Modeling Fertility Intention and Working: A Longitudinal Analysis Focused on U.S. Women Aged 18–39

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Introduction

Since the mid-20th century, American women have made significant strides in achieving equality in the workforce and education, bolstered by legislative changes and social advancement [1]. Policies such as the Equal Pay Act of 1963, Title IX of the Education Amendments of 1972, and the Pregnancy Discrimination Act of 1978 have significantly increased female participation in higher education and the workforce. These advancements have provided women with more opportunities, but have also presented challenges in balancing career, education, and family responsibilities.

Previous studies have shown that working status was significantly related to risk factors for adverse pregnancy outcomes [2]. In addition, economic status and education level also have a significant impact on women's reproductive decisions [3]. These bring us to the focus of our study. We intend to gain a deeper understanding of the association between work/study time and fertility intentions. Longitudinal analyses will be conducted to assess predictors of changes in women's pregnancy intentions over time.

We used data from the Continuity and Change in Contraceptive Use study. This is a longitudinal study that followed U.S. women aged 18–39 over 18 months, from November 2012 to May 2014 [4]. The study included four waves of data collection that examined contraceptive behaviors and influencing factors such as pregnancy intentions, life events, and access to healthcare. Of the 11,365 women initially invited to participate, 4,647 were eligible to participate, and 1842 completed the baseline survey across, with subsequent response rates of 69%, 75%, and 77% for Waves 2, 3, and 4, respectively. This longitudinal dataset provides a valuable foundation for analyzing how working and studying time correlates with the fertility intentions of females.

Data Processing

Data Description

The data used is an integrated, balanced longitudinal panel dataset, ensuring that all 1,842 U.S. female participants aged 18 to 39 completed the survey in all four waves from 2012 to 2014. Each participant is assigned a unique CASEID for identification.

In response to our research question, we selected the current pregnancy intention as the outcome variable (indicating INTEND), with the total hours worked or studied in the past week (indicating HOURTOT) as the primary independent variable. Some demographic variables, such as age, total household size, race, marital status, education level, and household income are selected as covariates. Among these, race and marital status are categorical variables, while the others are continuous variables. Notably, the pregnancy intention variable (INTEND) in the survey ranges from 1 to 5, representing five distinct levels of pregnancy intention. In the modelling process, this variable is treated as an ordinal variable, where larger values indicate a higher intention to become pregnant. Specifically, INTEND = 1 indicates no intention to have more children, INTEND = 2 represents uncertainty about having children, INTEND = 3 signifies an expectation to try for children in the future, INTEND = 4 denotes actively trying to conceive, and INTEND = 5 indicates that the individual is already pregnant.

In the original dataset, the AGE variable for each ID remained constant across the four waves, which could potentially affect the precision of the results. To address this issue, we redefined the age variable to account for its dynamic nature. Given that the interval between each wave is six months (0.5 years), we updated the age for each ID using the following formula: The dynamic age for each ID was calculated using the following formula:

$$\text{AGE}_j = \text{AGE}_1 + (j-1)\cdot 0.5, \quad j = 2,3,4$$

where AGE_j represents the dynamic age at wave j, AGE_1 is the baseline age, and j corresponds to the wave number. This adjustment ensures that age reflects its progression over time, improving the accuracy and reliability of our analysis.

Table 1 shows the descriptive statistics of variables in the integrated dataset. From the summary statistics table, it can be observed that the distribution of certain variables does not follow a uniform or normal distribution. For instance, marital status shows that only a small proportion of individuals are in the widowed or separated categories. Additionally, the distribution of the intention to have children (INTEND) is left-skewed, indicating that the majority of individuals are either uncertain about having children or intend to have children in the future.

Some variables in the study were derived by combining or recoding variables from the original dataset. Below are detailed steps on how we constructed these composite variables. The variable HOURTOT, our predictor of interest, representing the total hours spent on work and study in the previous week, is the summation of HOUREMP (hours spent on employment) and HOURED (hours spent on schooling). The variable HOUSEMEM, which represents the total number of household members, was generated by aggregating data on household composition across five categories: infants (0–1 years), toddlers (2–5 years), kids (6–12 years), teens (13–17 years), and adults (18+ years). These processed variables help provide a clear picture of participants' household and work-study contexts, which are relevant to our investigation of fertility intentions. Table 2 provides the abbreviations and definitions for the variables used in the study.

Data Imputation

The fertility intention variable in this dataset exhibited a missing data rate of less than 1% (Table 1). Notably, all other variables in the dataset were fully observed, making this a straightforward case for addressing missing data. We assume that this dataset is missing at random (MAR). This means the probability of INTEND being missing depends only on fully observed covariates, such as marital status, age, and work hours. Multiple imputation was applied to ensure unbiased estimates and preserve the integrity of the analysis. Since INTEND is an ordinal variable, we applied the ordinal logistic regression method (polr) for imputing missing values. The process generated five imputed datasets, and the results were pooled using Rubin's rules to account for variability between imputations.

Statistical Analysis

The spaghetti plot in Figure 1 illustrates the changes in pregnancy intention (INTEND) over four occasions for a randomly selected subset of 20 subjects. Each line represents the trajectory of an individual's response over time, showing both the variability in initial intention levels and the fluctuation patterns across the waves. Some subjects demonstrate consistent intention levels, as seen by flat lines, while others show significant changes, suggesting shifts in pregnancy intentions over time. Overall, this plot highlights the differences between individuals and illustrates the trends in individual pregnancy intentions over time, with the possibility that these trends are nonlinear. This observation supports the choice of our modeling approach, which will be discussed in detail in the following section.

The relationships between variables such as AGE-HHINC, AGE-MARSTAT, and HOURTOT-HHINC reveal notable interaction patterns that warrant further investigation. Prior research has established that income levels generally increase with age [5], while marital status is more likely to transition toward marriage with advancing age [6]. Moreover, a positive correlation exists between working hours and income, where longer working hours are associated with relatively higher income levels [7]. These observed interactions suggest an intricate interrelationship between age, marital status, working hours, and income, meriting deeper exploration in future analyses.

Method

Model Building

The null hypothesis for this analysis is that working/studying hours have no effect on the response variable ($H_0 : \beta_1 = 0$), while the alternative hypothesis is that working hours have a significant effect ($H_1 : \beta_1 \neq 0$). Given that the response variable, fertility intention, is ordinal, we selected the Cumulative Link Mixed Model (CLMM) as the appropriate analytical framework. This model is well-suited for analyzing clustered ordinal data as it employs a logit link function to transform cumulative probabilities into a linear predictor. Furthermore, including random effects for individuals and waves allows the model to account for intra-individual correlations and inter-wave variability, providing a robust approach to the longitudinal nature of the dataset. Sequential nested models were constructed as follows:

1. Unadjusted model
2. Adjusting for quadratic terms $(HOURTOT_i)^2$ to consider the potential nonlinear relationship
3. Adjusting for demographic variables (age, marital status, degree, race, household income, and members)
4. Adjusting for interaction terms to capture the joint effects of these variables on fertility intention, and quadratic terms $(AGE_i)^2$ to consider the potential nonlinear relationship

Model 1: $$\log\left(\frac{P(Y_{it} \leq k)}{P(Y_{it} > k)}\right) = \text{logit}(P(Y \leq k)) = \eta_k - \left(\beta_0 + \beta_1 \text{HOURTOT}_i + u_i + v_\text{t}\right)$$

Model 2: $$\log\left(\frac{P(Y_{it} \leq k)}{P(Y_{it} > k)}\right) = \text{logit}(P(Y \leq k)) = \eta_k - \left(\beta_0 + \beta_1 \text{HOURTOT}_i + \beta_2 (\text{HOURTOT}_i)^2 + u_i + v_t\right)$$

Model 3: $$\log\left(\frac{P(Y_{it} \leq k)}{P(Y_{it} > k)}\right) = \text{logit}(P(Y \leq k)) = \eta_k - \left(\beta_0 + \beta_1 \text{HOURTOT}_i + \beta_2 (\text{HOURTOT}_i)^2 + \beta_3 \text{AGE}_i \right.$$
$$\left. + \beta_4 \text{MARSTAT}_i + \beta_5 \text{RACETH}_i + \beta_6 \text{HOUSEMEM}_i + \beta_7 \text{DEGREE}_i + \beta_8 \text{HHINC}_i + u_i + v_t\right)$$

Model 4: $$\log\left(\frac{P(Y_{it} \leq k)}{P(Y_{it} > k)}\right) = \text{logit}(P(Y \leq k)) = \eta_k - \left(\beta_0 + \beta_1 \text{HOURTOT}_i + \beta_2 (\text{HOURTOT}_i)^2 + \beta_3 \text{AGE}_i \right.$$
$$+ \beta_4 (\text{AGE}_i)^2 + \beta_5 \text{MARSTAT}_i + \beta_6 \text{RACETH}_i + \beta_7 \text{HOUSEMEM}_i + \beta_8 \text{DEGREE}_i + \beta_9 \text{HHINC}_i$$
$$\left. + \beta_{10} \text{AGE}_i : \text{HHINC}_i + \beta_{11} \text{HOURTOT}_i : \text{HHINC}_i + \beta_{12} \text{AGE}_i : \text{MARSTAT}_i + u_i + v_t\right)$$

Model 4 is our final model where fixed effects β_i correspond to individual variables to capture the overall average effect of these variables on fertility intention. The random intercepts for individuals and waves (u_i and v_t) are assumed to follow a normal distribution, allowing the model to account for unobserved heterogeneity within subjects and across waves. There are five (K = 5) ordinal categories of response variables, making the model applicable to ordinal outcomes. This comprehensive model structure allows for a detailed examination of both main effects and interactions while addressing the clustered and ordinal of the data.

Model Selection

To determine the best model for our study, we conducted stepwise model comparisons using likelihood ratio tests (LRTs). Four models were compared sequentially, progressively adding quadratic terms, demographic variables, and interaction terms. The results in Table 3 indicated a consistent decrease in AIC values and statistically significant LRT results at each step. This demonstrates that incorporating quadratic terms, demographic variables, and interactions significantly improved model performance. Therefore, Model 4, which includes these adjustments, was selected as the final model.

Based on Figure 2, the residuals vs. fitted values plot shows that the residuals are randomly scattered around zero, with no clear patterns, suggesting an overall good fit. However, slight heteroscedasticity is observed, as the residual variance increases for larger fitted values. The Q-Q plot indicates that the residuals are approximately normally distributed, with most points lying along the 45-degree reference line. Some deviations are visible in the tails, suggesting potential mild departures from normality, but they are not severe. Overall, the model appears to perform reasonably well.

Results

According to the result of the final model, total working/studying hours (HOURTOT) have a significant positive association with fertility intentions ($\beta = 0.1738$, $p < 0.001$) (Table 4). This means that for each additional hour spent working and/or studying, the log odds of being in a higher category of fertility intention increase by 0.1738, adjusting all other variables. Although surprising, this finding aligns with the notion that individuals who dedicate substantial time to work or study tend to have stronger planning and organizational abilities, which may also extend to their consideration of family planning. Moreover, those who plan to have children often want to gain enough abilities to raise them, which motivates them to work harder.

Interestingly, in Model 2 which included only working/studying hours and its quadratic term, HOURTOT^2 exhibited a significant negative coefficient($\beta = -0.0551$, $p = 0.0456$), indicating a potential diminishing effect at higher levels of time commitment. This finding aligns with the idea that excessive work stress could reduce the feasibility of family planning. However, after adjusting for other demographic confounders, it no longer showed statistical significance. However, when demographic variables and interaction terms were included in the third and final models, the importance of the quadratic term disappeared ($\beta = -0.0429$, $p = 0.119$).

This implies that the diminishing effect observed earlier was likely explained by demographic differences rather than a true non-linear relationship.

In addition to our main findings regarding fertility intentions and working/studying time, age, marital status, and household composition were significant predictors, emphasizing their critical role in influencing females' fertility intentions.

Both AGE and AGE^2 are significant in the final model ($p < 2e{-16}$ and $p = 3.38e{-6}$, respectively). The negative coefficient for AGE ($\beta = -1.4365$, OR $= 0.2377$) indicates that fertility intentions decrease with age, with odds reducing by 76.3% per year. The negative coefficient for AGE^2 ($\beta = -0.3179$, OR $= 0.7277$) suggests that the rate of decrease in fertility intentions slows down as age increases further. These reveal a nonlinear relationship: fertility intentions are higher at younger ages but decline as priorities like career and finances take precedence. At older ages, this decline fades away, likely due to solidified decisions or life milestones. This underscores the importance of considering age as a confounder in analyzing working hours and fertility intentions.

The interaction between age and household income is significant and negatively associated with fertility intentions ($\beta = -0.1556$, $p = 0.027$), suggesting that the effect of income on fertility intentions decreases as age increases. Higher household income may strongly boost fertility intentions among younger individuals due to a stronger focus on family planning, but as age increases, other factors may reduce this positive effect.

Meanwhile, the marital status variable (MARSTAT) shows significant associations with fertility intentions. Compared to married individuals, those who are divorced ($\beta = -1.4863$, $p = 0.001$), separated ($\beta = -2.0343$, $p = 0.013$), never married ($\beta = -0.8566$, $p = 4.01e{-6}$), or living with a partner ($\beta = -0.5483$, $p = 0.01$) have lower fertility intentions. These findings suggest that unstable relationships or lack of formal commitment may reduce the desire for children. Moreover, older individuals in groups who lived with a partner or were never married show higher fertility intentions, possibly reflecting increased urgency with age.

The number of current household members is negatively associated with the outcome ($\beta = -0.2326$, $p = 3.54e{-6}$), indicating that individuals in larger families may have lower fertility intentions.

The residual variance (σ^2 =3.29) indicates moderate residual variability in the data. The random effects analysis revealed a higher variance of between-subject differences of 7.21, highlighting that differences across participants contribute significantly to variations in fertility intentions (Table 4). By contrast, the within-individual variance across the four waves was 0.01, indicating that fertility intentions are relatively stable over time for a given individual. Approximately 68.5% of the variability in the outcome is attributable to differences between individuals, while the remaining variability is explained by within-individual differences and other factors.

Discussion

Despite providing substantial evidence that working and studying time is significantly associated with fertility intentions, it is important to recognize that our findings are not without limitations. Factors such as the approximated aging process, the short study period, and broader societal and cultural influences need to be considered to better understand the nuances of this relationship, ensure the robustness of our conclusions, and guide future research.

Limitation

The study collects data from four waves spanning 18 months. Although we adjusted the constant AGE values across waves by incrementally adding 0.5 years for each subsequent wave, this is only an approximation and does not fully reflect the natural aging process of individuals over time. Therefore, even though we can partially examine the effects of aging within the same individual, the precision of this analysis is limited. The lack of exact aging data restricts our ability to comprehensively investigate nuanced longitudinal changes at the individual level.

Moreover, the short 18-month timeframe limits the ability to capture long-term trends and stable behaviors related to fertility intentions. Factors like career progression, financial stability, and life milestones, which often influence such intentions, may not fully manifest within this short period. Temporary circumstances or societal events during this timeframe may introduce temporal bias, potentially reflecting short-term fluctuations rather than lasting patterns.

The questionnaires across the four waves exhibit slight variations in the options provided for the pregnancy intention question, which may introduce potential bias in the results. Specifically, Wave 1 included only four options, excluding the ‘pregnant’ category, while the subsequent three waves featured five options, with ‘pregnant’ added as a choice. However, since the proportion of respondents selecting the ‘pregnant’ option in the integrated dataset is very small (4.3%), we did not consider it necessary to conduct a detailed analysis of this variable.

Another potential limitation is that we relied on the fact that no other variables in the dataset had missing values, and the missingness of INTEND (less than 1%) was presumed to depend only on fully observed covariates (MAR). However, this assumption remains unverified, and the absence of a sensitivity analysis to explore alternative missing data mechanisms (Not Missing at Random) may limit the robustness of our findings.

Our study population is limited to U.S. women aged 18–39, representing a relatively young and progressive demographic in a developed country with advanced gender equality measures and access to opportunities. As a result, the findings are context-specific and may not be generalizable to broader female populations, particularly those in regions or countries with different social, cultural, and economic backgrounds.

Future Work

Future studies should explore female populations in different countries and regions with diverse social, cultural, and economic contexts, as well as legislative systems. Such studies could provide more global and comprehensive insights into how societal norms and policies influence the association between working/studying time and fertility intentions. This broader approach would also offer region-specific policy recommendations.

Although our findings are focused on the U.S. female, they hold potential relevance for other regions. In areas where workplace and educational equity for women still lag behind, these results could guide policy discussions. For example, implementing measures such as equal pay legislation, anti-discrimination laws, and programs promoting work-life balance—designed for all genders, not just women—might help address issues like low fertility rates or negative population growth rates. By improving equity and creating supportive environments, these policies could serve as effective strategies for fostering reproductive intentions and addressing demographic challenges.

Conclusion

Our study demonstrates a positive association between the time women spend on working/studying and their fertility intentions, even after adjusting for demographic variables and interaction terms. This suggests that individuals who dedicate more time to work or study may possess stronger planning abilities and higher financial aspirations, which can drive their intention to have children. More importantly, those who wish to have children often prioritize achieving sufficient financial resources, a broader perspective, and more experiences, which can motivate their engagement in work and education. These findings underscore the intricate relationship between personal aspirations, external factors, and fertility intentions.

Additionally, the substantial between-subject variance underscores the importance of individual differences in fertility-related decision-making. Demographic factors such as age, marital status, and the existing family members also play critical roles in influencing females' fertility intentions.

These findings highlight the need for policies that support individuals balancing work or study with family planning. Specifically, workplace flexibility, financial stability initiatives, and work-life balance programs can empower individuals to pursue their family goals without undue stress or barriers.

References

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Appendix

Variable	Overall (N=7368)
AGE	
Mean (SD)	29.4 (5.34)
Median [Min, Max]	28.5 [18.0, 40.5]
MARSTAT	
Married	3416 (46.4%)
Widowed	12 (0.2%)
Divorced	236 (3.2%)
Separated	64 (0.9%)
Never married	2396 (32.5%)
Living with partner	1244 (16.9%)
INTEND	
No (more) kids	1548 (21.0%)
Not sure	1725 (23.4%)
Expect to try in future	3173 (43.1%)
Trying	547 (7.4%)
Currently pregnant	318 (4.3%)
Missing	57 (0.8%)
RACETH	
White, Non-Hispanic	5060 (68.7%)
Black, Non-Hispanic	600 (8.1%)
Other, Non-Hispanic	415 (5.6%)
Hispanic	1044 (14.2%)
2+ Races, Non-Hispanic	249 (3.4%)
HOUSEMEM	
Mean (SD)	3.04 (1.54)
Median [Min, Max]	3.00 [1.00, 13.0]
HOURTOT	
Mean (SD)	26.4 (20.4)
Median [Min, Max]	35.0 [0, 168]
DEGREE	
High school graduate and below (2–9)	1172 (15.9%)
Some college no degree (10)	1720 (23.3%)
Associate degree and Bachelors degree (11-12)	3336 (45.3%)
Masters degree and Professional or Doctorate degree (13–14)	1140 (15.5%)

Table 1: Descriptive Statistics of Variables in four waves

Variable name	Description
INTEND (Outcome)	Current plans regarding having a baby (No more kids(1), Not sure(2), Expect to try in future(3), Trying(4), Living with partner(5))
OCCASION	The number of waves (1 - 4)
AGE	Age of participants (18 - 39)
HOUSEMEM	Household Members in total
RACETH	Ethnicity & Race (White(1), Black(2), Other(3), Hispanic(4), 2+ Races(5)
MARSTAT	Marital Status (Married(1), Widowed(2), Divorced(3), Separated(4), Never married(5), Living with a partner(6))
DEGREE	Education (Highest degree received, 1- 14, higher numbers mean higher education)
HHINC	Household income (1 - 19, the higher the number, the higher the income.)
HOURTOT	Approximately how many hours did you spend on working/studying last week
Interaction parts	
HHINC:AGE	Interaction of household income and age
HHINC:HOURTOT	Interaction of household income and working/studying hours
MARSTAT:AGE	Interaction of marital status and age

Table 2: Main Variables

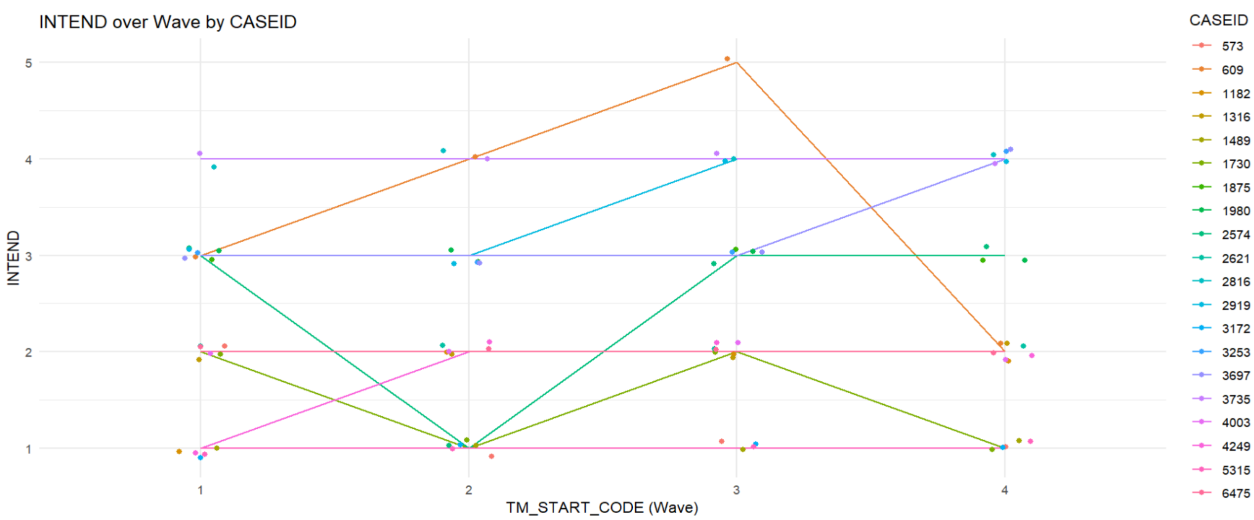

Figure 1: Spaghetti plot of 20 individual responses over time.

Comparison	Model	AIC	Log-Likelihood	LR Statistic	df	p-value
Model1 vs Model2	Model1	16280	-8133.2			
	Model2	16278	-8131.2	4.0171	1	< 0.04504 *
Model2 vs Model3	Model2	16278	-8131.2			
	Model3	15995	-7976.6	309.18	13	$<$ 2.2e-16 ***
Model3 vs Model4	Model3	15995	-7976.6			
	Model4	15946	-7944.1	64.966	7	$<$ 4.9e-11 ***

Table 3: Likelihood Ratio Tests for Nested Models

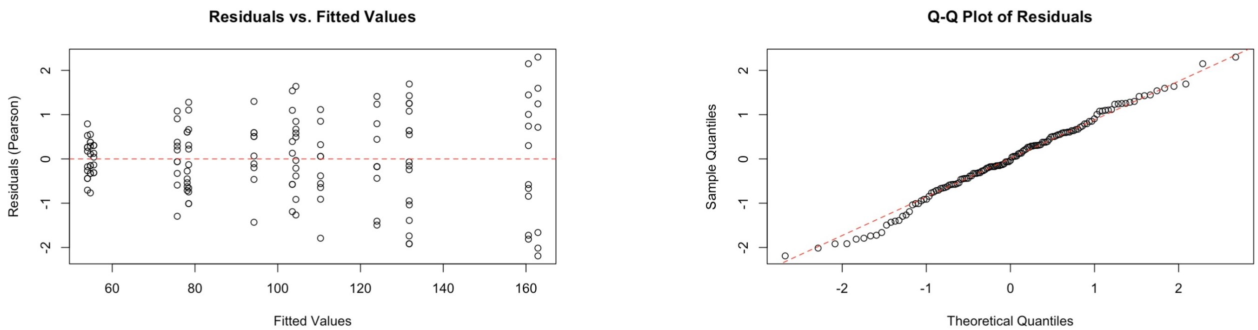

Figure 2: Residuals and QQ Plots.

Predictors	**Estimate**	**Odds Ratios**	**95% CI**	**p-value**
1–2	-3.9126	0.01999	0.00603 – 0.06624	< 0.001
2–3	-1.2048	0.29975	0.09091 – 0.98841	0.048
3–4	3.1097	22.41404	6.78764 – 74.01537	< 0.001
4–5	4.5428	93.95022	28.33554 – 311.50440	< 0.001
HOURTOT	0.17220	1.18791	1.08846 – 1.29645	< 0.001
HOURTOT_sq	-0.04289	0.95801	0.90773 – 1.01109	0.119
AGE	-1.43659	0.23774	0.18529 – 0.30503	$< 2e{-16}$
AGE_sq	-0.31788	0.72769	0.63636 – 0.83212	$3.38e{-6}$
MARSTAT[2]	1.75303	5.77205	0.00036 – 93619.92896	0.723
MARSTAT[3]	-1.48632	0.22620	0.09048 – 0.56553	0.001
MARSTAT[4]	-2.03430	0.13077	0.02605 – 0.65638	0.013
MARSTAT[5]	-0.85664	0.42459	0.29500 – 0.61110	$4.01e{-6}$
MARSTAT[6]	-0.54829	0.57793	0.38127 – 0.87604	0.010
RACETH[2]	0.51579	1.67496	1.00044 – 2.80425	0.050
RACETH[3]	0.02419	1.02449	0.61473 – 1.70738	0.926
RACETH[4]	0.10625	1.11210	0.74080 – 1.66949	0.608
RACETH[5]	-0.07134	0.93115	0.52654 – 1.64666	0.806
HOUSEMEM	-0.23259	0.79248	0.71827 – 0.87434	$3.54e{-6}$
DEGREE	0.04882	1.05003	0.95539 – 1.15405	0.311
HHINC	0.13642	1.14616	0.97495 – 1.34743	0.098
AGE × HHINC	-0.15556	0.85594	0.74559 – 0.98262	0.027
HOURTOT × HHINC	0.01366	1.01375	0.93552 – 1.09853	0.739
AGE × MARSTAT[2]	0.08493	1.08864	0.00372 – 319.00830	0.977
AGE × MARSTAT[3]	0.09731	1.10220	0.48783 – 2.49029	0.815
AGE × MARSTAT[4]	0.52034	1.68260	0.23873 – 11.85910	0.601
AGE × MARSTAT[5]	0.43556	1.54584	1.07837 – 2.21595	0.018
AGE × MARSTAT[6]	0.74928	2.11548	1.35715 – 3.29755	0.001
Random Effects				
σ^2			3.29	
τ_{00} CASEID			7.21	
τ_{00} occasion			0.01	
ICC			0.69	
N CASEID			1842	
N occasion			4	
Observations			7368	
Marginal R^2 / Conditional R^2			0.158 / 0.736	

Table 4: Ordered Logistic Regression Results