Estimating the Effect of Grandparent Death on Fertility

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Abstract

I examine the relationship between parent mortality and child fertility decision through the causal channel of provision of grandparent support in childcare. Using data from the Survey of Income and Program Participation (SIPP), I find no evidence that grandparent death is negatively associated with total fertility. In order to address omitted variables, I develop an instrumental variable estimation strategy using influenza mortality risk as an exogenous source of grandparent death. I find evidence against a large negative causal effect of grandparent mortality on fertility.

1 Introduction

The study of fertility and its determinants is a long-standing topic of interest in the social sciences. Phenomena such as the demographic transition posit a close relationship between fertility and economic development. Furthermore, the analysis of fertility is important for shaping policy, both for population projection and to guide the policy of countries looking to raise chronically low fertility. The analysis of fertility in economics dates back to Becker (1960). The Becker model attempts to explain parental choices of fertility using a model of quantity-quality trade-off. Parents choose how many children to have according to a utility function for the number of children and the quality of each child, which they maximize according to the unit and fixed costs of having children as well as their income. The cost of child-rearing for a parent should matter a great deal in fertility.

One potential source of variation in childbearing cost is the presence of grandparents who can provision labor for childcare. It is reasonable to think that grandparents can reduce the minimum cost of having a child through babysitting and similar activities, but cannot easily improve the quality of a child. Thus grandparent childcare should make it relatively cheaper to have more children and so should increase fertility according to the Becker model.

This paper will attempt to empirically test the above hypothesis. We examine the coefficient of grandparent death on fertility in a OLS regression with fixed effects. In our preferred regression model, we find no evidence of a causal effect of grandparent death on fertility. We attempt to address potential omitted variables bias by developing an instrument, influenza mortality, that is an exogenous source of grandparent death. In the instrumental variables model, we find no significant evidence that grandparent death affects fertility, and we can rule out very large negative coefficients on grandparent death.

This paper is organized as follows. Section 2 describes the previous literature on income effects and women's fertility, and specifically the role of grandparent child care. Section 3 describes the dataset that contains my main variables of interest. Section 4 contains the results of my initial OLS estimation and discusses the implications of these results. Section

5 describes a secondary dataset as well as how it will be used in an instrumental variable methodology. Section 6 contains and discusses the results of this instrumental variable regression. Section 7 concludes.

2 Literature Review

Black et al. (2013) estimates a postive income effect on fertility and finds that household fertility increases with the father's income. Meanwhile, Angrist and Evans (1998) finds that women's labor supply, but not men's, is decreasing in the number of children, which is taken to mean that the women's time is substituted away from working towards child care. Taken together, these two facts can mean that the provision of free childcare (possibly by a grandparent) can increase the mother's labor force participation, increasing the household income and thereby increasing fertility.

A number of existing articles have examined similar or related topics. Del Boca (2002) is a similar paper that studies the effect of parent death on womens fertility decision and labor force participation. This study uses Bank of Italys Survey of Households Income and Wealth (19911995), which is a 3-year panel data set which includes data on employment, fertility and whether the respondents parents are alive. This data set only includes data on Italy, and indeed much of the authors discussion focuses around specific institutional factors in Italy that cause parental support to be especially relevant in the employment and fertility decisions. The Del Boca paper runs both a cross-sectional logit regression and a panel fixed effect logit model to recover estimates of the effects of parent being alive on having a child in the time period. This measure of fertility, however, is unable to discern between differences in the timing of fertility and total fertility as the panel fixed-effects analysis can only consider effects on births within at most 3 years of parent death.

A few recent treatments of the specific topic of the effect of grandparents are Aassve et al. (2012) and Posadas and Vidal-Fernandez (2013). Aassve et al. (2012) is a paper that studies the effect grandparental care has on fertility. They use data gathered in the Survey of Health, Aging and Retirement in Europe (SHARE) to run a regression of grandparental care on fertility. Posadas and Vidal-Fernandez (2013) uses the National Longitudinal Survey of Youth 1979 to examine the impact of grandparent childcare availability on the labor supply decision, and finds a positive effect. These papers examine the child care provision as an independent variable, but the grandparents endogenously choose to help care for a child and so this methodology is unable to falsify the reverse causality case in which parents who plan for more future children enlist the aid of their parents in child care.

None of these papers are able to satisfactorily identify a causal effect of parent death which is free from endogeneity concerns and potential omitted variable bias. Compared to study designs that treat the presence of grandparent childcare as an independent variable, this paper adds a double instrument. I analyze first the effect of grandparent death, which is a source of child care variation that is not an endogenous decision of the grandparent, but which is subject to other forms of omitted variable bias. I then address this problem by using the seasonal, age-specific and geography-specific variation in influenza mortality risk as source of exogenous variation in grandparent death. To the extent of my knowledge, this instrument is novel to the literature and has not been used to examine this question or similar questions about the effect of mortality.

3 Data: SIPP

I use the Survey of Income and Program Participation as my data set. The SIPP is a US census survey on the income and program participation of US households. I am specifically interested in the 2014 Panel Wave 1, which for the first time includes information about parental mortality on the respondents, along with data on number of children as well as childcare expenditure. While this survey consists of many panel waves, each with data for each month, I will be using only the cross-section of one month (January) of the 2014

	count	mean	sd	min	max
white	46504	.7395493	.4388853	0	1
black	46504	.1490194	.3561115	0	1
asian	46504	.0089455	.0941575	0	1
hispanic	46504	.0776062	.2675538	0	1
ebmom	46504	.4017074	.4902486	0	1
tceb	46504	1.66347	1.556299	0	7
tbmomdob_y	46504	1939.935	19.0415	1895	1984
tdob_byear	46504	1965.089	18.61959	1927	1998
tftotinc	46504	5891.346	7204.658	-30585	219566
hschool	46504	.8832359	.3211425	0	1
ecert	46504	.1441166	.3512117	0	1

Figure 1: Summary statistics for variables of interest from the SIPP dataset.

panel wave. Because the data only spans a few years, the panel structure does not contain many deaths in the time frame, and I instead rely entirely on cross-sectional variables in my analysis. This data set includes information on each individual in the sampled household. However, as I am interested in fertility, I restrict the data to only those individuals who are 15 years or older. I also exclude observations without data on the respondents mother (this excludes only 1 row). After this cleaning I am left with 46504 observations. The SIPP contains a massive number of variables for each respondent, but for my analysis I am interested in variables related to fertility, parent birth and death, and various demographic covariates for which I must control. My dependent variable is total number of children ever born/fathered, while my independent variables are indicators for the mortality status of the mother and father of the respondent. My control variables include race, age, income, age of parents, income and education attainment.

4 Methodology: OLS

My initial methodology is to run the OLS regression of mother and father mortality on fertility. I run the following regression:

$$\mathrm{TCEB}_i = \alpha_i + \beta_i \mathrm{EBDAD}_i + \gamma_i \mathrm{EBMOM}_i + \delta_i X_i + \epsilon_i \tag{1}$$

where TCEB_i is total fertility and EBDAD_i and EBMOM_i are parental mortality status. X_i is a list of covariates.

Table 1 reports the results from building the OLS regressions with varying covariates. It depicts the results of regression specifications that do not include fixed effects for age and mother age. We can see that in specifications with linear controls for age and mother age, the estimated coefficient on mother death is significantly negative. The point estimates and errors of these estimates show grandmother death is associated with a average decrease of 0.1 number of children, which implies that grandmother death is a major factor affecting fertility. Adding demographic, educational and geographic controls do not seem to change the point estimate or the standard error by much. We also want to control for household income, however, it is unclear which measure of income is appropriate in this context. Total income reflects the sum of earnings of all members of the household, and so may capture the presence of children who earn money or the effect of being in a two-parent household on fertility. Income-to-poverty line ratio adjusts household earnings to number of people in the household, but in doing so captures the number of children in its denominator. Specifications 9-11 include household income-to-poverty as a control, while specifications 6-8 uses total household income. None of these controls change the coefficients on parent mortality in a significant way. For ease of interpretability, subsequent regressions will use total household income exclusively.

Table 2 reports the results of regression specifications that include fixed effects for age and mother age. These include the fully specified regression model with maximal fixed effects

Table 1: Regression Specifications No Fixed Effects

Specification	Covariates	Fixed Effects	Coefficient (Standard Error)
1	None	None	0.870*** (0.0145)
2	Age	None	-0.139*** (0.0186)
3	MotherAge	None	0.0621*** (0.0188)
4	Age, MotherAge	None	-0.0827*** (0.0188)
5	Age, MotherAge, Race	None	-0.103*** (0.0187)
6	Age, MotherAge, Race, Income	None	-0.0964*** (0.0188)
7	Age, MotherAge, Race, Income, HighSchool	None	-0.118*** (0.0188)
8	Age, MotherAge, Race, Income, HighSchool, Postsecondary	None	-0.117*** (0.0188)
9	Age, MotherAge, Race, PovertyRatio	None	-0.118*** (0.0188)
10	Age, MotherAge, Race, PovertyRatio, HighSchool	None	-0.137*** (0.0188)
11	Age, MotherAge, Race, PovertyRatio, HighSchool, Postsecondary	None	-0.136*** (0.0188)

Table 2: Regression Specifications Fixed Effects

Specification	Covariates	Fixed Effects	Coefficient (Standard Error)
12	Age, MomAge	State	-0.0873*** (0.0182)
13	Age, MomAge, Race	State	-0.105*** (0.0181)
14	Age, MomAge, Race, Income	State	-0.0969*** (0.0182)
15	Age, MomAge, Race, Income, Education	State	-0.116*** (0.0182)
16	MomAge, Race, Income, Education	State, Age	-0.00571 (0.0185)
17	Age, Race, Income, Education	State, MomAge	0.0264 (0.0182)
18	Race, Income, Education	State, Age, MomAge	0.0245 (0.0183)

and covariates at specification 18. These regressions result in coefficients of small magnitude around zero, and are generally consistent with each other but not with estimates returned by the preceding regressions. This is not necessarily unexpected, as the data we use is of a cross-section of ages in one year, and so we might expect the relationship between fertility and age to be very nonlinear.

Thus the OLS analysis returns a null result, one that rejects very large negative effects and cannot reject estimates of zero of the effect of mother death on fertility. This could be due to the presence of grandmothers not having much effect on the cost of having a child. However, in the same specification we estimate an extremely small coefficient on household income, which raises the prospect that fertility is simply not elastic (at least at the individual level) to income, a finding in opposition to the established literature. Of course, the covariates in the specification are not comprehensive, and there is the possibility of omitted variable bias in our OLS estimates. Therefore, we attempt to construct an instrumental variable to help control for omitted variables and validate our null result.

5 Data: CDC

The simple ordinary least squares regression may suffer from omitted variables problems. Latent variables that are not within the data set, for example religious beliefs shared among family members, may be associated with lower mortality and higher fertility. I solve this problem by using an instrumental variable to estimate the true coefficients on father and mother mortality. Influenza is a seasonal disease that infects people in the US mostly in the fall and winter. The severity of the seasonal influenza outbreak also varies year-by-year as well as state-by-state. Figure 2 depicts the severity of influenza by state during the first week of the last four years. We can see that the severity of influenza reported by the Centers for Disease Control (CDC) varies significantly from year-to-year. Furthermore, even though it is a comparatively milder year overall, Colorado experiences a more severe epidemic in

2019 versus in 2018. Thus there is some variation within states that is independent of the variation by year. Influenza deaths also vary by age, with older adults being more affected by the disease. Thus, people of different ages in different places should have different likelihoods of dying due to influenza.

As the differences in flu severity is seasonal and thus likely to be exogenous, the deaths caused by it is an exogenous source of parental mortality. Nguyen and Noymer (2013) is a paper which estimates the excess mortality caused by the 2009 influenza epidemic. As part of this study, they calculate the age-specific death rate of influenza, and I emulate their method to generate my instrument. The CDC National Center for Health Statistics publishes death records by state and for each year going back to 1968. Each record contains a cause-of-death, and so for each year, I count the total number of deaths that result from influenza and pneumonia in each state and for each age. I then divide this count by the total population of each age in each state as taken from the Survey of Epidemiology and End Results, which is a survey conducted by the National Cancer Institute, and which goes back to 1969. This is the age specific mortality rate of influenza for each state for every year after 1969. For each respondent in the SIPP sample, there is data for which state they were born in, in which year, and when their parents were born.

I filter out respondents who were born out of the country. Thus I know that the respondent's mother was alive in the year they were born and lived in the state in which they were born. I assume that she does not move states. Thus I sum the age specific influenza mortality rate for the mother's age in that state for every year until 2004, which is the last year I have state-level influenza data. This is the cumulative risk of death caused by influenza for the specific respondent's mother, and doing this for all respondents in the SIPP sample forms the fluriskmom column. The results of this filtering and calculation can be seen in Figure 3. This sample excludes foreign-born respondents and assumes all mothers never move from the state in which they gave birth. While an unrealistic assumption, this should only bias my estimate of flu mortality if those who moved did so systematically to places where flu

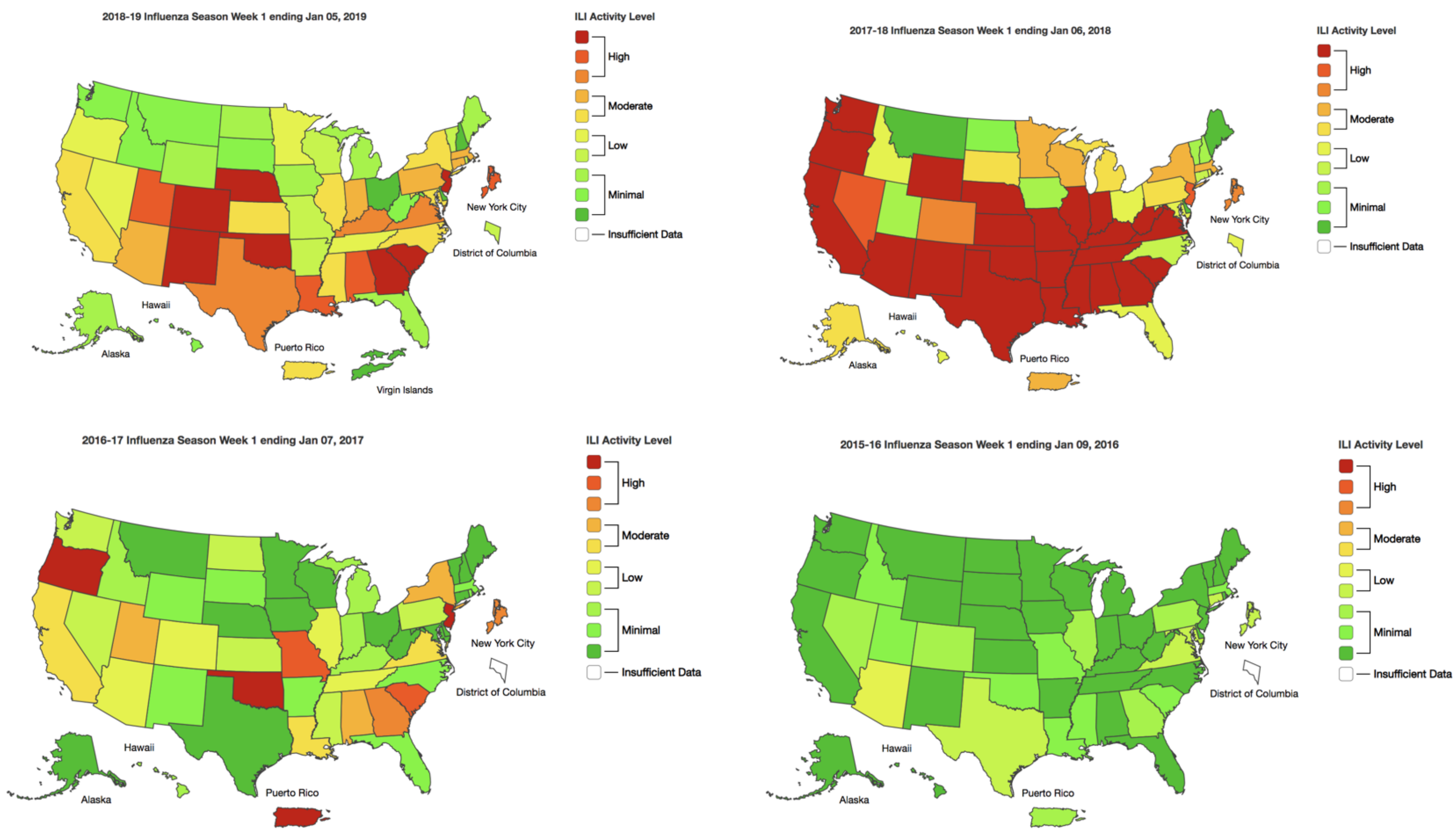

Figure 2: Maps taken from the Weekly U.S. Influenza Surveillance Report website of the CDC.

mortality is higher or lower. This does not seem plausible, and I thus assume the error to the risk index caused by movers is random noise.

6 Methodology: Instrumental Variables

I run the following two stage instrumental variables regression:

$$\mathrm{TCEB}_i = \alpha_i + \beta_i \mathrm{FLURISKMOM}_i + \delta_i X_i + \gamma_i \mathrm{STATES}_i + \epsilon_i \tag{2}$$

$$\mathrm{EBMOM}_i = a_i + b_i \mathrm{FLURISKMOM}_i + d_i X_i + g_i \mathrm{STATES}_i + \epsilon_i \tag{3}$$

where X_i is the previous list of covariates and STATES_i are controls for state and age fixed effects. Thus the true coefficient on EBMOM is estimated by β_i/b_i. I cannot estimate the same regression specification as in the maximally controlled OLS, as my flu risk index is calculated using mother age and state. However, as shown in the Appendix Table 7, using nonlinear terms for mother age instead of mother age fixed effects result in essentially the same OLS estimates as in our preferred specification. Thus we bring these specifications down into my instrumental variables estimation.

The validity of this estimation methodology depends on two conditions. The first is relevance, or that mother's risk of flu mortality is sufficiently correlated with actual mother mortality. This is shown in column 1 of Table 3, where the coefficient on fluriskmom on ebmom is shown to be high and extremely significant. In fact, the coefficient generally is too large in our regression estimates, and if we take it literally it means that a 1 percent increase in influenza mortality risk is associated with greater than 1 percent increase in odds of dying. One possible explanation for this large coefficient is that year-state influenza mortality is positively associated with other causes of death; perhaps people who are sick from other diseases are more likely to die from the flu, then in years where more people are

Table 3: IV Specification Polynomial MomAge

Specification	Polynomial	Relevance (Standard Error)	Coefficient (Standard Error)
19	Linear	7.775***	0.291
		(0.463)	(0.235)
20	Quadratic	6.830***	-0.0594
		(0.498)	(0.287)
21	Cubic	4.145***	0.889
		(0.558)	(0.543)
22	Quartic	1.248	-2.305
		(0.733)	(2.689)

sick there are more influenza deaths but also more deaths from other diseases.

The second condition is the exclusion restriction. This means that influenza mortality risk cannot be related to fertility except through its effect on parent mortality (given the other covariates in the regressions). This is a reasonable assumption because the unique determinants of influenza severity in any particular year (not caused by geography) are unlikely to persist and affect the fertility decision of those in the future, except through its permanent effect of those it kills. One potential violation of the exclusion restriction is if there are cohort-specific traits that both increase influenza death rate and affect the fertility of their children. For example, if a specific cohort happened to smoke more than others close to them in age, and smoking increased chances of influenza mortality as well as affected through secondhand smoke their children, then this would be a non-mortality channel through which fluriskmom is related to total fertility. However it is difficult to imagine that any one cohort should be vastly different from others as most general social trends happen gradually across longer time periods.

Table 3 reports the results of IV estimation with increasingly many polynomial controls. While the standard errors do not fulfill the relevance condition in Table 11, the relevance condition is met in Tables 8-10. These regressions estimate either extremely small negative coefficients or relatively large (but not significantly far from zero) positive coefficients. Thus these estimates allow us to very large negative coefficients on mother mortality against fertility, which is consistent with the (insignificant) positive coefficient estimated by the OLS. Taken with our OLS results, these coefficients rule out a very large decrease in fertility caused by grandparent death and in fact suggest the effect is close to null. This may be because grandparent child care does not do much to decrease the cost of having a child, or that grandparent death increases fertility through a different channel, but the extremely small estimated coefficient brings up the possibility that children are simply not elastic to income, and are neither normal nor inferior goods.

7 Conclusion

In this paper, I empirically examine the relationship between grandparent death and fertility. I find no evidence of a correlation between grandparent mortality and reduced fertility. In order to address potential omitted variables and identify causation, I use historical exposure to influenza risk as an instrumental variable for grandparent mortality. Using this method, I reject very large negative effects of grandparent mortality on fertility. These results suggest that parents do not at an individual level make decision about fertility based on cost of child care, and possibly not on income at all. This study may be evidence against policies that want to promote childbearing by provisioning public childcare. However, the unique way in which deaths are identified in this paper may make interpreting external validity complicated, and further studies of how different populations respond to grandparent death may help clarify this. Moreover, the instrumental variable developed in this paper could potentially be used to study other topics that involve an endogenously determined death rate.

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8 Appendix: Full Regression Tables

Table 4: OLS Regressions

	Total Fertility	Total Fertility	Total Fertility	Total Fertility	Total Fertility
ebmom	0.870***	-0.139***	0.0621***	-0.0827***	-0.103***
	(0.0145)	(0.0186)	(0.0188)	(0.0188)	(0.0187)
age		0.0389***		0.0613***	0.0595***
		(0.000471)		(0.00114)	(0.00114)
momage			0.0305***	-0.0240***	-0.0207***
			(0.000475)	(0.00114)	(0.00114)
white					-0.302***
					(0.0421)
black					0.0124
					(0.0449)
asian					-0.593***
					(0.0653)
hispanic					-0.0188
					(0.0460)
Constant	1.314***	-0.186***	-0.623***	0.475***	0.559***
	(0.00847)	(0.0180)	(0.0300)	(0.0373)	(0.0547)
Observations	46504	46504	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: OLS Regressions

	Total Fertility	Total Fertility	Total Fertility
ebmom	-0.0964***	-0.118***	-0.117***
	(0.0188)	(0.0188)	(0.0188)
age	0.0597***	0.0588***	0.0586***
	(0.00114)	(0.00113)	(0.00113)
momage	-0.0210***	-0.0201***	-0.0201***
	(0.00114)	(0.00114)	(0.00114)
white	-0.309***	-0.284***	-0.278***
	(0.0422)	(0.0423)	(0.0423)
black	0.0140	0.0165	0.0196
	(0.0449)	(0.0451)	(0.0450)
asian	-0.607***	-0.578***	-0.570***
	(0.0652)	(0.0650)	(0.0649)
hispanic	-0.0194	-0.0289	-0.0244
	(0.0460)	(0.0461)	(0.0460)
tftotinc	0.00000404***	0.00000595***	0.00000602***
	(0.000000842)	(0.000000848)	(0.000000849)
hschool		-0.362***	-0.376***
		(0.0239)	(0.0239)
ecert			0.110***
			(0.0183)
Constant	0.552***	0.827***	0.819***
	(0.0547)	(0.0575)	(0.0574)
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: OLS Regressions

	Total Fertility	Total Fertility	Total Fertility
ebmom	-0.118***	-0.137***	-0.136***
	(0.0188)	(0.0188)	(0.0188)
age	0.0591***	0.0582***	0.0581***
	(0.00114)	(0.00113)	(0.00113)
momage	-0.0197***	-0.0189***	-0.0189***
	(0.00114)	(0.00114)	(0.00114)
white	-0.279***	-0.258***	-0.253***
	(0.0420)	(0.0422)	(0.0422)
black	0.0103	0.0122	0.0152
	(0.0448)	(0.0449)	(0.0449)
asian	-0.554***	-0.528***	-0.521***
	(0.0654)	(0.0653)	(0.0652)
hispanic	-0.0170	-0.0254	-0.0211
	(0.0459)	(0.0459)	(0.0459)
tfincpov	-0.0159***	-0.0131***	-0.0130***
	(0.00132)	(0.00129)	(0.00129)
hschool		-0.321***	-0.334***
		(0.0238)	(0.0239)
ecert			0.106***
			(0.0183)
Constant	0.559***	0.805***	0.797***
	(0.0545)	(0.0574)	(0.0573)
Observations	46502	46502	46502

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: OLS Regressions (Fixed State)

	Total Fertility	Total Fertility	Total Fertility	Total Fertility
ebmom	-0.0873***	-0.105***	-0.0969***	-0.116***
	(0.0182)	(0.0181)	(0.0182)	(0.0182)
age	0.0605***	0.0590***	0.0593***	0.0583***
	(0.00115)	(0.00115)	(0.00115)	(0.00114)
momage	-0.0230***	-0.0202***	-0.0206***	-0.0197***
	(0.00112)	(0.00113)	(0.00113)	(0.00113)
white		-0.293***	-0.302***	-0.272***
		(0.0381)	(0.0381)	(0.0380)
black		0.0333	0.0338	0.0437
		(0.0407)	(0.0407)	(0.0405)
asian		-0.540***	-0.554***	-0.522***
		(0.0780)	(0.0781)	(0.0778)
hispanic		0.0126	0.0143	0.00529
		(0.0428)	(0.0428)	(0.0427)
tftotinc			0.00000497***	0.00000679***
			(0.000000908)	(0.000000910)
hschool				-0.371***
				(0.0205)
ecert				0.110***
				(0.0183)
Constant	0.443***	0.532***	0.522***	0.790***
	(0.0370)	(0.0513)	(0.0513)	(0.0535)
Observations	46504	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: OLS Regressions (Age Fixed Effects)

	Total Fertility (Fixed State Fixed Age)	Total Fertility (Fixed State Fixed MomAge)
ebmom	-0.00571	0.0264
	(0.0185)	(0.0182)
age	0.0612***	
	(0.00117)	
white	-0.269***	-0.279***
	(0.0376)	(0.0372)
black	0.0526	0.0228
	(0.0401)	(0.0397)
asian	-0.519***	-0.447***
	(0.0770)	(0.0762)
hispanic	0.0598	0.0338
	(0.0423)	(0.0418)
tftotinc	0.00000561***	0.00000437***
	(0.000000909)	(0.000000901)
hschool	-0.418***	-0.456***
	(0.0204)	(0.0206)
ecert	0.0843***	0.0625***
	(0.0182)	(0.0180)
momage		-0.0158***
		(0.00111)
Constant	-0.813***	3.392***
	(0.0710)	(0.0889)
Observations	46503	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: OLS Regressions (Age Fixed Effects)

	Total Fertility (Fixed State Fixed MomAge Fixed Age)
ebmom	0.0245
	(0.0183)
white	-0.275***
	(0.0372)
black	0.0273
	(0.0397)
asian	-0.433***
	(0.0763)
hispanic	0.0404
	(0.0419)
tftotinc	0.00000458***
	(0.000000902)
hschool	-0.457***
	(0.0206)
ecert	0.0593***
	(0.0180)
Constant	2.222***
	(0.0410)
Observations	46503

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: OLS Regressions (Nonlinear Age)

	Total Fertility (Fixed State)	Total Fertility (Fixed State)	Total Fertility (Fixed State)
ebmom	0.0264	0.0228	0.0279
	(0.0182)	(0.0183)	(0.0183)
momage	-0.0158***	-0.0329***	0.0340
	(0.00111)	(0.00461)	(0.0181)
white	-0.279***	-0.278***	-0.277***
	(0.0372)	(0.0372)	(0.0372)
black	0.0228	0.0208	0.0235
	(0.0397)	(0.0397)	(0.0397)
asian	-0.447***	-0.436***	-0.437***
	(0.0762)	(0.0763)	(0.0763)
hispanic	0.0338	0.0298	0.0357
	(0.0418)	(0.0418)	(0.0418)
tftotinc	0.00000437***	0.00000444***	0.00000449***
	(0.000000901)	(0.000000901)	(0.000000901)
hschool	-0.456***	-0.456***	-0.458***
	(0.0206)	(0.0206)	(0.0206)
ecert	0.0625***	0.0616***	0.0616***
	(0.0180)	(0.0180)	(0.0180)
momagesq		0.000110***	-0.000819***
		(0.0000288)	(0.000244)
momageth			0.00000403***
			(0.00000105)
momagequar			
Constant	3.392***	4.018***	2.526***
	(0.0889)	(0.186)	(0.431)
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: IV Regressions (FE)

	Relevance	Total Fertility	Total Fertility
fluriskmom	7.775***	2.263	
	(0.463)	(1.823)	
white	-0.0277**	-0.280***	-0.271***
	(0.00945)	(0.0372)	(0.0379)
black	0.0161	0.0229	0.0183
	(0.0101)	(0.0397)	(0.0400)
asian	-0.0490*	-0.446***	-0.432***
	(0.0194)	(0.0763)	(0.0776)
hispanic	-0.0325**	0.0325	0.0420
	(0.0106)	(0.0418)	(0.0425)
tftotinc	-0.00000275***	0.00000430***	0.00000511***
	(0.000000228)	(0.000000900)	(0.00000111)
hschool	-0.0536***	-0.457***	-0.441***
	(0.00523)	(0.0206)	(0.0243)
ecert	0.00373	0.0624***	0.0613***
	(0.00457)	(0.0180)	(0.0181)
momage	0.00533***	-0.0165***	-0.0181***
	(0.000344)	(0.00135)	(0.00233)
ebmom			0.291
			(0.235)
Constant	0.0367	3.445***	
	(0.0254)	(0.100)	
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: IV Regressions (FE)

	Relevance	Total Fertility	Total Fertility
fluriskmom	6.830***	-0.406	
	(0.498)	(1.960)	
white	-0.0275**	-0.279***	-0.281***
	(0.00945)	(0.0372)	(0.0380)
black	0.0155	0.0212	0.0221
	(0.0101)	(0.0397)	(0.0399)
asian	-0.0460*	-0.438***	-0.440***
	(0.0194)	(0.0763)	(0.0776)
hispanic	-0.0338**	0.0290	0.0270
	(0.0106)	(0.0418)	(0.0429)
tftotinc	-0.00000273***	0.00000438***	0.00000422***
	(0.000000228)	(0.000000900)	(0.00000119)
hschool	-0.0539***	-0.458***	-0.461***
	(0.00523)	(0.0206)	(0.0259)
ecert	0.00347	0.0617***	0.0619***
	(0.00457)	(0.0180)	(0.0180)
momage	-0.000565	-0.0332***	-0.0332***
	(0.00119)	(0.00470)	(0.00473)
momagesq	0.0000406***	0.000115***	0.000117**
	(0.00000785)	(0.0000309)	(0.0000368)
ebmom			-0.0594
			(0.287)
Constant	0.243***	4.028***	
	(0.0474)	(0.187)	
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: IV Regressions (FE)

	Relevance	Total Fertility	Total Fertility
fluriskmom	4.145***	3.684	
	(0.558)	(2.201)	
white	-0.0286**	-0.277***	-0.252***
	(0.00944)	(0.0372)	(0.0412)
black	0.0134	0.0243	0.0124
	(0.0101)	(0.0397)	(0.0412)
asian	-0.0467*	-0.437***	-0.395***
	(0.0193)	(0.0763)	(0.0823)
hispanic	-0.0383***	0.0360	0.0700
	(0.0106)	(0.0418)	(0.0480)
tftotinc	-0.00000275***	0.00000442***	0.00000686***
	(0.000000228)	(0.000000900)	(0.00000176)
hschool	-0.0532***	-0.459***	-0.412***
	(0.00523)	(0.0206)	(0.0359)
ecert	0.00353	0.0616***	0.0584**
	(0.00457)	(0.0180)	(0.0185)
momage	-0.0543***	0.0486*	0.0968*
	(0.00521)	(0.0206)	(0.0437)
momagesq	0.000784***	-0.00102***	-0.00172**
	(0.0000707)	(0.000279)	(0.000618)
momageth	-0.00000316***	0.00000481***	0.00000762**
	(0.000000299)	(0.00000118)	(0.00000251)
ebmom			0.889
			(0.543)
Constant	1.432***	2.217***	
	(0.122)	(0.481)	
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: IV Regressions (FE)

	Relevance	Total Fertility	Total Fertility
fluriskmom	1.248	-2.877	
	(0.733)	(2.891)	
white	-0.0283**	-0.277***	-0.342***
	(0.00943)	(0.0372)	(0.0875)
black	0.0138	0.0253	0.0572
	(0.0101)	(0.0397)	(0.0592)
asian	-0.0467*	-0.437***	-0.544***
	(0.0193)	(0.0763)	(0.154)
hispanic	-0.0378***	0.0371	-0.0500
	(0.0106)	(0.0418)	(0.113)
tftotinc	-0.00000274***	0.00000443***	-0.00000189
	(0.000000228)	(0.000000900)	(0.00000745)
hschool	-0.0539***	-0.460***	-0.585***
	(0.00522)	(0.0206)	(0.147)
ecert	0.00344	0.0614***	0.0693**
	(0.00457)	(0.0180)	(0.0229)
momage	0.0767***	0.345***	0.522
	(0.0221)	(0.0872)	(0.275)
momagesq	-0.00206***	-0.00747***	-0.0122
	(0.000473)	(0.00186)	(0.00704)
momageth	0.0000231***	0.0000643***	0.000117
	(0.00000432)	(0.0000170)	(0.0000760)
momagequar	-8.63e-08***	-0.000000195***	-0.000000394
	(1.42e-08)	(5.58e-08)	(0.000000278)
ebmom			-2.305
			(2.689)
Constant	-0.716	-2.648	
	(0.373)	(1.471)	
Observations	46504	46504	46504

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$