018 (p < 0.01). This effect highlights the considerable caregiving responsibilities associated with very young children, which may limit the amount of time a mother can spend working.

The variable for the age of the youngest child shows a negative effect on hours worked in 2008 and 2018 (p < 0.05), with each additional year of the child's age reducing hours worked by about 0.054 hours in 2008 and 0.033 hours in 2018. However, this effect is not statistically significant in 2013, suggesting variability in how the age of the youngest child impacts hours worked over time. Marital status has a highly significant negative effect on hours worked, with married women working approximately 9.4 hours fewer in 2008, 9.8 hours fewer in 2013, and 10.5 hours fewer in 2018 compared to non-married women (p < 0.01). This substantial reduction indicates that married mothers tend to work significantly fewer hours, likely due to additional domestic and caregiving responsibilities.

Education has a strong positive effect on hours worked, with each additional level of education increasing hours worked by about 1.4 hours in 2008, 1.5 hours in 2013, and 1.7 hours in 2018 (p < 0.01). This result suggests that higher educational attainment is associated with an increase in the number of hours worked, reflecting greater job opportunities and earning potential associated with more education.

Total family income also has a small but significant positive effect on hours worked, with each additional dollar in family income increasing hours worked by approximately 0.00002 hours in 2008, 0.00003 hours in 2013, and 0.00002 hours in 2018 (p < 0.01). This effect, while minimal, indicates that higher family income is associated with a slight increase in the number of hours worked.

The time spent on transportation (trantime) shows a significant positive effect on hours worked, with each additional minute of transportation increasing hours worked by about 0.595 hours in 2008, 0.598 hours in 2013, and 0.499 hours in 2018 (p < 0.01). This suggests that longer commutes are associated with working more hours, potentially reflecting the need to travel further for work.

Full Dataset

Table 5.4 presents the Tobit regression results for hours worked (uhrswork) in the full dataset, including estimated coefficients and standard errors.

The average childcare price has a statistically significant negative effect on hours worked (p < 0.01). Specifically, each additional dollar in childcare price decreases hours worked by approximately 1.9 hours. This result indicates that higher childcare costs are associated with a significant reduction in the number of hours worked, reflecting the increased financial burden of childcare.

The number of children also significantly impacts hours worked, with each additional child reducing hours worked by about 2.1 hours (p < 0.01). This substantial negative effect underscores the considerable impact that having more children has on a mother's ability to work more hours, likely due to increased caregiving demands.

	Dependent variable:
	uhrswork
avg_childcare_price	-0.019^{***} (0.001)
nchild	-2.071^{***} (0.066)
nchlt5	-3.014^{***} (0.144)
yngch	-0.565^{***} (0.049)
age	-0.019(0.012)
marst	-9.902^{***} (0.172)
educ	1.532^{***} (0.030)
ftotinc	0.00003*** (0.00000)
trantime	0.557^{***} (0.003)
Constant	$18.684^{***}(0.477)$
Observations	141,819
Log Likelihood	$-473,\!246.100$
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.4: Tobit Regression for Hours Worked in Full Dataset

The presence of more children under the age of 5 has a significant negative effect on hours worked. Each additional young child decreases hours worked by approximately 3.0 hours (p < 0.01). This significant reduction highlights the considerable caregiving responsibilities associated with very young children, which may limit the time available for paid work.

The variable for the age of the youngest child shows a negative effect on hours worked, but it is not statistically significant (p > 0.05). This suggests that the age of the youngest child does not have a significant impact on the number of hours worked in the full dataset, indicating that other factors may play a more substantial role.

Marital status has a highly significant negative effect on hours worked, with married women working approximately 9.9 hours fewer compared to nonmarried women (p < 0.01). This substantial reduction indicates that married mothers tend to work significantly fewer hours, likely due to additional domestic and caregiving responsibilities.

Education has a strong positive effect on hours worked, with each additional level of education increasing hours worked by about 1.5 hours (p < 0.01). This result suggests that higher educational attainment is associated with an increase in the number of hours worked, reflecting greater job opportunities and earning potential associated with more education.

Total family income also has a small but significant positive effect on hours worked, with each additional dollar in family income increasing hours worked by approximately 0.00003 hours (p < 0.01). This indicates that higher family income is associated with a slight increase in the number of hours worked, which may reflect the capacity to afford more work-related expenses.

The time spent on transportation (trantime) shows a significant positive effect on hours worked, with each additional minute of transportation increasing hours worked by about 0.557 hours (p < 0.01). This suggests that longer commutes are associated with working more hours, potentially reflecting the necessity to travel further for work.

Overall, the Tobit regression results for the full dataset highlight that various factors, including childcare costs, number of children, and education, have significant and impactful effects on the number of hours worked. These findings provide a comprehensive view of the determinants influencing maternal labor supply.

5.2 Discussion of Results

The results of our analysis reveal important insights into the dynamics of maternal employment and hours worked, influenced by factors such as childcare costs, family composition, and personal characteristics. These findings provide a broader understanding of how economic and social factors interact to shape working patterns over time.

Our results highlight a significant and evolving relationship between childcare costs and maternal employment. Initially, in 2008, higher childcare costs were associated with a reduced likelihood of maternal employment, indicating that financial barriers can restrict mothers' ability to work. However, by 2018, this relationship appeared to reverse, with higher childcare costs correlating with a slight increase in employment probability. This shift may reflect changes in the economic environment, such as increased flexibility in work arrangements or improvements in childcare subsidies, which could offset some of the financial burdens associated with childcare. The evolving nature of this relationship suggests that as childcare costs rise, other compensatory factors might come into play, influencing maternal employment decisions in complex ways.

The analysis consistently shows that the number of children has a strong negative effect on maternal employment. This finding underscores the substantial caregiving responsibilities associated with larger family sizes, which can limit mothers' opportunities to engage in paid work. The presence of young children also significantly impacts employment, with mothers of young children facing greater challenges in maintaining full-time employment. This aligns with the notion that very young children require intensive care, which can constrain mothers' work hours and employment status.

While the age of the youngest child generally increases the likelihood of employment, this effect varies over time. In 2008 and 2013, older children were associated with higher employment probabilities, likely due to reduced caregiving demands as children age. However, this effect was not significant in 2018, suggesting that other factors, such as changes in the labor market or family dynamics, might have influenced maternal employment decisions.

Marital status continues to play a significant role in maternal employment, with married women being less likely to be employed compared to their nonmarried counterparts. This finding reflects the additional domestic responsibilities often borne by married mothers, which can limit their ability to participate in the workforce. The persistent negative impact of marital status on employment highlights the need for policies that support working mothers, particularly those with significant family responsibilities.

The positive relationship between education and employment is consistent across all years, indicating that higher educational attainment enhances job opportunities and career prospects for mothers. This result underscores the importance of educational attainment in facilitating employment and suggests that policies aimed at improving access to education could have a beneficial impact on maternal employment.

Total family income also shows a positive association with employment, although the effect is relatively small. This suggests that financial stability contributes to employment decisions, but other factors may also play a significant role.

The Tobit regression results reveal that higher childcare costs are associated with reduced hours worked, reinforcing the notion that financial constraints related to childcare can limit working hours. This effect is consistent across the years studied, highlighting the ongoing impact of childcare expenses on working patterns.

The findings of this study have several implications for policy and practice. First, they underscore the importance of addressing childcare costs through targeted subsidies or support programs to alleviate financial burdens on working mothers. Second, they highlight the need for policies that support working mothers with young children and those with larger families, such as flexible work arrangements and family leave policies.

Additionally, the results suggest that educational attainment and family income are crucial factors influencing maternal employment, indicating that initiatives aimed at improving educational access and financial stability could have positive effects on employment outcomes for mothers.

Looking overall, the childcare costs of the respective counties are not as influential of maternal employment as could be imagined. Questions in the survey did not ask about willingness to commute children to other counties, etc. It is likely that in the United States with high mobility, it is unsure whether a family would put their child in an institution where they specifically live. Commutes to work could cause mroe convenience in another area, but it is noticeable at a small percentage that childcare costs affect women's employment in some capacity.

Chapter 6

Conclusion

This thesis explored the intricate relationship between childcare costs, family composition, and maternal employment, focusing on the impact of these factors across different years and datasets. The primary aim was to understand how variations in childcare costs influence maternal employment patterns and hours worked, while accounting for family size, marital status, education, and income.

The analysis utilized logistic and Tobit regression models to examine these relationships, revealing several key findings:

Higher childcare costs were initially associated with reduced maternal employment. However, this relationship shifted over time, with recent data suggesting that increased childcare costs might be linked to higher employment probabilities. This change highlights the evolving dynamics of the labor market and the potential mitigating effects of improved childcare policies.

The number of children and the presence of young children consistently affected maternal employment, with larger families and younger children correlating with lower employment probabilities. This underscores the significant caregiving responsibilities that can constrain mothers' ability to work.

Married mothers were less likely to be employed compared to their nonmarried counterparts, reflecting additional domestic responsibilities. This finding emphasizes the need for supportive policies that accommodate the workfamily balance.

Higher educational attainment and family income positively influenced employment, highlighting the importance of access to education and financial stability in facilitating maternal employment.

The Tobit regression results confirmed that higher childcare costs are asso-

ciated with fewer hours worked, reinforcing the notion that financial constraints significantly impact working hours.

This work contributes to the understanding of maternal employment by providing a comprehensive analysis of how childcare costs, family composition, and personal characteristics interact to shape employment patterns. By examining data from multiple years and applying both logistic and Tobit regressions, the study offers valuable insights into the evolving nature of these relationships and their implications for policy.

The findings emphasize the importance of addressing childcare costs and supporting working mothers through flexible work arrangements and familyoriented policies. Additionally, the results highlight the role of education and income in enhancing employment opportunities, suggesting that targeted interventions in these areas could improve maternal employment outcomes.

Looking ahead, several paths for further research emerge from this study alongside what has already been researched and discovered. Future work could explore the long-term effects of changes in childcare policies on maternal employment and working hours, especially possibilities of facilities right at work, to stimulate maternal employment willingness. Additionally, examining the impact of other factors, such as workplace flexibility and parental leave policies, could provide a more comprehensive understanding of the challenges faced by working mothers. This would be worth contacting IPUMS and having them expand their studies on more maternal-related questions

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.1 Appendix A

I

Appendix A

Descriptive Statistics

Statistic	Mean	St. Dev.	Min	Max	Median
empstat	0.655	0.475	0	1	1
uhrswork	23.481	18.834	0	60	30
avg_childcare_price	179.120	43.754	76.750	300.130	180.610
nchild	2.161	1.139	1	9	2
nchlt5	1.293	0.518	1	5	1
yngch	1.797	1.385	0	4	2
age	32.967	6.063	18	55	33
marst	0.825	0.380	0	1	1
educ	7.831	2.507	0	11	8
ftotinc	88,943.540	88,585.320	-19,600	$1,\!284,\!000$	68,100
trantime	13.396	19.439	0	200	5

 Table A.1: Descriptive Statistics for 2008 Sample

A.1 Appendix B

Statistic	Mean	St. Dev.	Min	Max	Median
empstat	0.655	0.475	0	1	1
uhrswork	24.209	19.153	0	60	30
avg_childcare_price	194.839	50.064	85.090	346.557	195.637
nchild	2.149	1.136	1	9	2
nchlt5	1.289	0.512	1	6	1
yngch	1.805	1.399	0	4	2
age	33.039	5.825	18	55	33
marst	0.814	0.389	0	1	1
educ	8.054	2.493	0	11	8
ftotinc	$95,\!055.650$	$97,\!418.780$	-5,500	1,302,200	70,700
trantime	14.482	19.931	0	161	5

 Table A.2: Descriptive Statistics for 2013 Sample

 Table A.3: Descriptive Statistics for 2018 Sample

Statistic	Mean	St. Dev.	Min	Max	Median
empstat	0.694	0.461	0	1	1
uhrswork	25.935	18.860	0	60	35
avg_childcare_price	225.938	62.145	81.493	413.333	216.667
nchild	2.146	1.157	1	9	2
nchlt5	1.287	0.510	1	7	1
yngch	1.810	1.390	0	4	2
age	33.849	5.526	18	55	34
marst	0.845	0.362	0	1	1
educ	8.451	2.414	0	11	10
ftotinc	128,273.700	128,938.900	-7,250	1,500,000	97,000
trantime	16.683	21.726	0	164	10

 Table A.4: Descriptive Statistics for Full Sample of All Years

Statistic	Mean	St. Dev.	Min	Max	Median
empstat	0.669	0.470	0	1	1
uhrswork	24.640	18.985	0	60	32
avg_childcare_price	201.889	56.684	76.750	413.333	198.333
nchild	2.151	1.144	1	9	2
nchlt5	1.289	0.513	1	7	1
yngch	1.804	1.392	0	4	2
age	33.316	5.800	18	55	33
marst	0.828	0.377	0	1	1
educ	8.138	2.481	0	11	8
ftotinc	$105,\!546.200$	109,348.200	-19,600	1,500,000	$78,\!600$
trantime	14.988	20.522	0	200	8

Appendix B

Correlation Matrix

	empstat	uhrswork	avg_childcare_price	nchild	nchlt5	yngch	age	marst	educ	ftotinc	multgen	trantime
empstat	1	0.747	-0.005	-0.163	-0.115	0.043	0.011	-0.124	0.157	0.072	0.024	0.500
uhrswork	0.747	1	-0.009	-0.187	-0.124	0.008	0.018	-0.109	0.190	0.136	0.023	0.485
avg_childcare_price	-0.005	-0.009	1	-0.034	-0.021	0.017	0.135	0.059	0.064	0.170	0.054	0.024
nchild	-0.163	-0.187	-0.034	1	0.350	0.034	0.233	-0.002	-0.237	-0.059	0.019	-0.117
nchlt5	-0.115	-0.124	-0.021	0.350	1	-0.353	-0.102	0.039	0.011	0.013	-0.011	-0.083
yngch	0.043	0.008	0.017	0.034	-0.353	1	0.269	-0.032	-0.037	0.019	0.016	0.054
age	0.011	0.018	0.135	0.233	-0.102	0.269	1	0.203	0.233	0.307	0.008	0.056
marst	-0.124	-0.109	0.059	-0.002	0.039	-0.032	0.203	1	0.236	0.283	-0.032	-0.053
educ	0.157	0.190	0.064	-0.237	0.011	-0.037	0.233	0.236	1	0.433	-0.061	0.133
ftotinc	0.072	0.136	0.170	-0.059	0.013	0.019	0.307	0.283	0.433	1	0.016	0.099
multgen	0.024	0.023	0.054	0.019	-0.011	0.016	0.008	-0.032	-0.061	0.016	1	0.020
trantime	0.500	0.485	0.024	-0.117	-0.083	0.054	0.056	-0.053	0.133	0.099	0.020	1

 Table B.1: Correlation Matrix for 2008 Sample

 Table B.2: Correlation Matrix for 2013 Sample

	empstat	uhrswork	avg_childcare_price	nchild	nchlt5	yngch	age	marst	educ	ftotinc	multgen	trantime
empstat	1	0.772	0.027	-0.167	-0.102	0.046	0.033	-0.136	0.188	0.117	0.026	0.527
uhrswork	0.772	1	0.017	-0.195	-0.109	0.018	0.047	-0.092	0.225	0.193	0.028	0.505
avg_childcare_price	0.027	0.017	1	-0.052	-0.020	0.003	0.135	0.064	0.101	0.167	0.044	0.057
nchild	-0.167	-0.195	-0.052	1	0.345	0.039	0.227	-0.013	-0.241	-0.070	0.015	-0.120
nchlt5	-0.102	-0.109	-0.020	0.345	1	-0.361	-0.088	0.054	0.014	0.016	-0.019	-0.070
yngch	0.046	0.018	0.003	0.039	-0.361	1	0.254	-0.055	-0.045	0.015	0.024	0.053
age	0.033	0.047	0.135	0.227	-0.088	0.254	1	0.194	0.219	0.299	0.018	0.065
marst	-0.136	-0.092	0.064	-0.013	0.054	-0.055	0.194	1	0.263	0.293	-0.023	-0.051
educ	0.188	0.225	0.101	-0.241	0.014	-0.045	0.219	0.263	1	0.423	-0.046	0.157
ftotinc	0.117	0.193	0.167	-0.070	0.016	0.015	0.299	0.293	0.423	1	0.018	0.129
multgen	0.026	0.028	0.044	0.015	-0.019	0.024	0.018	-0.023	-0.046	0.018	1	0.019
trantime	0.527	0.505	0.057	-0.120	-0.070	0.053	0.065	-0.051	0.157	0.129	0.019	1

 Table B.3: Correlation Matrix for 2018 Sample

	empstat	uhrswork	avg_childcare_price	nchild	nchlt5	yngch	age	marst	educ	ftotinc	multgen	trantime
empstat	1	0.788	0.058	-0.169	-0.091	0.021	0.038	-0.107	0.219	0.137	0.020	0.510
uhrswork	0.788	1	0.051	-0.194	-0.102	-0.002	0.039	-0.093	0.236	0.196	0.024	0.484
avg_childcare_price	0.058	0.051	1	-0.073	-0.019	-0.003	0.169	0.065	0.138	0.229	0.052	0.107
nchild	-0.169	-0.194	-0.073	1	0.345	0.054	0.216	-0.018	-0.237	-0.078	0.013	-0.125
nchlt5	-0.091	-0.102	-0.019	0.345	1	-0.361	-0.102	0.055	0.012	0.014	-0.017	-0.072
yngch	0.021	-0.002	-0.003	0.054	-0.361	1	0.273	-0.056	-0.050	0.005	0.024	0.040
age	0.038	0.039	0.169	0.216	-0.102	0.273	1	0.154	0.215	0.263	0.018	0.067
marst	-0.107	-0.093	0.065	-0.018	0.055	-0.056	0.154	1	0.259	0.265	-0.026	-0.044
educ	0.219	0.236	0.138	-0.237	0.012	-0.050	0.215	0.259	1	0.398	-0.056	0.157
ftotinc	0.137	0.196	0.229	-0.078	0.014	0.005	0.263	0.265	0.398	1	0.025	0.128
multgen	0.020	0.024	0.052	0.013	-0.017	0.024	0.018	-0.026	-0.056	0.025	1	0.037
trantime	0.510	0.484	0.107	-0.125	-0.072	0.040	0.067	-0.044	0.157	0.128	0.037	1

	empstat	uhrswork	avg_childcare_price	nchild	nchlt5	yngch	age	marst	educ	ftotinc	multgen	trantime
empstat	1	0.771	0.043	-0.167	-0.102	0.037	0.031	-0.121	0.193	0.118	0.024	0.513
uhrswork	0.771	1	0.042	-0.193	-0.111	0.008	0.039	-0.095	0.223	0.185	0.026	0.493
avg_childcare_price	0.043	0.042	1	-0.055	-0.019	0.005	0.161	0.068	0.134	0.238	0.050	0.091
nchild	-0.167	-0.193	-0.055	1	0.347	0.043	0.224	-0.012	-0.238	-0.070	0.015	-0.121
nchlt5	-0.102	-0.111	-0.019	0.347	1	-0.359	-0.097	0.050	0.012	0.013	-0.016	-0.074
yngch	0.037	0.008	0.005	0.043	-0.359	1	0.264	-0.048	-0.044	0.012	0.022	0.048
age	0.031	0.039	0.161	0.224	-0.097	0.264	1	0.185	0.227	0.287	0.016	0.067
marst	-0.121	-0.095	0.068	-0.012	0.050	-0.048	0.185	1	0.255	0.275	-0.026	-0.047
educ	0.193	0.223	0.134	-0.238	0.012	-0.044	0.227	0.255	1	0.416	-0.052	0.156
ftotinc	0.118	0.185	0.238	-0.070	0.013	0.012	0.287	0.275	0.416	1	0.022	0.130
multgen	0.024	0.026	0.050	0.015	-0.016	0.022	0.016	-0.026	-0.052	0.022	1	0.027
trantime	0.513	0.493	0.091	-0.121	-0.074	0.048	0.067	-0.047	0.156	0.130	0.027	1

Table B.4: Correlation Matrix for Full Sample for All Years

It is visible from the matrices that most variables exhibit correlations related to the two dependent variables, although the externally constructed variable of *avg_childcare_price* seems to move on its own not influencing the movement of *empstat* or *uhrswork* as could be thought.

B.1 Appendix C

Appendix C

Robustness Tests

C.0.1 Logit Robustness

Table C.1:	Logistic Regression for Employment in Individual	Sample
	Years (Robustness Check)	

		Dependent variable:	
		$empstat_recode$	
	(2008)	(2013)	(2018)
avg_childcare_price	-0.001^{***} (0.0003)	-0.001^{***} (0.0002)	0.0002 (0.0002)
nchild	-0.197^{***} (0.011)	-0.233^{***} (0.010)	-0.198^{***} (0.010)
nchlt5	-0.274^{***} (0.024)	-0.171^{***} (0.022)	-0.192^{***} (0.022)
yngch	0.027^{***} (0.009)	0.033^{***} (0.008)	0.009(0.008)
age	0.010^{***} (0.002)	0.013^{***} (0.002)	0.007^{***} (0.002)
marst	$-0.726^{***}(0.031)$	$-0.966^{***}(0.027)$	$-1.040^{***}(0.030)$
educ	0.148^{***} (0.005)	0.151^{***} (0.005)	0.181*** (0.005)
ftotinc	0.00000^{***} (0.00000)	$0.00000^{***}(0.00000)$	$0.00000^{***}(0.00000)$
Constant	0.259^{***} (0.084)	0.063 (0.076)	0.203^{**} (0.079)
Observations	39,311	50,487	52,021
Log Likelihood	-24,961.420	-31,148.620	-30,311.170
Akaike Inf. Crit.	49,940.850	62,315.250	60,640.340
Note:		*p<0.1	1; **p<0.05; ***p<0.01

When compared with the values demonstrated in Figures 5.1 and 5.2, avg_childcare_price is not statistically significant while the other variables remain significant, signifying robustness of their inclusion.

C.0.2 Tobit Robustness

The tobit regression robustness check has confirmed the significance and consistency of the used variables. Unlike in the logistic regression affecting em-

	Dependent variable:
	$empstat_recode$
avg_childcare_price	$0.0001 \ (0.0001)$
nchild	-0.207^{***} (0.006)
nchlt5	-0.209^{***} (0.013)
yngch	0.023^{***} (0.005)
age	0.010^{***} (0.001)
marst	$-0.917^{***}(0.017)$
educ	0.161*** (0.003)
ftotinc	0.00000^{***} (0.00000)
Constant	0.042 (0.045)
Observations	141,819
Log Likelihood	-86,603.480
Akaike Inf. Crit.	173,225.000
Note:	*p<0.1; **p<0.05; ***p<0.01

 Table C.2: Logistic Regression for Employment in Full Dataset (Robustness Check)

Table C.3:	Tobit	Regression	for	Hours	Worked	in	Individual	Years
		(Robust	ness	s Check	к - 80 Hc	ur	Bound)	

		Dependent variable:	
		uhrswork	
	(2008)	(2013)	(2018)
avg_childcare_price	-0.023^{***} (0.003)	-0.021^{***} (0.002)	-0.017^{***} (0.002)
nchild	-1.923^{***} (0.125)	-2.343^{***} (0.110)	-1.889^{***} (0.100)
nchlt5	-3.832^{***} (0.271)	$-2.731^{***}(0.240)$	-2.520^{***} (0.222)
yngch	-0.632^{***} (0.093)	-0.469^{***} (0.081)	$-0.596^{***}(0.076)$
age	$-0.057^{**}(0.023)$	0.017 (0.021)	$-0.039^{*}(0.020)$
marst	-9.150^{***} (0.323)	-9.662^{***} (0.280)	-10.203^{***} (0.275)
educ	1.354*** (0.056)	1.454*** (0.050)	1.661^{***} (0.047)
ftotinc	0.00002^{***} (0.00000)	0.00003^{***} (0.00000)	0.00002*** (0.00000)
trantime	0.581*** (0.006)	0.586^{***} (0.005)	0.487*** (0.004)
Constant	22.066*** (0.912)	17.100*** (0.807)	19.285*** (0.767)
Observations	39,311	50,487	52,021
Log Likelihood	-130,982.300	$-168,\!267.900$	-180,424.700
Note:		*p<0.1	l; **p<0.05; ***p<0.01

	Dependent variable:
	uhrswork
avg_childcare_price	-0.018^{***} (0.001)
nchild	-2.047^{***} (0.064)
nchlt5	-2.960^{***} (0.140)
yngch	-0.560^{***} (0.048)
age	$-0.023^{*}(0.012)^{-0.012}$
marst	-9.684^{***} (0.168)
educ	1.510*** (0.029)
ftotinc	0.00002^{***} (0.00000)
trantime	0.545^{***} (0.003)
Constant	18.872*** (0.465)
Observations	141,819
Log Likelihood	-479,919.200
Note:	*p<0.1; **p<0.05; ***p<0.01

Table C.4: Tobit Regression for Hours Worked in Full Dataset(Robustness Check - 80 Hour Bound)

ployment, variable *avg_childcare_price* is statistically significant even in the robustness test and still positive.

C.1 Appendix D

Appendix D

Likelihood Ratio

Model	LR Statistic	p-value
Logistic Regression		
2008	2306.208	0
2013	3905.566	0
2018	4379.935	0
Full Dataset	10543.15	0
Tobit Regression		
2008	12341.85	0
2013	17643.82	0
2018	17382.84	0
Full Dataset	47363.25	0

 Table D.1: Likelihood Ratio Test Statistics and p-values for Logistic and Tobit Regressions

For the logistic regression models, the LR statistics are quite high for all years and the full dataset. The LR test assesses the fit of the logistic regression models by comparing the fitted model to a model with no predictors. A high LR statistic indicates that the model with predictors significantly improves the fit compared to the null model. In all cases, the p-value is 0, suggesting that the improvements in model fit are statistically significant.

These results underscore the effectiveness of the logistic regression models in explaining variations in employment status across the years and in the full dataset. The high LR statistics and significant p-values indicate that the predictors of the model (such as average childcare price, number of children, age, marital status, etc.) contribute meaningfully to the prediction of employment status. Similarly, for the Tobit regressions, which account for censored data (e.g., hours worked being truncated at 60 hours), the LR statistics are also notably high. The Tobit LR statistics demonstrate a strong fit of the model to the data, with all p-values being 0. This indicates that the Tobit model's predictors are also significant in explaining variations in usual hours worked, accounting for the left-censoring at 0 hours and the right-censoring at 60 hours.