A CONTEMPORARY FERTILITY MODEL:
HAVE THE FACTORS INFLUENCING WOMEN'S DECISIONS TO HAVE CHILDREN CHANGED SINCE THE MID-TWENTIETH CENTURY?

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Arts

By

Brooke Veale

May 2019

A CONTEMPORARY FERTILITY MODEL:
HAVE THE FACTORS INFLUENCING WOMEN'S DECISIONS TO HAVE CHILDREN CHANGED SINCE THE MID-TWENTIETH CENTURY?

Brooke Veale

May 2019

Economics

Abstract

The bulk of fertility research—or research surrounding which factors influence women's decisions to have children—was conducted in the mid-twentieth century, when women joined the labor force at unprecedented rates and drastically altered the nature of the United States economy. Very little research has been conducted since. This study therefore aims to generate a contemporary fertility model in order to determine how the factors influencing women's fertility decisions have changed since the 1950s, especially considering how women's rights and the traditional family structure have changed since the 1950s. Using a probit regression model, it is found that a woman's age, marital status, race, education, employment status, and income all significantly impact her likelihood of having a child. It is also found that, contrary to findings from the mid-twentieth century, extrinsic variables such as spouse's income, women's wages relative to men's, and relative economic aspirations do not impact women's decisions to have children. The results of this study therefore suggest that the factors influencing women's fertility decisions have in fact changed since the mid-twentieth century—changes likely attributable to women's increased independence, both in terms of the economy and the structure of the family.

KEYWORDS: (Children, Family, Fertility, Marriage, Women)
JEL CODES: (J12, J13, J16)

ON MY HONOR, I HAVE NEITHER GIVEN NOR RECEIVED UNAUTHORIZED AID ON THIS THESIS.

Brooke Veale

Signature

Acknowledgments

I would first like to thank my thesis advisor, Vibha Kapuria-Foreman, for her advice and support, and for assuring me that “you shouldn’t be worried” every time I walked into her office panicked. This thesis would not have come together without her. I would also like to thank my Economics of Gender professor in Sweden, Jim Breen, for sparking my interest in women’s fertility decisions and for inspiring the topic of this thesis. Further, I would like to thank the Department of Economics and Business at Colorado College for motivating me to work ever harder, so as to the learn the most I can and perform the best I can. Finally, I would like to thank my parents for making my education possible, and for telling me that I can accomplish whatever I set my mind to for as long as I can remember.

TABLE OF CONTENTS

Introduction

The "traditional marriage," or the marriage pattern that emerged with industrialization in the nineteenth century, involved a long-term division of labor between husband and wife. The husband acquired marketable skills and developed them through use as he gained experience and further training. The wife, by contrast, stayed at home, cared for the children, tended to the house and the kitchen, and developed skills of little value outside of marriage. This arrangement obviously put the woman in a vulnerable economic position, and one that was tolerable only as long as marriage was based on a lifetime contract. As more women experienced divorce, the financial implications of lacking marketable skills became more apparent, and young women found it sensible to insure themselves against this highly undesirable fate (Lee & Casterline, 1996). The insurance took the form, in part, of getting a foothold in the labor market and acquiring the training and skills necessary to do so, and, in part, of having fewer children (Lee & Casterline, 1996).

This is precisely what happened in the 1950s, a period widely recognized by economists and sociologists alike as a fascinating time of change for women and the economy. Over the course of the twentieth century, the gap between men's and women's labor-force participation rates narrowed by more than 50 percentage points, from 65 percent to 12 percent (Hoffman & Averett, 2015). Whereas throughout the 1960s the ratio of women to men was around 0.1 in medicine, 0.04 in law, 0.01 in dentistry, and 0.03 in business administration, it had risen to 0.42 in medicine, 0.57 in law, 0.24 in dentistry, and 0.39 in business administration by 1980 (Goldin & Katz, 2000). As women's labor force participation rate increased, the fertility rate decreased. Among non-

Catholic female college students in 1963, 80 percent desired three or more children, and 44 percent wanted at least four (Goldin & Katz, 2000). By 1973, just 29 percent wanted three or more, and almost 10 percent wanted no children (Goldin & Katz, 2000).

Women's decision to enter the labor market in the 1950s, necessitated by the erosion of the marriage contract, itself eroded the gains to marriage as it lessened the division of labor that formed the economic and social basis of the union (Lee & Casterline, 1996). The result has been a shift from the unstable equilibrium of the traditional family to a new stable equilibrium in which the nuclear family is less common and/or in which there is less division of labor and less difference between the marketable skills of men and women (Lee & Casterline, 1996). In 1970, among women with children under the age of five, the majority, 70 percent, were out of the labor force, presumably full-time homemakers (Isen & Stevenson, 2010). In the ensuing decades, labor market participation became the norm for mothers with young children and only 36 percent were out of the labor force in 2007 (Isen & Stevenson, 2010). Furthermore, marriage is no longer the only socially acceptable context for childbearing, as the share of children born outside of marriage has greatly increased (Lee & Casterline, 1996). In 1940, less than 4 percent of births were non-marital; in 2014, however, more than 40 percent of all births were to single women (Hoffman & Averett, 2015). Even though the mid-twentieth century was a fascinating time for women and the economy precisely because the traditional marriage structure was changing, the traditional marriage structure has undergone yet further substantial change in the decades since.

One of the biggest questions of the mid-twentieth century that continues to preoccupy economists today is why fertility decreased as women's employment increased. What factors impacted women's fertility decisions in the 1950s, and to what extent? As women's employment increased and therefore as household income increased, shouldn't fertility have increased? Wouldn't we expect families with more income to want more children? Many of the economic approaches that attempted to explain the fertility trends of the mid-twentieth century assumed a traditional family structure. Because the traditional family structure has undergone significant change since the 1950s, it is likely that the factors impacting fertility have also changed. I therefore intend to generate a contemporary fertility model in order to determine which factors are impacting fertility in the twenty-first century, as well as how changes in the family structure have influenced changes in these factors.

Literature Review

The earliest economic approach to fertility is due to Thomas Malthus, an early nineteenth-century economist best known for his pessimistic theory about population growth outpacing food supplies. Malthus's theory of population focused exclusively on the effects of income. Higher incomes encouraged earlier marriages, which in turn caused fertility to commence sooner, and also lowered infant mortality. As a result, the population grew more rapidly. Eventually, however, the larger population fed back negatively to reduce wage rates and society fell back toward a subsistence standard of living with a lower fertility rate (Hoffman & Averett, 2015).

Much empirical research has been conducted to test the existence, or lack thereof, of Malthusian checks in the past. Due to a lack of accurate historical demographic and wage data, this research is typically confined to European countries in the early modern era with reliable birth and death records (Evans, 2017). The results of this research are conflicted: some studies, like Lee (1981) and Eckstein, Schultz, and Wolpin (1984), find support for the existence of Malthusian checks, while others, such as Lee and Anderson (2002), Nicolini (2007), and Crafts and Mills (2009), find that such checks are weak or nonexistent. The Malthusian hypothesis predicts that birth rates respond positively and death rates respond negatively to a shock in real wages (the preventive check and the positive check, respectively), and that wages respond negatively to population over time (diminishing returns to labor) (Evans, 2017). Using a vector autoregression (VAR) model, Evans (2017) found that the Malthusian hypothesis provides a good explanation for population dynamics in Sweden from 1751 to 1870. Sweden's Malthusian regime can be described as high pressure, as most of the population adjustment came from a large and statistically significant positive check, while the preventive check was smaller and not significant over many sub-periods. While Evans (2017) found strong support for the Malthusian hypothesis, Nicolini (2007) found only weak support for the Malthusian hypothesis. Nicolini was able to confirm the existence of both the positive and preventive checks in pre-industrial England, but the significant results stemmed from a higher incidence of Malthusian behavior in rural settings, which masked the absence of Malthusian behavior in urban settings.

While Malthus's approach to fertility focused exclusively on the income effect, later approaches to fertility considered the income effect in combination with the substitution effect. New Home Economics is a school of household economics that stresses the role of female wages, representing the opportunity cost of childbearing, as a determinant of fertility (McNown & Rajbhandary, 2003). Female wages are seen to have both (positive) income and (negative) substitution effects on fertility, with opposite effects on the woman's hours of work (McNown & Rajbhandary, 2003). An increase in women's wages increases household income, and therefore increases fertility, as children are viewed, at least through an economic lens, as normal goods that bring parents utility (Siegel, 2017). An increase in women's wages may therefore increase fertility through the income effect (Siegel, 2017). An increase in women's wages also, however, increases the cost of women's time, and thus the opportunity cost of household production (Galor & Weil, 1996; Siegel, 2017). An increase in women's wages may therefore decrease fertility, through the substitution effect, by causing women to substitute away from household production and toward the labor market (Galor & Weil, 1996; Siegel, 2017). Although the conflicting income and substitution effects of an increase in women's wages technically have an ambiguous effect on women's fertility, economic theory postulates that the substitution effect often outweighs the income effect, and thus that women have fewer children in the presence of higher wages (Galor & Weil, 1996; Hoffman & Averett, 2015).

While the earliest economic approach to fertility was developed by Thomas Malthus in the nineteenth century and focused exclusively on the income effect, the modern economic approach to fertility was developed in the early 1960s, primarily by Gary Becker, and utilized both the income and substitution effects (Hoffman & Averett, 2015). Becker suggested that children were a kind of consumer durable for which both quantity and quality were centrally important attributes (Lee & Casterline, 1996). He reasoned that a family must determine not only how many children to have (quantity), but also how much to spend on them (quality)—including whether the family should provide children with separate bedrooms, send them to nursery school and private colleges, give them dance or music lessons, etc. (Becker, 1960). Increasing quantity—having a baby—inevitably involves the very time-intensive years of infancy and early childhood. In contrast, increasing quality can often be accomplished by increasing consumption goods (e.g., educational spending) at older ages. This suggests that when women's wages increase, the cost of quantity will increase by more than the cost of quality, because quantity is likely to be more time-intensive than quality (Hoffman & Averett, 2015). Becker therefore hypothesized that when the price of time increases, or when women's wages increase, families opt for fewer children (through the substitution effect), but spend more on each of them (through the income effect) (Hoffman & Averett, 2015). Fertility falls but child quality increases.

In line with Becker's hypothesis, most data tend to show a negative relationship between income and fertility. In the Indianapolis survey he cites, the lowest income class was most fertile, with 2.3 children per couple, and a relatively high class was least fertile, with 1.5 children per couple (the highest class averaged slightly more children than the next highest) (Becker, 1960). This relationship between income level and fertility is about the same as that shown by the Census data of 1910, 1940, and 1950 (Becker, 1960). Census Bureau studies in 1952 and 1957 also confirm Becker's expectation. For both urban and rural nonfarm families in the United States in 1952 and for all families in the United States in 1957, children born per 100 wives 15-44 years old and children born per 100 wives over 45 years old decreased as income increased (Becker, 1960). Although the quality dimension of Becker's hypothesis is harder to prove than its quantity dimension, Becker proposes that the negative relationship between income and fertility can be at least partially explained by an increase in the cost of children (Becker, 1960). While the details of Becker's hypothesis may require further investigation, the overarching idea—that fertility decreases as income increases—is widely supported by the data.

In the 1970s, Richard Easterlin countered Becker's economic approach to fertility, claiming that women's fertility decisions are not a function of women's wages, but rather a function of men's (McNown & Rajbhandary, 2003). Easterlin's Relative Income Hypothesis emphasizes the role of male incomes, relative to economic aspirations, as the driving force behind fertility and female labor force participation (McNown & Rajbhandary, 2003). He used men's income, and not women's, based on the assumption that he was operating in a world where men were still the primary breadwinners (Easterlin, 1976). He claimed that male relative incomes are governed by relative cohort size, as large cohorts are disadvantaged in education, employment opportunities, and rates of pay (McNown & Rajbhandary, 2003). The size of the cohort of young adult males, relative to that of their parents' generation, is an indicator of the earnings potential of young men relative to their economic aspirations as determined by parental incomes (McNown & Rajbhandary, 2003). The thrust of this hypothesis is that young couples establish minimal expected standards of living on the basis of their experience as children growing up in their parents' household. If these expectations are not met, young people will defer births, having children of their own only when this minimal level of income is reached (Butz & Ward, 1979; Easterlin, 1973). Easterlin's hypothesis is similar to Malthus's in that it employs only the income effect, it differs from Becker's in its neglect of the substitution effect and focus on men's wages rather than women's, and it adds to the literature the ideas of relative economic aspirations and relative male cohort size.

Using data from both the US Public Health Service National Center for Health Statistics and the Bureau of the Census, Easterlin demonstrated that the total fertility rate from 1940-1975 was a positive function of relative male income and a negative function of relative male cohort size. As young men's income as a percentage of that in their family of orientation increased, total fertility increased, and as the relative number of young adult males aged 15-34 decreased, total fertility increased as well (Easterlin, 1976). Easterlin's idea of relative male income is also supported by data on the growth in farm acreage values over the period 1860-1890—lower growth rates in farm acreage values led to lower levels of farm family fertility (Easterlin, 1976). Easterlin therefore demonstrated the effects of relative economic aspirations and relative male cohort size on fertility, thereby strongly substantiating his two main contributions to the literature.

Contrary to both Becker's and Easterlin's claims, more recent research has indicated that women's fertility is likely a function of women's wages relative to men's, rather than a function of either alone. In 1996, Diane J. Macunovich examined the trends of the mid-twentieth century and found that the effect of women's wages on fertility was significantly negative when men's wages were high and was significantly positive when men's wages were low. The rationale behind this finding is as follows: when men's wages are low, women's wages are relatively high, so the income effect dominates and the fertility rate increases (Macunovich, 1996). When men's wages are high, on the other hand, women's wages are relatively low, so the income effect of women's wages diminishes, the substitution effect dominates, and the fertility rate decreases (Macunovich, 1996). Macunovich (1996) therefore concluded that the impact of women's wages on fertility is an inverse function of men's wages.

Christian Siegel (2017) similarly found women's fertility to be a function of women's wages relative to men's, as his analysis of the trends of the mid-twentieth century led him to believe that the common driving force behind the trends in fertility and female employment was the narrowing of the gender wage gap, as it changed the division of labor within the family. In the 1960s, when the wage gap was large, the catching up of female wages increased women's labor supply. The associated increase in the opportunity cost of women's time, who shouldered most of child care, lowered fertility. But as relative wages become more equal over time, specialization in the household decreases. Consequently, male home hours increase, a father's time at home becomes more important for raising children, and the allocation of time between home and market work becomes more evenly balanced for men and women. When the complementarity between mother's and father's time working at home is sufficiently large, the cost of reallocating home production from the wife to the husband falls, and thus the marginal cost of having an additional child can become constant, or even fall, despite women working more hours in the market (Siegel, 2017). Siegel's analysis therefore explains why the fertility rate may have fallen as women's wages increased in the mid-twentieth century, as well as why the fertility rate may have leveled off in recent years.

As the evolution of fertility research clearly shows, there exist many conflicting economic approaches to fertility that have yet to be reconciled. The fact that a comprehensive fertility model has yet to be developed, combined with the fact that current fertility research still chooses to focus on trends of the mid-twentieth century rather than on trends of the present, suggests that fertility is an immensely complicated field in need of researchers' attention. Not only has the literature failed to agree on the causes of the trends of the mid-twentieth century, but it has failed to even begin to assess the trends of the twenty-first century. Because of fertility's enormous societal, political, and economic implications, as well as its relative neglect since the mid-twentieth century, I have chosen to leave the trends of the mid-twentieth century to its previous researchers, and to instead turn my attention toward present-day trends in fertility. I have set out to generate a contemporary fertility model in order to determine which factors are currently impacting fertility, how these factors have changed since the mid-twentieth century, and finally, what these changes mean regarding the nature of the family and future fertility.

Model

The empirical model used to test the hypotheses in this analysis describes a woman's fertility decisions as a function of her age, marital status, race, education, employment status, income, and spouse's income. The dependent variable is a binary response variable measuring whether or not the woman had a child that year. The independent variables age, income, and spouse's income are measured as continuous variables. Marital status, race, and employment status are measured as binary response variables with the options of married or not married, white or not white, and employed or not employed, respectively, while education is measured as a categorical variable with more than two outcomes. The education variable takes on twelve values ranging from no schooling to five plus years of college. The model is shown below in Equation 1. See Table 1 for a description of the variables.

$$\text{Fertility} = f(A, MS, R, E, ES, I, SI)$$

A = Age

MS = Marital Status

R = Race

E = Education

ES = Employment Status

I = Income

SI = Spouse's Income

(1)

Table 1. *Variable Descriptions*

Variable	Abbreviation	Description
Children born within the last year	fertyr	Binary response variable indicating whether the woman had a child that year: yes = 1, no = 0
Age	age	Continuous variable indicating the woman's age
Marital Status	marst	Binary variable indicating whether the woman is married: yes = 1, no = 0
Race	race	Binary variable indicating the woman's race: white = 1, non-white = 0
Education	educ	Categorical variable indicating the woman's level of education: takes on twelve values ranging from no schooling = 0 to five plus years of college = 12
Employment Status	empstat	Binary variable indicating whether the woman is employed: yes = 1, no = 0
Income	incwage_adj	Continuous variable indicating the woman's income
Spouse's Income	incwage_sp_adj	Continuous variable indicating the woman's spouse's income

In line with previous research, I hypothesize that marital status, income, and spouse's income will exhibit a positive relationship with fertility: married women will be more likely to have children than non-married women, and couples with higher incomes will be more likely to have children than couples with lower incomes. I also predict that age, race, education, and employment status will exhibit a negative relationship with fertility: as a woman's age and years of education increase, she will be less likely to have children. Furthermore, white women will be less likely to have children than non-white women, and employed women will be less likely to have children than non-employed women.

Methodology

The data in this study comes from the Integrated Public Use Microdata Series (IPUMS USA). IPUMS USA collects, preserves, and harmonizes U.S. census microdata, including decennial censuses from 1790 to 2010 and American Community Surveys (ACS) from 2000 to the present.

My objective in conducting this study is to generate a contemporary fertility model. I therefore chose to analyze ACS data across the ten-year period from 2008 to 2017 in order to utilize the most recent data available. Because I do not expect fertility or the factors impacting fertility to differ substantially between the years in this time period, I treat the data as cross-sectional data without regard to difference in time. I also limit my observations to females between the childbearing ages of 15 and 50, as only women between these ages are measured by ACS on the dependent variable.

The final sample used in this model includes observations from 93,018 women. The mean age is 33 years old, 45.09% are married, and 73.82% are white. The women in this study are fairly highly educated, as 30.45% of the sample graduated from high school and another 29.76% attained four or more years of college. Finally, 65.86% of the sample are employed, and the mean income is $25,000 per year.

All dollar amounts in IPUMS USA are nominal dollars—that is, they are given as measured in the original census year. I therefore used IPUMS's adjustment variable, which converts all dollar figures to constant 1999 dollars, to account for inflation, and then used yet another adjustment factor to convert the constant 1999 dollars to constant 2017 dollars. All dollar amounts present in this study are therefore represented by 2017 dollars.

I also generated variables to mirror the ideas of relative economic aspirations and women's wages relative to men's, as mentioned in the above literature review and as analyzed by prior research. I calculated relative economic aspirations by dividing a woman's income by her parents' income, and I calculated women's wages relative to men's by dividing a woman's income by her spouse's income. I was unable to use parental variables, or variables calculated using parental variables, in the model because the large number of missing data points associated with the parental variables substantially reduces the number of usable observations. Although including spousal variables in the model also reduces the number of usable observations, it does so to a much lesser extent than including parental variables in the model. I thus chose to include spousal variables while excluding parental variables, reducing the number of usable observations from 93,018 to 48,658. Although neither relative economic aspirations nor women's wages relative to men's are variables in the final model, I will briefly discuss findings related to them in the discussion section to follow.

Finally, I generated an education squared variable ("educ2") to appear alongside education in the final model because it is necessary for capturing the true relationship between education and women's fertility decisions. Likewise, I generated an interaction term ("interaction") between marital status and race because it, too, is necessary for capturing the true relationship between marital status, race, and women's fertility decisions.

In order to analyze the data in this study, I use a probit model. I elect to use a probit model in place of a linear probability model as the dependent variable under investigation is a binary response variable, and probit models overcome many of the shortcomings associated with the linear probability model. Furthermore, as stated previously, I disregard changes in time and analyze the data at hand as cross-sectional data.

Analysis and Results

In order to determine the effect of the independent variables on the binary response variable, the following regression (Equation 2) was estimated. Table 2 reports the regression results.

$$\text{fertyr} = \beta_0 + \text{age}\beta_1 + \text{marst}\beta_2 + \text{race}\beta_3 + \text{educ}\beta_4 + \text{educ2}\beta_5 + \text{empstat}\beta_6 + \text{incwage\_adj}\beta_7 + \text{incwage\_sp\_adj}\beta_8 + \text{interaction}\beta_9 \quad (2)$$

Table 2. *Probit Regression Results*

Variable	**Coefficient (p-value)**	**Significance Level (if any)**
fertyr		
age	-0.0674 (0.000)	***
marst	0.2426 (0.000)	***
race	-0.2091 (0.000)	***
educ	-0.0891 (0.000)	***
educ2	0.0087 (0.000)	***
empstat	-0.3347 (0.000)	***
incwage_adj	8.54e-07 (0.000)	***
incwage_sp_adj	1.70e-07 (0.206)	
interaction	0.1682 (0.008)	***
constant	1.0537 (0.000)	***
N	48,658	
Significance Level	*** = 1%	

The predicted probability of fertility can be calculated using these coefficients as in Equation 3. For a given observation, the predicted probability of having a child is:

$$\text{fertyr} = 1.0537 + \text{age} \times -0.0674 + \text{marst} \times 0.2426 + \text{race} \times -0.2091 + \text{educ} \times -0.0891 + \text{educ2} \times 0.0087 + \text{empstat} \times -0.3347 + \text{incwage\_adj} \times 8.54\text{e-}07 + \text{incwage\_sp\_adj} \times 1.70\text{e-}07 + \text{interaction} \times 0.1682 \quad (3)$$

However, interpretation of the coefficients in probit regression is not as straightforward as interpretation of the coefficients in linear regression or logit regression. The increase in probability attributed to a one-unit increase in a given predictor is dependent both on the values of the other predictors as well as on the starting values of the given predictors. There are therefore limited ways in which we can interpret the individual regression coefficients. A positive coefficient means that an increase in the predictor leads to an increase in the predicted probability, while a negative coefficient means that an increase in the predictor leads to a decrease in the predicted probability.

The individual regression coefficients support the hypotheses of this study. As predicted, marital status, income, and spouse's income exhibit a positive relationship with fertility, while age, race, education, and employment status exhibit a negative relationship with fertility. In order to obtain more informative coefficients, however, and in order to determine the effect of a one-unit change in the predictor variables on the probability of having a child, the marginal effects were also estimated. Table 3 reports the marginal effects.

Table 3. *Marginal Effects*

Variable	**Coefficient (p-value)**	**Significance Level (if any)**
fertyr		
age	-0.0069 (0.000)	***
marst	0.0215 (0.000)	***
race	-0.0237 (0.001)	***
educ	-0.0091 (0.000)	***
educ2	0.0009 (0.000)	***
empstat	-0.0386 (0.000)	***
incwage_adj	8.75e-08 (0.000)	***
incwage_sp_adj	1.75e-08 (0.205)	
interaction	.0164 (0.005)	***
Significance Level	*** = 1%	

The signs on the individual regression coefficients remain unchanged, but the coefficients can now be interpreted as the effect of a one-unit change in the predictor variables on the probability of having a child. The coefficients on continuous variables such as age, income, and spouse's income indicate that a one-unit change in these variables affects the probability of having a child by X percentage points. Similarly, the coefficients on binary variables such as marital status, race, and employment status indicate that a change in these variables from zero to one affects the probability of having a child by X percentage points. For example, a one-unit increase in age decreases the probability of having a child by -0.6910 percentage points, while a change in marital status from zero (not married) to one (married) increases the probability of having a child by 2.1535 percentage points. Marital status, race, and employment status thus have the largest coefficient values. All predictors are significant at the 1% significance level, except for spouse's income, which is only significant at the 20.5% significance level. See Appendix A for the full regression output, both from the probit regression and the marginal effects.

As stated previously, the signs on the individual regression coefficients support the hypotheses of this study. Being married and high income increases the probability of having a child while being older, white, educated, and employed decreases the probability of having a child. Furthermore, the significance of the variables suggests that women's age, marital status, race, education, employment status, and income are in fact powerful predictors of women's fertility decisions.

Diagnostic Tests

Three diagnostic tests were conducted following the initial regression: the Pearson goodness of fit test, Akaike's and Schwarz's Bayesian information criteria, and a link test for model specification.

The Pearson goodness of fit test is a test of the observed number of responses against the expected number of responses using cells defined by the covariate patterns. The initial test indicates that the model indeed fits the data, as the test yields an insignificant p-value of 0.9556. However, because the number of covariate patterns (46,930) closely matches the number of observations (48,658), the applicability of the Pearson goodness of fit test is questionable, and as suggested by Hosmer, Lemeshow, and Sturdivant (2013), the data must be regrouped by ordering on the predicted probabilities to form ten nearly equal-sized groups. When the "estat gof, group(10) table" command is used in place of the "estat gof" command, as it should be in cases where the number of covariate patterns closely matches the number of observations, the Pearson goodness of fit test yields a p-value of less than 0.001, and thus indicates that the model does not fit the data.

Akaike's and Schwarz's Bayesian information criteria are used to compare models. In general, smaller is better: given two models, the one with the smaller Akaike Information Criterion (AIC) fits the data better than the one with the larger AIC. As with the AIC, a smaller Bayesian Information Criterion (BIC) indicates a better-fitting model. I therefore utilized Akaike's and Schwarz's Bayesian information criteria to compare the model without education squared and the interaction term to the model with education squared and the interaction term. Akaike's and Schwarz's Bayesian information criteria suggest that the model with education squared and the interaction term fits the data better than the model without education squared and the interaction term, although the differences in the AICs and BICs do not appear large.

The link test for model specification is formally a test of the specification of the dependent variable, although it is often interpreted as a test that, conditional on the specification, the independent variables are incorrectly specified. Following the regression command, "linktest" uses the linear predicted value and the linear predicted value squared as predictors to rebuild the model. The linear predicted value ("_hat") should be a statistically significant predictor, as it is the predicted value from the model. The linear predicted value squared ("_hatsq"), however, should not be a statistically significant predictor. The link test for model specification indicates that the linear predicted value squared is indeed a significant predictor, and thus that the model is in some way misspecified. The variable education squared as well as the interaction term were added to the model in an attempt to correct for this issue, but even with the addition of education squared and the interaction term, the link test persists to indicate model misspecification.

The results from the Pearson goodness of fit test and the link test for model specification should therefore be understood as limitations of this study, as they suggest that the model does not fit the data and that the model is in some way misspecified. Tests for heteroskedasticity and multicollinearity were also conducted, however, and both yield positive results. The only variables with a correlation greater than 0.5 are the variables education and education squared, as well as the variables marital status and race with the interaction term (which is to be expected). Furthermore, the results remain significant even after controlling for heteroskedasticity by using the robust regression command. The signs on the coefficients as well as the significance of the predictors should therefore not be overlooked, as they indicate that the independent variables do in fact predict the dependent variable, and in the hypothesized direction. See Appendix B for output from the diagnostic tests.

Discussion

Although some of the results presented in this study appear axiomatic, others appear contrary to current trends and past research. For example, it is not altogether surprising that income positively affects the probability of having a child while age, race, and employment status negatively affect the probability of having a child. It is however surprising that marital status positively impacts the probability of having a child, and that spouse's income does not significantly impact the probability of having a child.

Non-marital fertility is measured by two related terms. The non-marital fertility rate (NMFR) is the number of births to single women divided by the number of single women aged 15-44. The non-marital birth ratio (NMBR) is the proportion of all births that are non-marital—that is, the number of births to single women divided by the total number of births. Both measures of non-marital fertility have increased enormously, and for the most part, they have moved together. In 1940, there were just 7.0 births per 1,000 single women between the ages of 15 and 44 and less than 4 percent of births were non-marital. In 2014, there were 44.0 births per 1,000 single women aged 15-44, and more than 40 percent of all births were to single women. By comparison, the marital birth rate in 2014 was 86.9 births per 1,000 married women (Hoffman & Averett, 2015).

Non-marital fertility has increased partially because marriage rates have decreased. Although marriage is by far the dominant form of living arrangement in the United States and elsewhere, both now and in the past, the proportion of adult women (and men) married at a point in time has declined. In 2005, U.S. women crossed a numerical threshold when the Census Bureau reported that for the first time ever, more than half of all women aged 15 or older were living without a husband. Back in 1950, just

35 percent of women fell into that category. The trends are quite clear. The proportion currently married with their spouse present has fallen steadily and quite sharply, from two-thirds in 1950 to well under 50 percent in the mid-2010s. In the 60 plus years since 1950, the proportion married dropped by almost exactly 20 percent, nearly equally divided between an increase in the proportion who had never married (up 9 percent) and an increase in the proportion who were divorced or separated (up 11 percent) (Hoffman & Averett, 2015). Given the increase in non-marital fertility combined with the simultaneous and related decrease in marriage rates, it is therefore interesting, if not altogether surprising, that marital status is still a significant predictor of women's fertility decisions.

It is also interesting that spouse's income is not a significant predictor of women's fertility decisions. Spouse's income specifically, and spousal indicators more generally, are commonly included in fertility models precisely because they are consistently found to impact women's fertility decisions. This study, however, finds that spouse's income does not significantly impact a woman's likelihood of having a child.

Likewise, while past studies using data from the mid-twentieth century have found women's wages relative to men's to be a significant predictor of women's fertility decisions, this study does not. When the variable generated to represent women's wages relative to men's ("relinc_spouse") is included in the probit model, it, like spouse's income, is insignificant.

The variable generated to represent relative economic aspirations ("relinc_parents") is also insignificant when included in the probit model. Although past studies define relative economic aspirations as the spouse's income as a proportion of his parents' income, this study defines relative economic aspirations as the woman's income as a proportion of her parents' income (due to a lack of available data on the spouses' parents). Nevertheless, the results of this study suggest that relative economic aspirations do not significantly impact a woman's probability of having a child. See Appendix C for the regression results when women's wages relative to men's and relative economic aspirations are included in the model.

It is possible that the variables not directly based on the woman herself, including spouse's income, women's wages relative to men's, and relative economic aspirations, are insignificant predictors of women's fertility decisions because women are substantially more independent now than they were in the 1950s. When the bulk of fertility research was conducted in the 1950s and 60s, a woman was highly dependent on her spouse and parents, as she was just beginning to enter the labor market and did not have the skills or experience necessary to support herself on her own. The incomes of her spouse and parents were therefore likely large determinants in her decisions surrounding having children. In the 2000s and 2010s, however—the timespan covered by the data in this study—women are in fact able to support themselves on their own, and it is thus likely that the incomes of other family members are therefore not significant determinants in their decisions surrounding having children. Although the increased independence of women since the bulk of fertility research was conducted in the 1950s and 60s appears to be a plausible explanation as to why once-significant predictors of women's fertility decisions are no longer significant, further research is needed before the exact cause of the change can be accurately determined.

Finally, the relationship between a woman's education and her probability of having a child is not as straightforward as one might think. The negative coefficient on education combined with the positive coefficient on education squared, as well as the significance of both variables, suggests that there are diminishing effects of education on fertility. Increased years of education do in fact reduce fertility, but by decreasing amounts. Furthermore, the positive interaction term between marital status and race indicates that white, married women are more likely to have children than non-white, single women. The likelihood that a white, married woman has a child—compared to the likelihood that a non-white, single woman has a child—can be calculated by adding together the coefficients on marital status, race, and the interaction term (0.0142). Thus, although the regression results indicate that being white tends to decrease women's probability of having a child, the combination of being white and married actually increases women's probability of having a child by 1.4178 percentage points.

While the results of this study may appear self-evident, a closer examination reveals that many of the results of this study are, in actuality, in direct conflict with current trends and past research. Although it makes sense that age, race, employment status and income would have the aforementioned impacts on a woman's probability of having a child, the results associated with education conflict with basic intuition, the results associated with the interaction term provide further insight on the regression output, the results associated with marital status conflict with current trends, and the results associated with spouse's income conflict with past research. The results of this study therefore allow for powerful comparisons between the factors impacting women's fertility decisions in the 1950s and the factors impacting women's fertility decisions in the present.

Limitations

Several limitations of this study are important to note. First, the dependent variable is a binary response variable indicating whether or not each woman had a child that year. A continuous variable that instead indicates the total number of children ever born to each woman may have been a better measure of women's fertility decisions. Although IPUMS USA has such a variable, it is only available for samples predating the year 2000, and it is thus not available for the 2008 to 2017 time period examined by this study. It is imperative that I examine the most current data available, as the objective of this study is to generate a contemporary fertility model.

As mentioned previously, the large number of missing data points associated with both the spousal and parental variables substantially reduces the number of usable observations when spousal variables are included in the model, and necessitates the exclusion of parental variables from the model altogether. Furthermore, although IPUMS USA allows for the attachment of characteristics pertaining to other members in the main respondent's household, and thus allows for the attachment of characteristics such as "spouse's income" and "father's income," it does not allow for the attachment of characteristics such as "spouse's father's income" or "spouse's mother's income." I was therefore unable to calculate relative economic aspirations as calculated by prior research. A data set with more comprehensive information on the woman's spouse and parents, as well as information on the spouse's parents, would allow for more accurate estimations of variables such as women's wages relative to men's and relative economic aspirations. Finally, results from the Pearson goodness of fit test as well as the link test for model specification indicate that the model does not fit the data and that one or more of the variables are misspecified.

Even with these limitations, however, the findings of this study are reliable. IPUMS USA is a well-known and well-respected data source, and the regression results are significant at the 1% significance level, robust to heteroskedasticity, and in line with hypotheses based on current trends and past research.

Conclusion

This study set out to generate a contemporary fertility model in order to determine whether the factors impacting women's decisions to have children have changed since the 1950s, when the bulk of fertility research was conducted. Using data on women aged 15-50 and a probit regression model, it is found that a woman's age, marital status, race, education, employment status, and income all significantly impact her likelihood of having a child, as one might expect. It is also found, however, that contrary to prior research, spouse's income, women's wages relative to men's, and relative economic aspirations do not impact women's fertility decisions. The results of this study therefore suggest that the factors impacting women's decisions to have children have in fact changed since the mid-twentieth century.

As the majority of fertility research was conducted in the mid-twentieth century and as even present-day studies choose to analyze trends of the mid-twentieth century over trends of the present, this study contributes contemporaneity to the literature on women's fertility decisions. As far as I am aware, it is the first study to use data from the twenty-first century and through the year 2017 in order to determine which factors are currently impacting women's fertility decisions. It is therefore the first step in determining how the factors influencing women's decisions to have children have changed since the 1950s, as well as how the factors influencing women's decisions to have children might continue to change in the future.

The results of this study suggest that the factors influencing women's fertility decisions have in fact changed since the mid-twentieth century—however, they may not have changed as much as one might expect. The insignificance of the variables spouse's income, women's wages relative to men's, and relative economic aspirations may indicate that women have become more independent, both in terms of the economy and within the family structure, and are thus less influenced by the financial circumstances of others when making decisions about whether or not to have children. However, the significance of the variable marital status, with married women being substantially more likely to have children than non-married women, even in the presence of increasing non-marital fertility and decreasing marriage rates, suggests that marriage and the traditional family structure continue to foster childbearing and childrearing unlike any other form of living arrangement. Thus, although women have become more independent of men, and we could therefore hypothesize that marriage would not significantly impact women's fertility decisions as women would be equally likely to have children on their own, in the absence of marriage and the security that comes with it, women who choose to marry choose to have children, and vice versa, and thus the traditional family structure endures. Although further research on the factors influencing women's present-day fertility decisions is undoubtedly needed, the results of this study suggest that the traditional family structure persists across time, and that it continues to thrive today, even in the face of its slow decline and women's increasing independence. If the traditional family structure can survive the 60 plus years as well as all of the changes in women's rights and alternate family structures that have occurred since the 1950s, it may just survive time. We should therefore expect marital status to continue to be a significant predictor of women's fertility decisions, even as women's independence continues to rise and as the significance of external predictors such as spouse's income continues to decline.

References

Becker, G. S. (1960). An economic analysis of fertility. *Demographic and Economic Change in Developed Countries*, 209-240.

Butz, W. P., & Ward, M. P. (1979). The emergence of countercyclical U.S. fertility. *American Economic Review*, *69*, 318-328.

Crafts, N., & Mills, T. C. (2009). From Malthus to Solow: How did the Malthusian economy really evolve? *Journal of Macroeconomics*, *31*, 68-93.

Easterlin, R. A. (1973). Relative economic status and the American fertility swing. *Family Economic Behavior: Problems and Prospects*, 170-223.

Easterlin, R. A. (1976). The conflict between aspirations and resources. *Population and Development Review*, *2*, 417-425.

Eckstein, Z., Schultz, T. P., & Wolpin, K. I. (1984). Short-run fluctuations in fertility and mortality in pre-industrial Sweden. *European Economic Review*, *26*, 295-317.

Evans, B. (2017). Empirical testing of the Malthusian population model: Evidence of the positive and preventive checks in Sweden from 1751 to 1870.

Galor, O., & Weil, D. N. (1996). The gender gap, fertility, and growth. *American Economic Review*, *86*, 374-387.

Goldin, C., & Katz, L. F. (2000). Career and marriage in the age of the pill. *American Economic Review*, *90*, 461-465.

Hoffman, S. D., & Averett, S. L. (2015). *Women and the economy: Family, work, and pay* (3rd ed.). Macmillan Education UK.

Hosmer, D. W., Lemeshow, S. A., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Hoboken, NJ: Wiley.

Isen, A., & Stevenson, B. (2010). Women's education and family behavior: Trends in marriage, divorce and fertility. *National Bureau of Economic Research Working Paper Series*.

Lee, R. D. (1981). Short-term variation: Vital rates, prices, and weather. In E. A. Wrigley & R.S. Schofield (Eds.), *The population history of England, 1541-1971: A reconstruction*. London, UK: Edward Arnold.

Lee, R. D., & Anderson, M. (2002). Malthus in state space: Macro economic-demographic relations in English history, 1540 to 1870. *Journal of Population Economics*, *15*, 195-220.

Lee, R. D., & Casterline, J. B. (1996). Introduction. *Population and Development Review*, *22*, 1-15.

Macunovich, D. J. (1996). Relative income and price of time: Exploring their effects on US fertility and female labor force participation. *Population and Development Review*, *22*, 223-257.

McNown, R., & Rajbhandary, S. (2003). Time series analysis of fertility and female labor market behavior. *Journal of Population Economics*, *16*, 501-523.

Nicolini, E. (2007). Was Malthus right? A VAR analysis of economic and demographic interactions in pre-industrial England. *European Review of Economic History*, *11*, 99-121.

Siegel, C. (2017). Female relative wages, household specialization, and fertility. *Review of Economic Dynamics*, *24*, 152-174.

Appendix A

Regression Output

Probit Regression Results

```
. probit fertyr age marst race educ educ2 empstat incwage_adj incwage_sp_adj interaction, vce(robust)

Iteration 0:   log pseudolikelihood = -13121.047
Iteration 1:   log pseudolikelihood = -11455.957
Iteration 2:   log pseudolikelihood = -11357.044
Iteration 3:   log pseudolikelihood = -11356.685
Iteration 4:   log pseudolikelihood = -11356.685

Probit regression                               Number of obs     =     48,658
                                                Wald chi2(9)      =    3183.31
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -11356.685               Pseudo R2         =     0.1345

-------------------------------------------------------------------------------
               |               Robust
        fertyr |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+---------------------------------------------------------------
           age |  -.0674298   .0012573   -53.63   0.000     -.069894   -.0649656
         marst |   .2426496   .0547607     4.43   0.000     .1353207    .3499786
          race |  -.2090669   .0583406    -3.58   0.000    -.3234124   -.0947214
          educ |  -.0891108   .0172395    -5.17   0.000    -.1228996   -.0553219
         educ2 |   .0086553   .0011822     7.32   0.000     .0063383    .0109723
       empstat |  -.3346967   .0217503   -15.39   0.000    -.3773265    -.292067
   incwage_adj |   8.54e-07   2.44e-07     3.49   0.000     3.75e-07    1.33e-06
incwage_sp_adj |   1.70e-07   1.35e-07     1.27   0.206    -9.34e-08    4.34e-07
   interaction |   .1681656   .0629304     2.67   0.008     .0448243    .2915069
         _cons |   1.053734    .086801    12.14   0.000     .8836071    1.223861
-------------------------------------------------------------------------------
```

Marginal Effects

```
. mfx compute

Marginal effects after probit
      y  = Pr(fertyr) (predict)
         =  .04959672
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]      X
---------+--------------------------------------------------------------------
     age |  -.0069096      .00013  -55.19   0.000  -.007155 -.006664   37.6786
  marst* |   .0215346      .00417    5.17   0.000   .013364  .029706   .862058
   race* |  -.0237419      .00729   -3.25   0.001  -.038038 -.009446   .795655
    educ |  -.0091313      .00176   -5.18   0.000  -.012586 -.005676   7.79923
   educ2 |   .0008869      .00012    7.35   0.000   .000651  .001123   66.4526
empstat* |  -.0386452      .00277  -13.94   0.000  -.044078 -.033212   .708188
in~e_adj |   8.75e-08      .00000    3.50   0.000   3.8e-08  1.4e-07   30765.3
i~sp_adj |   1.75e-08      .00000    1.27   0.205  -9.5e-09  4.4e-08   60318.7
intera~n*|   .0163855      .00582    2.81   0.005   .004973  .027798   .687636
------------------------------------------------------------------------------
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Appendix B

Diagnostic Tests

Pearson Goodness of Fit Test

```
. estat gof

Probit model for fertyr, goodness-of-fit test

       number of observations =     48658
 number of covariate patterns =     46930
           Pearson chi2(46920) =     46399.85
                   Prob > chi2 =        0.9556

. estat gof, group(10) table

Probit model for fertyr, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)
```

Group	Prob	Obs_1	Exp_1	Obs_0	Exp_0	Total
1	0.0084	36	27.4	4830	4838.6	4866
2	0.0140	35	53.9	4831	4812.1	4866
3	0.0219	66	85.9	4800	4780.1	4866
4	0.0332	84	132.2	4782	4733.8	4866
5	0.0487	175	197.2	4690	4667.8	4865
6	0.0696	289	284.8	4577	4581.2	4866
7	0.0971	489	404.1	4377	4461.9	4866
8	0.1326	658	555.8	4208	4310.2	4866
9	0.1858	817	764.4	4049	4101.6	4866
10	0.5230	1064	1202.7	3801	3662.3	4865

```
       number of observations =     48658
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =       101.01
                   Prob > chi2 =        0.0000
```

Akaike's and Schwarz's Bayesian Information Criteria

With Education Squared and the Interaction term

```
. estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	48,658	-13121.05	-11356.69	10	22733.37	22821.3

Note: N=Obs used in calculating BIC; see [R] BIC note.

Without Education Squared and the Interaction term

```
. estat ic

Akaike's information criterion and Bayesian information criterion
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	48,658	-13121.05	-11384.97	8	22785.94	22856.28

Note: N=Obs used in calculating BIC; see [R] BIC note.

Link Test for Model Specification

```
. linktest

Iteration 0:   log likelihood = -13121.047
Iteration 1:   log likelihood = -11507.085
Iteration 2:   log likelihood = -11334.696
Iteration 3:   log likelihood = -11330.997
Iteration 4:   log likelihood = -11330.997

Probit regression                               Number of obs     =     48,658
                                                LR chi2(2)        =    3580.10
                                                Prob > chi2       =     0.0000
Log likelihood = -11330.997                     Pseudo R2         =     0.1364
```

fertyr	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_hat	.3679224	.0917335	4.01	0.000	.1881279	.5477168
_hatsq	-.229629	.0329159	-6.98	0.000	-.294143	-.165115
_cons	-.3811926	.0599866	-6.35	0.000	-.4987642	-.263621

Correlation Matrix

```
. correl fertyr age marst race educ educ2 empstat incwage_adj incwage_sp_adj interaction
(obs=48,658)
```

	fertyr	age	marst	race	educ	educ2	empstat	in~e_adj	i~sp_adj	intera~n
fertyr	1.0000									
age	-0.2368	1.0000								
marst	0.0101	0.2371	1.0000							
race	-0.0173	0.0128	0.0125	1.0000						
educ	0.0207	0.0043	0.0896	0.0788	1.0000					
educ2	0.0252	0.0115	0.0982	0.0582	0.9758	1.0000				
empstat	-0.0839	0.0474	-0.0386	0.0579	0.2030	0.1901	1.0000			
incwage_adj	-0.0355	0.1158	0.0364	0.0264	0.3431	0.3593	0.4350	1.0000		
incwage_sp~j	-0.0136	0.1449	0.1302	0.0568	0.2772	0.2868	-0.0623	0.1243	1.0000	
interaction	-0.0034	0.1495	0.5935	0.7519	0.1067	0.0955	0.0181	0.0388	0.1195	1.0000

Appendix C

Regression Output when Women's Wages Relative to Men's and Relative Economic Aspirations are Included in the Model

Women's Wages Relative to Men's

Spouse's Income still included

```
. probit fertyr age marst race educ educ2 empstat incwage_adj incwage_sp_adj relinc_spouse interaction, vce(robust)

Iteration 0:   log pseudolikelihood = -11761.215
Iteration 1:   log pseudolikelihood = -10298.744
Iteration 2:   log pseudolikelihood = -10215.794
Iteration 3:   log pseudolikelihood = -10215.494
Iteration 4:   log pseudolikelihood = -10215.494

Probit regression                               Number of obs     =     42,520
                                                Wald chi2(10)     =    2777.50
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -10215.494               Pseudo R2         =     0.1314
```

fertyr	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.0668974	.001356	-49.34	0.000	-.0695551	-.0642397
marst	.2610179	.0602375	4.33	0.000	.1429546	.3790813
race	-.2392959	.0642659	-3.72	0.000	-.3652547	-.1133371
educ	-.0920118	.018771	-4.90	0.000	-.1288023	-.0552214
educ2	.0090254	.0012767	7.07	0.000	.0065231	.0115277
empstat	-.3462382	.0232229	-14.91	0.000	-.3917541	-.3007222
incwage_adj	9.00e-07	2.60e-07	3.46	0.001	3.91e-07	1.41e-06
incwage_sp_adj	4.11e-08	1.47e-07	0.28	0.779	-2.46e-07	3.29e-07
relinc_spouse	-.0001026	.0001394	-0.74	0.462	-.0003759	.0001707
interaction	.1926586	.0688895	2.80	0.005	.0576376	.3276795
_cons	1.043046	.0946283	11.02	0.000	.8575778	1.228514

Spouse's Income removed

```
. probit fertyr age marst race educ educ2 empstat incwage_adj relinc_spouse interaction, vce(robust)

Iteration 0:   log pseudolikelihood = -11761.215
Iteration 1:   log pseudolikelihood = -10298.389
Iteration 2:   log pseudolikelihood = -10215.829
Iteration 3:   log pseudolikelihood = -10215.531
Iteration 4:   log pseudolikelihood = -10215.531

Probit regression                               Number of obs     =     42,520
                                                Wald chi2(9)      =    2778.27
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -10215.531               Pseudo R2         =     0.1314
```

fertyr	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	-.066819	.0013153	-50.80	0.000	-.0693969	-.0642412
marst	.2612554	.0602351	4.34	0.000	.1431969	.379314
race	-.2391299	.064251	-3.72	0.000	-.3650596	-.1132002
educ	-.0919243	.0187726	-4.90	0.000	-.1287178	-.0551307
educ2	.0090407	.0012742	7.10	0.000	.0065434	.011538
empstat	-.3473572	.0227804	-15.25	0.000	-.3920058	-.3027085
incwage_adj	9.08e-07	2.59e-07	3.51	0.000	4.01e-07	1.42e-06
relinc_spouse	-.0001061	.0001474	-0.72	0.471	-.000395	.0001827
interaction	.1928013	.0688895	2.80	0.005	.0577804	.3278222
_cons	1.041419	.0944247	11.03	0.000	.8563504	1.226488

Relative Economic Aspirations

Spouse's Income still included

```
. probit fertyr age marst race educ educ2 empstat incwage_adj incwage_sp_adj relinc_parents interaction, vce(robust)

note: marst != 1 predicts failure perfectly
      marst dropped and 3 obs not used

note: interaction omitted because of collinearity
Iteration 0:   log pseudolikelihood = -119.06701
Iteration 1:   log pseudolikelihood = -111.88422
Iteration 2:   log pseudolikelihood = -111.74398
Iteration 3:   log pseudolikelihood = -111.74289
Iteration 4:   log pseudolikelihood = -111.74289

Probit regression                               Number of obs     =        274
                                                Wald chi2(8)      =      14.34
                                                Prob > chi2       =     0.0732
Log pseudolikelihood = -111.74289               Pseudo R2         =     0.0615

--------------------------------------------------------------------------------
               |               Robust
        fertyr |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
           age |  -.0390061   .0165896    -2.35   0.019    -.0715212    -.006491
         marst |          0  (omitted)
          race |    .005559   .2048453     0.03   0.978    -.3959305    .4070485
          educ |   .1243311   .2244476     0.55   0.580    -.3155781    .5642404
         educ2 |  -.0068634   .0154458    -0.44   0.657    -.0371367    .0234099
       empstat |  -.4063453   .2333178    -1.74   0.082    -.8636398    .0509492
   incwage_adj |  -4.78e-06   5.81e-06    -0.82   0.411    -.0000162    6.61e-06
incwage_sp_adj |  -2.04e-06   1.65e-06    -1.24   0.216    -5.27e-06    1.19e-06
relinc_parents |   .1513053   .0709119     2.13   0.033     .0123205    .2902901
   interaction |          0  (omitted)
         _cons |  -.1389146   .8804289    -0.16   0.875    -1.864524    1.586694
--------------------------------------------------------------------------------
```

Spouse's Income removed

```
. probit fertyr age marst race educ educ2 empstat incwage_adj relinc_parents interaction, vce(robust)

Iteration 0:   log pseudolikelihood = -1446.8932
Iteration 1:   log pseudolikelihood = -1375.5886
Iteration 2:   log pseudolikelihood = -1365.9332
Iteration 3:   log pseudolikelihood = -1365.9143
Iteration 4:   log pseudolikelihood = -1365.9143

Probit regression                               Number of obs     =     11,354
                                                Wald chi2(9)      =     220.00
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -1365.9143               Pseudo R2         =     0.0560

--------------------------------------------------------------------------------
               |               Robust
        fertyr |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
           age |   .0252205    .003631     6.95   0.000     .0181039     .032337
         marst |   .6587518   .1754266     3.76   0.000      .314922    1.002582
          race |   -.283017   .0554123    -5.11   0.000     -.391623   -.1744109
          educ |   .2198202   .0795176     2.76   0.006     .0639686    .3756718
         educ2 |  -.0198587   .0056638    -3.51   0.000    -.0309595   -.0087579
       empstat |  -.0014509   .0590427    -0.02   0.980    -.1171724    .1142706
   incwage_adj |   1.00e-06   1.69e-06     0.59   0.555    -2.32e-06    4.32e-06
relinc_parents |  -.0071023   .0056235    -1.26   0.207    -.0181241    .0039196
   interaction |   .2138103   .2100723     1.02   0.309    -.1979238    .6255444
         _cons |  -2.855728   .2589388   -11.03   0.000    -3.363239   -2.348218
--------------------------------------------------------------------------------
```