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MACROECONOMIC EFFECTS AND MICROECONOMIC DETERMINANTS OF FERTILITY

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MACROECONOMIC EFFECTS AND MICROECONOMIC DETERMINANTS OF FERTILITY

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Business and Economics at the University of Kentucky

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ABSTRACT OF DISSERTATION

MACROECONOMIC EFFECTS AND
MICROECONOMIC DETERMINANTS OF FERTILITY

This dissertation focuses on the relationship between the education-based fertility gap and economic growth and on policy as a determinant of fertility.

In the first essay I evaluate the impact of differential fertility (the difference between fertility rates of women with high educational attainment and women with low educational attainment) on economic growth by accounting for critical marginal effects and the general level of educational attainment in a given country. I also examine the possibility that this effect varies based on level of inequality and income levels. I find that for a less developed country with high income inequality, higher fertility rates of women with lower education has a favorable impact on economic development.

In the second essay I examine the transmission and magnitude of the effect of differential fertility on economic growth at the subnational level. I explore the relationship between differential fertility and economic growth in a cross-U.S. state context. I find that a larger gap in fertility rates between highly-educated and less-educated women is strongly associated with a decrease in the rate of long-run economic growth across U.S. states, even after accounting for the levels of inequality and overall fertility.

In the third essay I explore policy as a determinant of the education-based fertility gap. I use the 2007 Massachusetts healthcare reform which provides a good setting for evaluating the effect of an exogenous policy on the fertility. I find that fertility increases among young married women and decreases among young unmarried women but that there is no asymmetrical fertility response based on the education level of the mother.

KEYWORDS: Economic Growth, Inequality, Fertility, Human Capital, Health Insurance

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1. Introduction

A significant decline in fertility rates has been observed in developed countries over the last century. The same trend has emerged later in parts of the developing world. This decline in fertility rates is strongly associated with substantial gains in income per capita. Therefore, an important question that needs to be addressed is the existence of a causal relationship between population trends and changes in income levels. However, demographic dynamics are not exogenously determined but are the result of the complicated interplay of a variety of factors among which policy plays an important role. The first and second essays examine the role of group-specific fertility on long-run economic growth at the cross country level and at the state level respectively, while the third essay evaluates healthcare policy as a determinant of fertility rates in the U.S.

Differential Fertility and Economic Growth: The Role of Inequality and Human Capital

In the first essay, I evaluate the impact of fertility on economic growth by accounting for critical marginal effects of differential fertility (the difference between fertility rates of women with low levels of education and women with high levels of education) and the general level of educational attainment in a given country. More specifically, I analyze the relevance of differential fertility for growth of income per capita in a cross-section of countries while accounting for direct effects of human capital. I also examine the possibility that this effect might vary based on the level of inequality and income. As in De la Croix and Doepke (2003), a higher education-based fertility differential has an effect on economic growth. However, I find that the direction of this relationship varies based on a country's level of development and income inequality. My results suggest that for a highly unequal country, higher fertility rates of women with lower education have a favorable impact on economic development, while for more equal countries the opposite is true. A higher level of differential fertility changes the proportion of skilled to unskilled labor in favor of unskilled labor. Intuitively, since countries that are highly unequal are typically also poor and abundant in unskilled labor, such an increase in the relative proportion of unskilled labor might have a favorable effect on growth rates. However, for developed countries with lower inequality and higher reliance on skilled labor, this relative decrease in the share of skilled labor could reduce future growth rates.

Is Differential Fertility a Determinant of Regional Economic Growth? A Study of the U.S.

The transmission and magnitude of the effect of differential fertility on economic growth are likely to be different at the cross country level compared to the subnational level. The existing literature has focused exclusively on the cross-country relationship, thus in the second essay, I explore the relationship between differential fertility and economic growth in a cross-U.S. state context in order to explicitly identify these differences. The central question is whether differential fertility is a determinant of economic growth at the U.S. state level, beyond the combined effects of other variables affecting economic development. In addition, I test the hypothesis that differential fertility serves as a channel through which income inequality affects growth. A novel contribution of this essay is the use of micro-level data to construct a state-level differential fertility measure for 1970-2000. A nonlinear model, where the relationship between differential fertility and growth can vary by the level of inequality, suggests that differential fertility has a negative and statistically significant effect on the average annual rate of economic growth of most U.S. states, although for a small set of states at the beginning of the period under study, differential fertility and growth are positively correlated. Intuitively, in the cross-country setting, the positive relationship between differential fertility and growth rates of highly unequal countries can be explained by the fact that the change in the relative proportion of unskilled labor due to higher differential fertility increases growth because of these countries' dependence on unskilled labor. However, in the U.S. production is more skilled-labor intensive even in states that are highly unequal and poorer which explains the presence of a negative relationship.

Health Insurance, Fertility, and the Wantedness of Pregnancies: Evidence from Massachusetts

If changes in differential fertility drive economic activity (De la Croix and Doepke, 2003; Apostolova-Mihaylova, 2014), understanding the determinants of fertility for various demographic groups is important for assessing the root causes of economic growth. The third essay explores the effect of nearly universal health insurance on fertility rates using the 2007 Massachusetts healthcare reform as a natural experiment. Since the primary goal of the reform was to mandate and subsidize health care coverage for all residents of the state, including coverage for birth-related expenses, it provides a good setting for evaluating the effect of the exogenous provision of health insurance on the fertility decision. Recognizing that the fertility behavior varies by demographic and socioeconomic characteristics and that the reform did not affect all residents of the state equally, this paper explores possible differences in the fertility response based on age, marital status, and education level. The results suggest that there is no overall fertility effect, but that there is an economically significant heterogeneous effect by age/marital status groups where fertility of young single women decreased while fertility of young married women increased as a result of the reform. These results are consistent with the idea that child "wantedness" is higher for married women than for single women. For married women, the nearly universal access to health insurance promotes fertility, while single women switch to better contraceptive methods once they gain access to affordable health insurance. There is no effect on fertility rates of women with different levels of educational attainment, which implies that providing health insurance coverage does not affect the education-based fertility gap, at least not in the short run.

2. Differential Fertility and Economic Growth: The Role of Inequality and Human Capital

2.1 Introduction

There is a large literature on how fertility relates to economic growth. In a highly regarded paper, de la Croix and Doepke (2003) find that differential fertility (the difference between the fertility rates of women with low levels of education and women with high levels of education) has a statistically significant, negative effect on economic growth in a sample of developed and developing countries. I expand on this finding in two ways. First, de la Croix and Doepke (henceforth DD) do not directly control for a country's current level of human capital, implicitly assuming that the effect of human capital on economic growth occurs entirely through the differential fertility channel. My first contribution is accounting explicitly for primary school completion rate in a DD-type framework. Second, since differential fertility matters because educational opportunities differ for children of high- and low-educated women, it seems plausible that the effect of differential fertility on economic growth might vary based on a country's overall level of inequality. For example, it is possible that in countries where the income distribution is more equal and access to education is more evenly distributed, the negative effect of differential fertility on economic growth will be weaker compared to its effect in highly unequal countries. Alternatively, it is also possible that economic growth in highly unequal countries which rely on unskilled labor might benefit from larger fertility differentials because of the positive effect on population size. In either case, the effect of differential fertility on economic growth would depend on a country's overall level of inequality. Thus, my second contribution is to investigate how the relationship between differential fertility and economic growth varies with a country's level of inequality.

My results indicate that income per capita is positively correlated with differential fertility for high inequality countries. However, the relationship is negative for more developed countries where income inequality is lower. I also find that differential fertility is not a robust determinant of economic growth once the current level of human capital is explicitly accounted for. In section 2.2 I provide a brief review of the literature on inequality, human capital, and economic growth. Specifics about the data and estimation methodology are discussed in section 2.3. Results are presented in section 1.44 and robustness checks are conducted in section 2.5. Section 2.6 concludes.

2.2 Literature Review

The literature on the effect of income inequality on economic growth is not conclusive about the direction or indeed the existence of a causal effect. Some papers find empirical support for a negative relationship between income inequality and economic growth (see Table 2.1 for a summary of the literature).

Table 2.1 Summary of the Literature

Author(s)	Year	Direction of effect	Inequality variable	Data	Estimation	Comments
Persson and Tabellini	1994	Negative	Income share of top 20%; Gini	Pooled cross section	OLS 2SLS	Low-quality Gini
Deininger and Squire (DS)	1996 1998	No effect	Gini (DS)	Panel	OLS	High quality Cross-country 4 decades
Forbes	2000	Positive	Gini (DS)	5-year panel	GMM	Robust
Barro	2000	Nonlinear	Gini (DS)	10-year panel	3SLS	Reverse causality
Easterly	2007	Negative	Gini (WIDER 2000)	Cross-section	OLS IV	Instrument with agricultural endowment
Li and Zou	1998	Positive	Gini (DS)	Panel	LSDV Random effects	Cross-country

For example, in their seminal study, Persson and Tabellini (1994) use pooled cross-sectional data from a sample of developed countries and find that income inequality (measured as the income share of the top two deciles or a Gini coefficient) has a negative effect on long-term economic growth in a 2SLS model. Recognizing the need for a reliable measure of income inequality across countries Deininger and Squire (1996) created higher-quality panel dataset on income inequality, which has become a primary source of cross-country income inequality data. Unlike previously used measures of income inequality, Deininger and Squire's Gini coefficient is based on gross income data from individual or household surveys (not on aggregated national accounts) using representative samples of the country's population. In addition to creating a more reliable Gini coefficient, Deininger and Squire analyze the relationship between income inequality and economic growth. They find a negative effect that is not robust to the inclusion of regional indicator variables. In the cross-country analysis of Barro (2000), the negative effect of income inequality on growth is attained only when fertility is omitted from the growth regression – if fertility is not controlled for, inequality becomes negatively and significantly related to growth rates. This suggests that the effect of inequality on economic growth occurs through a fertility channel, which is the intuition in DD.

Barro (2000) also finds that income levels are an important determinant of income inequality. He concludes that income inequality has a nonlinear effect on growth rates based on a country's level of development: he finds that inequality and growth are negatively correlated in poorer countries and positively correlated in richer countries. In a cross-country setting , Easterly (2007) addresses the endogeneity of inequality by using a novel instrument for the level of inequality - the abundance of land suitable for growing wheat relative to that suitable for growing sugarcane. His findings support the existence of a negative linear relationship between inequality and economic development.

However, other studies have found a positive correlation between inequality and economic growth. For example, Li and Zou (1998) show in a cross-country panel context that the correlation is positive when accounting for country fixed effects. In their study, increased taxation resulting from a more even income distribution affects economic growth negatively. Similarly, Forbes (2000) uses cross-country panel data to account for time-invariant country-specific effects and finds that higher inequality is positively correlated with economic growth in the short run. An important detail in her analysis that is relevant for this study is the fact that female schooling has a significant and positive effect on growth, even after controlling for inequality, while male schooling does not.

Several studies have incorporated fertility rates into the inequality-growth relationship in an effort to combine the demographic, income, and inequality shifts characterizing the transition to the modern growth regime. Dahan and Tsiddon (1998) develop a unified growth model that combines observed changes in fertility, the income distribution, and economic growth rates. They are able to successfully reproduce these historical shifts in one theoretical framework where subsequent economic growth results from the rapid accumulation of human capital. Doepke (2004) theoretically examines the effect of education policies and child labor regulations during the transition to the modern growth regime on fertility dynamics and the pace of subsequent economic growth. He finds that the timing of child labor regulations have a larger impact on the level of inequality and the speed of the demographic transition than the timing of education policies. Moav (2005) recognizes that parental human capital is a major determinant of child human capital and theoretically shows that when less-educated parents choose low child "quality" this can lead to a poverty trap. The study has important policy implications because it recommends expanded education financing in favor of redistribution policies for decreasing the opportunity cost of having a child as a tool to enhance future economic growth. Using the inverse relationship between fertility rates and income – poorer women (who are typically less educated) tend to have more children than richer women (who are typically more educated) - Kremer and Chen (2002) demonstrate empirically that in a country where income inequality is high, the proportion of low-income/low-educated women increases over time. As less-educated women tend to have more less-educated children, the low-income fraction of the population increases faster than the high-income fraction, increasing inequality further.

DD expand on Kremer and Chen (2002) by introducing the idea of differential fertility in the inequality-growth relationship. They show that differential fertility has a negative and statistically significant linear effect on economic growth. In their baseline model, the effect of income inequality on economic growth is channeled through differential fertility. More specifically, in a country with high inequality, the fertility rates of women with low levels of educational attainment are higher than those of women with high levels of educational attainment due to the inverse relationship between fertility rates and income[1]. According to the quantity-quality tradeoff (Becker 1960; Becker and Lewis 1973; Becker and Tomes 1976; Willis 1973), family income is positively correlated with child quality and negatively correlated with child quantity. This implies that poorer women will have more children who are less educated than the children of more educated women who will also have fewer children. In turn, this reduces growth (de la Croix and Doepke, 2003) based on the faster-expanding cohort of people with low levels of human capital. DD elaborate on a model combining differential fertility and income levels developed by Althaus (1980). They endogenize the fertility decision and parental choice of children's education. In their model,

[1] Education and income are assumed to be highly correlated across countries.

the education cost per child does not depend on parents' wages, so it is more costly to educate a child with lower parental income. The authors also demonstrate empirically that income inequality matters for growth solely through its effect on differential fertility. The empirical evidence, in line with the findings of Barro (2000), shows that inequality has no significant effect on rates of economic growth once the impact of the differential fertility channel is accounted for, while differential fertility itself has a negative effect on long-run growth rates.

I consider two modifications of their model.

In the first modification, I analyze the strength and significance of differential fertility on economic growth while explicitly controlling for level of human capital. There are several reasons why the level of educational attainment should be accounted for. First, the role of human capital as a primary determinant of economic growth has been recognized by many researchers (Mankiw, Romer, and Weil, 1992; Benhabib and Spiegel, 1994; Hall and Jones, 1999 and many others). Second, it is plausible to assume that differential fertility affects future education levels of a country and would thus matter for *future* growth but it is unclear how controlling for differential fertility captures the effect of *current* education levels on a country's growth rate. Thus, augmenting the DD model with human capital allows me to test more directly the DD hypothesis that differential fertility is the channel through which education affects growth.

In the second modification I examine potential nonlinearities in the differential fertility-growth relationship by exploring the possibility that the effect of differential fertility on economic growth varies based on a country's level of inequality. It seems plausible that the effect of differential fertility would be stronger in a country with high inequality, since in such a country there would presumably be more prominent differences in educational opportunities for a poor child compared to a rich child than in a country where the income distribution is more equal. Another possibility is that larger education-based fertility differentials will have a favorable impact on economic growth in highly unequal countries because of the resulting population increase which might contribute to economic growth if a country is heavily relying on unskilled labor (Galor and Mountford, 2008).

2.3 Data and Methodology

The data are cross-country data covering the period 1960-92, taken from DD[2]. In addition to data on income, investment, and other variables typically included in growth regressions, the DD data include income inequality data from Deininger and Squire (1996) and data on differential fertility from the World Fertility Survey (WFS) and the Demographic and Health Survey (DHS)[3]. The WFS covers 1960-1976 while the DHS covers 1976-1992, so the two periods I analyze are 1960-76 and 1976-92[4]. Variable definitions are included in Appendix A.

In the sections that follow, I first investigate whether the effect of differential fertility is robust to the inclusion of human capital, using the DD estimation methodology. Throughout this analysis I rely on the two-step GMM estimator[5] to analyze the magnitude and significance of differential fertility after controlling for education. The model is overidentified so it is appropriate to use the GMM framework instead of instrumental variables. Subsequently, in Section 4.3, I explore potential nonlinearities in the relationship

[2] I use the corrected DD dataset, which corrects coding errors that appeared in the published version of the paper. The corrected dataset is available at http://perso.uclouvain.be/david.delacroix/data/ultimate%20corrected%202008.xlsx

[3] The original data were assembled by Kremer and Chen (2002).

[4] Fifteen countries have data on differential fertility available for both periods, while 25 have data available only for the first period, and 25 only for the second period.

[5] I am thankful to the authors for sending me their TSP code. Using the two-step GMM estimator provides results closest to the DD findings.

between differential fertility and economic growth, allowing for a varying effect of differential fertility on growth based on the level of income inequality. I preserve the DD framework and estimation methodology in order to obtain comparable results for both extensions.

2.4 Differential Fertility, Economic Growth, and Human Capital

2.4.1 Baseline Specification

Following DD I estimate the model below using a two-equation[6] GMM estimator:

$$GROWTH_{it} = \beta_0 + \beta_1 \ln(GDP_{ini\_t}) + \beta_2 \, I/GDP_{it} + \beta_3 \, G/GDP_{it} + \beta_4 \, AFR_i + \beta_5 \, Gini_{it} + \beta_6 \ln(TFR_{it}) + \beta_7 \ln(DTFR_{it}) \quad (1)$$

for country *i* in period *t* (*t*=2 and corresponds to either 1960-1976 or 1976-1992). The dependent variable is the average growth rate of per capita GDP over the period and the explanatory variables are defined in Appendix A.

The first extension to the baseline model that I propose here is to include a measure of human capital in order to test if an effect of differential fertility on economic growth exists beyond the direct impact of human capital.

In order to minimize endogeneity, a standard approach in the long-run growth literature is to use initial levels of explanatory variables in the regression or to use them as instruments for the average values of these variables. In my baseline regression and subsequent extensions I use initial levels of the endogenous explanatory variables as

[6] DD estimate this model as a two-equation system with separate equations for each period. All coefficients except the constant terms are constrained to be equal across the two equations.

instruments for the investment ratio and the share of government spending of GDP. Appendix A provides details for the instrument set used in this analysis[7].

Table 2.2 presents the baseline results which are closely aligned with DD's findings. The published DD paper used heteroskedastic errors. However, once the dataset was corrected, the coefficient on differential fertility was statistically significant only under the homoscedasticity assumption[8]. For obtaining baseline results I assume homoscedasticity in order to align my methodology with that of DD. Since heteroskedasticity is a common issue for cross-country growth regressions I test the null hypothesis of homoskedasticity using Whites test (1980, 1982). Although this test could not reject homoscedastic errors, Long and Ervin (1998) show that tests for heteroskedasticity do not perform well in small samples. Since heteroskedasticity is a very common problem in growth regressions I operate under the heteroskedasticity assumption for my subsequent analysis.

The major determinants of economic growth included in the DD specification, have the usual signs and significance. An increase in initial GDP per capita by 1% results in a decrease of annual growth rates between 1.3 and 1.5 percentage points. The negative relationship between initial GDP per capita and subsequent growth rates supports the well-established theory that poor economies grow faster than rich ones (β-convergence). As evidenced by its positive and statistically significant coefficient, a higher investment to GDP ratio is favorable to growth. On the other hand, higher government spending is detrimental to GDP growth rates perhaps due to more resources being diverted away from investment and other growth-enhancing activities. The coefficient estimate on the sub-Saharan Africa variable is negative and statistically significant. In DD's theoretical model differential fertility

[7] I closely follow DD for the selection of the instrument set.
[8] Based on material provided by the authors.

is a channel for the effect of income inequality on economic growth. Regressions 1.1 and 1.2 provide empirical support for this theoretical argument. In specification 1.1 where a measure of income inequality is added to the standard growth regression, a more unequal income distribution is negatively correlated with economic growth. However, income inequality is no longer statistically significant once differential fertility is directly controlled for (specification 1.2). This provides empirical support to DD's hypothesis that differential fertility channels the effect of income inequality on economic growth. The major empirical result in the second baseline regression is that differential fertility has a statistically significant and negative effect on economic growth rates. The point estimate implies that increasing the gap between fertility rates of less-educated and more-educated women from 1 to 2 slows down growth by an average of 0.76 percentage points per year.

Table 2.2 Baseline Results

Dependent variable: Growth of GDP/capita	1.1	1.2
ln(GDP) initial	-1.348*** (0.254)	-1.259*** (0.280)
I/GDP	0.077*** (0.025)	0.073** (0.031)
G/GDP	-0.084*** (0.027)	-0.091*** (0.030)
AFR	-2.040*** (0.395)	-2.349*** (0.415)
Gini	-0.065*** (0.020)	-0.047 (0.036)
ln(TFR) initial		1.589 (1.076)
ln(DTFR)		-1.097** (0.465)
Observations	68	68

Notes: Significance levels: *** (1%), **(5%), *(10%). Constant term varies by period (not reported). Homoscedasticity-consistent standard errors. The instrument set includes: initial GDP per capita, initial GDP per capita squared, initial investment to GDP ratio, initial government spending to GDP ratio, initial total fertility rate, initial total fertility rate squared, life expectancy, life expectancy squared, indicator variable for Africa, share of land in tropics and an indicator variable for access to sea.

2.4.2 Incorporating Human Capital in the Linear Relationship

Although the theoretical growth literature recognizes human capital as a strong predictor of future economic development, not all measures of human capital are significant in empirical growth regressions. Barro (2000b) tests several such variables and shows that only one of them – average years of male secondary and higher schooling – mattered significantly in his model.

Regressions 2.1 - 2.4 incorporate measures of human capital as an additional explanatory variable to account directly for the effect of *current* human capital on growth[9]. I use female primary school completion rate for 2.1 and 2.2 and male and female primary school completion rate for 2.3 and 2.4. I use these variables as a proxy for the current stock of human capital based on evidence from earlier studies. Barro (1996) found that female primary school completion rates matter for growth through a reduction in total fertility rates. Forbes (2000) also finds that female schooling affects growth positively even after controlling for the level of income inequality.[10] The most interesting result is the lack of statistical significance of differential fertility after the inclusion of human capital. It appears that differential fertility is not a robust determinant of economic growth because its coefficient is not statistically significant when I directly control for the *current* level of educational attainment (regressions 2.2 and 2.4). For the primary determinants of economic growth the conclusions from the previous specifications remain largely unchanged. The magnitudes and signs of these variables are very comparable with the baseline results with

[9] Prior to incorporating human capital I conduct a robustness check to ensure that the baseline results are consistent with DD's findings for the subsample of countries for which data on educational attainment exists. Of the 68 countries in the original sample, three do not appear in the Barro and Lee dataset – Madagascar, Burkina Faso and Nigeria. My baseline results do not change in a significant way between the 68-country sample and the 65-country sample. I use the 65-country sample throughout the present analysis.

[10] Hanushek and Kimko (2000) explore alternative measures of human capital that better capture the quality of human capital. They find that the use of these measures improves the explanatory power of standard growth regressions.

the exception of investment which is no longer statistically significant.[11] It is also clear that these measures of human capital are positively correlated with growth and that this relationship is robust to the inclusion of total fertility rate and differential fertility, although their statistical significance decreases in 2.2 and 2.4 respectively. The model predicts that, all else equal, if female primary school completion rate improves by 10%, average annual growth rates will increase by 0.2 percentage points.

Table 2.3 Regressions with Human Capital

Dependent variable: Growth of GDP/capita	2.1	2.2	2.3	2.4
ln(GDP) initial	-1.387***	-1.396***	-1.369***	-1.378***
	(0.217)	(0.186)	(0.210)	(0.189)
I/GDP	0.010	0.014	0.010	0.014
	(0.025)	(0.035)	(0.024)	(0.036)
G/GDP	-0.096***	-0.072***	-0.093***	-0.076***
	(0.023)	(0.023)	(0.021)	(0.022)
AFR	-2.106***	-2.694***	-2.213***	-2.632***
	(0.495)	(0.389)	(0.463)	(0.394)
PRIMARY F	0.031***	0.019*		
	(0.011)	(0.011)		
PRIMARY MF			0.035**	0.024**
			(0.011)	(0.012)
Gini	-0.065***	-0.045	-0.066***	-0.051
	(0.016)	(0.034)	(0.015)	(0.034)
ln(TFR) initial		0.475		0.477
		(0.862)		(0.869)
ln(DTFR)		-0.653		-0.571
		(0.414)		(0.411)
Observations	65	65	65	65
Hansen's J-test	0.664	0.678	0.720	0.711

Notes: Heteroskedasticity-consistent standard errors in parenthesis. Constant term varies by period (not reported). The instrument set includes: initial GDP per capita, initial GDP per capita squared, initial investment to GDP ratio, initial government spending to GDP ratio, initial total fertility rate, initial total fertility rate squared, life expectancy, life expectancy squared, African dummy, share of land in tropics, access to sea, initial female primary school completion rate, and male and female primary school completion rates. Hansen's J-statistic confirms the validity of the instrument set for all regressions. ***(1%), **(5%), *(10%)

[11] It should be noted that the coefficient on the investment ratio is reduced from 0.07 in Table 2.2 to 0.01 in Table 2.3 after controlling for human capital. A robustness check confirms that this is not due to the loss of 3 countries in the regressions with human capital – baseline regressions on the 65-country sample produce results very similar to those of the baseline regressions on the 68-country sample (the coefficient on the investment ratio in the former case is 0.069 and it is statistically significant at the 5% level while in the latter case it is 0.077 and statistically significant at the 1% level). This is due to the high correlation (0.88) between human capital (male and female primary school completion rates) and the investment ratio in this sample.

Since it's not clear whether primary school completion rates are the most appropriate measure of human capital, in Table 2.4 I substitute other commonly used measures of human capital as a robustness check. I replace male and female primary school completion rates in specification 2.4 with four other measures of human capital – average years of schooling (male and female; female) and secondary school completion rate (male and female; female). Regardless of the chosen measure the coefficient on differential fertility is not statistically significant, providing additional evidence that differential fertility is not a robust determinant of economic growth. This is likely not due to a multicollinearity issue between those measures of human capital and differential fertility because in all instances where the standard errors increase after the inclusion of the education measure, the change of the coefficients of differential fertility is markedly larger than the increase in the standard errors when compared to regression 1.2. Furthermore, as Table 2.5 shows, the correlation between all six measures of human capital and differential fertility is fairly small which confirms that multicollinearity is not a severe problem in this model.

My results suggest that earlier empirical findings regarding the role of differential fertility for long-run economic growth change when the model is extended to directly account for the current level of human capital. In the next section I test the existence of a nonlinear effect of differential fertility on economic growth.

Table 2.4 Regressions with Other Measures of Human Capital

Dependent variable: Growth of GDP/capita	3.1	3.2	3.3	3.4
ln(GDP) initial	-1.304***	-1.276***	-1.067***	-1.054***
	(0.299)	(0.294)	(0.323)	(0.300)
I/GDP	0.052	0.056	0.075*	0.071
	(0.039)	(0.039)	(0.045)	(0.044)
G/GDP	-0.085***	-0.090***	-0.105***	-0.101***
	(0.025)	(0.026)	(0.029)	(0.028)
AFR	-2.624***	-2.600***	-2.439***	-2.454***
	(0.453)	(0.453)	(0.490)	(0.480)
Human Capital	0.048	0.036	-0.008	-0.014
	(0.111)	(0.110)	(0.024)	(0.023)
Gini	-0.076*	-0.080**	-0.105***	-0.100**
	(0.040)	(0.037)	(0.041)	(0.042)
ln(TFR) initial	0.409	0.330	0.610	0.517
	(1.106)	(1.053)	(1.170)	(1.130)
ln(DTFR)	-0.262	-0.163	0.016	-0.011
	(0.375)	(0.350)	(0.428)	(0.451)
Observations	65	65	65	65
Hansen's J-test	0.780	0.814	0.953	0.933
Human capital measure	AYSCHOOL (F)	AYSCHOOL (MF)	SSCHOOL (F)	SSCHOOL (MF)

Notes: Initial measures of human capital based on the respective regression replace initial primary school completion rates and male and female primary school completion rates to the instrument set. See Table 2.3 for additional notes.

Table 2.5 Correlation Coefficients

	AYSCHOOL MF	AYSCHOOL F	SSCHOOL MF	SSCHOOL F	PRIMARY MF	PRIMARY F
ln(DTFR)	-0.47	-0.40	-0.32	-0.27	-0.44	-0.45

2.5 Nonlinearities in the Differential Fertility – Growth Relationship

The argument in the original DD analysis focuses on differential fertility as a channel through which income inequality affects economic growth. However, it seems probable that this negative effect of larger education-based fertility differentials is weaker in less unequal countries where education access and quality is more likely to be evenly distributed across the population. The effect of differential fertility could actually be positive for a highly unequal, poor country heavily relying on unskilled labor where future growth of the unskilled labor share (resulting from higher differential fertility) would have a favorable effect on growth rates. In order to investigate such a possibility, I allow the effects of differential fertility on growth to vary based on a country's level of inequality.

The empirical model is now

$$GROWTH_{it} = \beta_0 + \beta_1 \ln(GDP_{ini\_t}) + \beta_2 I/GDP_{it} + \beta_3 G/GDP_{it} + \beta_4 AFR_i + \beta_5 Gini_{it} + \beta_6 \ln(TFR_{it}) + \beta_7 \ln(DTFR_{it}) + \beta_8 HK_{it} + \beta_9 \ln(DTFR)_{it} \times Gini_{it} + \varepsilon_{it} \quad (2)$$

for country *i* in period *t* (*t*=2 and corresponds to either 1960-1976 or 1976-1992). The dependent variable is the average growth rate of per capita GDP over the respective period and the explanatory variables are defined in Appendix A. In this model, the nonlinearity in the differential fertility-economic growth relationship is represented by an interaction term. Here the nonlinear effect of differential fertility on economic growth is measured by:

$$\beta_7 + \beta_9 \times Gini$$

I add different measures of educational attainment to this baseline specification to check the robustness of the nonlinear effect. The results from this extension provide several interesting insights.

First, differential fertility appears to be strongly correlated with growth through its statistically significant nonlinear effect even after the inclusion of a human capital variable. This finding is in stark contrast with the lack of statistical significance in the linear model once human capital was accounted for.

Second, this result is consistent across several different measures of human capital – regressions 5.1 and 5.2 use primary school completion rates (for females, and for males and females respectively), and regressions 5.3 and 5.4 use average years of schooling (for females, and for males and females respectively). In all cases the magnitude and sign of the coefficients on differential fertility are comparable.

Third, these results confirm that the effect of differential fertility varies based on the overall level of income inequality. In countries with low level of inequality, an increase in the education-based fertility gap slows down economic growth. In contrast, for countries with high levels of income inequality, economic development can benefit from an increase in differential fertility. The turning point of income inequality in regression 5.1 corresponds to a Gini coefficient of approximately 43.4. Countries with Gini coefficient lower than this threshold experience a reduction in average annual growth rates as a result of increasing differential fertility while countries with inequality levels at the high end of the inequality spectrum would be impacted positively by a similar increase in differential fertility. For example, in a low-inequality country like Norway where the coefficient on income inequality was 37.5 between 1960 and 1976, an increase in differential fertility from 1 to 2 would lead to an average reduction of its annual growth rate of approximately 0.7 percentage points. However, a high-inequality country like Lesotho, with an index of income inequality of 56.02 in the same period, would experience a higher annual growth rate of about 0.8 percentage points as a result of increasing the fertility gap from 1 to 2 children. It should be noted that in reality differential fertility experienced an overall decrease between the two periods. For countries which appear in both subsamples, differential fertility was reduced from 3.02 in 1960-1976 to 2.40 in 1976-1992. By using the results from regression 5.3 I estimate that for the average country in this subsample where the mean Gini coefficient is 49.26, average annual growth rates were reduced by 0.02 percentage points per year as a result of the actual reduction in differential fertility. Table 2.7 provides a comparison of the effects from the linear and nonlinear models. In this table the estimated effects are based on the actual *decrease* in differential fertility between the two periods. I conclude that the observed reduction in the education-based fertility gap has helped countries with more equal income distributions and has harmed countries where income inequality is high.

Table 2.6 Regressions with Nonlinearities

Dependent variable: Growth of GDP/capita	5.1	5.2	5.3	5.4
ln(GDP) initial	-1.475***	-1.483***	-1.124***	-1.251***
	(0.312)	(0.316)	(0.332)	(0.346)
I/GDP	0.063	0.068	0.116**	0.105**
	(0.062)	(0.068)	(0.049)	(0.049)
G/GDP	-0.046	-0.045	-0.067**	-0.053*
	(0.032)	(0.032)	(0.027)	(0.028)
AFR	-2.430***	-2.218***	-2.336***	-2.335***
	(0.506)	(0.554)	(0.586)	(0.552)
Human Capital	0.016	0.017	0.184	-0.135
	(0.025)	(0.028)	(0.132)	(0.153)
Gini	-0.100	-0.118	-0.158**	-0.169**
	(0.077)	(0.084)	(0.071)	(0.073)
ln(TFR) initial	0.952	1.016	1.743	-1.319
	(1.505)	(1.636)	(1.383)	(1.373)
ln(DTFR)	-5.280*	-6.132**	-5.706**	-6.635**
	(2.719)	(2.898)	(2.743)	(2.702)
ln(DTFR)*Gini	0.115*	0.135**	0.118*	0.143**
	(0.068)	(0.073)	(0.063)	(0.064)
Observations	65	65	65	65
Hansen's J-test	0.990	0.992	0.842	0.847
Human capital measure	PRIMARY F	PRIMARY MF	AYSCHOOL F	AYSCHOOL MF

Notes: The interaction term is assumed to be endogenous. Life expectancy squared multiplied by the share of a country's land in the tropics is used as an additional instrument. See Table 2.3 for additional notes.

One possible explanation for the direction of the marginal effects could be differences in the production function based on a country's level of development. In general, countries where income inequality is high rely more on unskilled labor relative to countries with low levels of inequality where skilled labor is more abundant. Thus, an increase in the education-based fertility gap in countries of the first type would be favorable to growth because of the productivity gains associated with the increased size of the main factor of production. Conversely, this would hurt low-inequality countries where higher differential fertility implies a reduction of the relative share of skilled labor and a negative effect on growth.

Table 2.7 Estimated Effects of the Actual Decrease in Differential Fertility

	Linear effect Specification (1)	Nonlinear effect Specification (3)		
		75th pctl Gini 51.9	50th pctl Gini 45.4	25th pctl Gini 36.7
Growth effect	0.252	-0.201	0.001	0.408
Marginal effect	-1.097**	0.874**	-0.003	-1.775**
Standard error	(0.465)	(0.370)	(0.699)	(0.551)

Notes: This table compares the effect of differential fertility on average annual growth rates at different levels of income inequality using the actual reduction in differential fertility for countries in both periods. The estimated linear effect is based on baseline regression 1.2. The estimated nonlinear effect is based on regression 5.2. For countries with observations in both periods differential fertility decreased from 3.02 in 1960-1976 to 2.40 in 1976-1992.

2.6 Robustness Checks

In this section, I undertake several robustness checks. First, I split the sample based on the median level of income inequality and run the baseline specification augmented with male and female primary school completion rates (regression 2.4). This allows me to check my findings beyond the suitability of the instruments for the interaction term in the nonlinear case. Appendix A details data availability for each country by period. I run regression 2.4 separately for the low-inequality and high-inequality sample.

Second, in order to test if the nonlinear effect is also related to the income level I split the sample by income level and run specification 2.4 separately for the low-income and high-income samples. This allows me to test indirectly whether the effect of differential fertility varies based on a country's level of GDP per capita.

2.6.1 Split Samples by Income Inequality

The robustness check based on the split samples provides additional evidence for the existence of a nonlinear effect. Table 2.8 reports results for countries with high and low coefficients of inequality. I split the sample based on the median of the two-period average level of income inequality[12]. I confirm that countries where the income distribution is more unequal have experienced a *reduction* in average GDP per capita growth rates in the order of 0.11 percentage points per year due to the decrease in the education-based fertility gap[13] from 1960-1976 to 1976-1992 (regressions 7.1 and 7.2). The magnitude of the effect is very similar to the result based on the full sample where the effect of the actual reduction in differential fertility for highly unequal countries was -0.10. The robustness check for the low-inequality sample does not support findings from the previous section since the coefficient on differential fertility is not statistically significant. However, the lack of statistical significance provides an interesting insight that is consistent with an asymmetric effect of differential fertility where its effect matters for highly unequal countries but is significantly attenuated for more equal countries. There are at least two reasons why this could be true. First, low-educated women in more equal countries are generally more educated, in relative terms, due to more equal access to education. Second, they have lower fertility rates as a result of the quantity-quality tradeoff than their counterparts in highly unequal countries. This combination of lower fertility rates and higher human capital has two implications. First, their children will be more educated than children of low-educated mothers in more unequal countries. Second, the share of low-educated population will not increase over time as fast as it would in less equal countries. As a result, in countries with lower levels of income inequality any deterioration of the human capital base resulting from higher differential fertility will be slower and less pronounced than in more unequal countries.

[12] The median two-period average coefficient of income inequality is 43.
[13] Differential fertility in the high-inequality sample decreased from 2.97 in 1960-1976 to 2.67 in 1976-1992.

Table 2.8 Split Sample Regressions by Income Inequality

Dependent variable: Growth of GDP/capita	7.1 High inequality	7.2 Low inequality
ln(GDP) initial	-2.106*** (0.476)	-1.601*** (0.168)
I/GDP	0.133*** (0.034)	0.056* (0.030)
G/GDP	-210*** (0.034)	-0.093*** (0.022)
AFR	1.284** (0.587)	-4.401*** (0.276)
Human Capital	0.110*** (0.018)	0.010 (0.08)
Gini	-0.103*** (0.023)	-0.051** (0.022)
ln(TFR) initial	-1.196 (1.193)	-0.333 (0.795)
ln(DTFR)	1.028* (0.567)	0.336 (0.262)
Observations	34	35
Hansen's J-test	0.841	0.575

Notes: See Table 2.3.

2.6.2 Split Samples by Income Level

Second, in order to test the theory that the nonlinear effect of differential fertility might be related to the level of income per capita, I split the sample by the median income level and run specification 2.4 separately for the low-income and high-income samples. This would be consistent with the theory that unskilled labor-abundant countries which specialize in unskilled labor-intensive production experience productivity gains related to the increase in the relative share of their primary resource as a result of the increases in differential fertility. For example, if unskilled labor has a larger share in a country's production function, increases in differential fertility will expand the unskilled-labor base and help promote growth. On the other hand, for richer countries which rely heavily on skilled-labor[14], an increase in differential fertility will decrease the share of skilled-labor in the population and slow down future economic growth.

[14] I assume that unskilled-labor abundant countries are relatively poorer than skilled-labor abundant countries.

I split the sample based on the median GDP per capita[15] and run specification 2.4 separately on the low-income and high-income samples. Results are reported in Table 2.9. I find partial evidence in favor of a nonlinear effect related to level of income per capita. Specifically, the coefficient of differential fertility in regression 8.1 is positive and statistically significant at the 1% level for countries in the low-GDP sample. Even though the effect based on the GDP sample split is lower than the effect based on the inequality sample split (0.50 vs 1.03), this confirms my findings for the sample of poorer countries. However, the result is not robust with respect to the high-GDP sample where the coefficient on differential fertility has the correct sign but lacks statistical significance.

Table 2.9 Split Sample Regressions by GDP Per Capita

Dependent variable: Growth of GDP /capita	8.1 Low GDP	8.2 High GDP
ln(GDP) initial	-0.748	-2.104***
	(0.692)	(0.295)
I/GDP	-0.042	0.034
	(0.270)	(0.025)
G/GDP	-0.218***	-0.139***
	(0.40)	(0.044)
AFR	-2.326***	-0.915
	(0.594)	(0.673)
MFPRIMARY	0.082***	-0.003
	(0.014)	(0.013)
GINI	0.030	-0.016
	(0.021)	(0.038)
ln(TFR) initial	-2.140***	-1.554*
	(0.535)	(0.821)
ln(DTFR)	0.496***	-0.457
	(0.145)	(0.517)
Observations	33	32
Hansen's J statistic	0.503	0.510

Notes: See Table 2.3.

[15] The median GDP/capita is $1,458.

2.7 Concluding Remarks

In this study I expand the framework of de la Croix and Doepke (2003) who previously found that differential fertility (the difference in fertility rates of women with low levels of educational attainment and women with high levels of educational attainment) matters for economic growth. I extend their work in two ways. First, I introduce human capital in a standard growth regression to directly account for the effect of the *current* level of human capital on economic growth since human capital has been widely recognized as one of its primary determinants. Second, I analyze the possibility for marginal effects that vary based on the level of income inequality and GDP per capita because it is plausible to assume that the effect of differential fertility might be different for countries with different income distributions.

I find that directly including a measure of human capital is important for assessing the effect of differential fertility on economic growth because the statistical significance of this effect disappears under the common linearity assumption once the effect of human capital is directly accounted for. However, when I allow the effect of differential fertility on economic growth to vary based on the level of income inequality and GDP per capita, I find some evidence that poor and more unequal countries tend to benefit from increases in differential fertility while countries with lower levels of income inequality are affected negatively by a larger education-based fertility spread even after directly controlling for human capital in the growth regression.

3. Is Differential Fertility a Determinant of Regional Economic Growth? A Study of the U.S.

3.1 Introduction

The empirical literature has recognized income inequality as an important factor affecting economic growth, but its exact effect is a source of controversy. Some authors find a positive relationship between income inequality and the rate of economic growth in the cross-country context (Li and Zou, 1998 and Forbes, 2000), while others find the opposite result (Persson and Tabellini, 1994; Deininger and Squire, 1996; Barro, 2000). Combining the literature on the demographic effects of income inequality and the cross-country growth literature, De la Croix and Doepke (2003)[16] analyze the effects of differential fertility (the difference between the total fertility rate[17] of women with low level of education and women with high level of education) and income inequality on rates of economic growth. Using cross-country data, they find that the negative effect of income inequality on growth is channeled through differential fertility which affects the aggregate level of human capital in a country. In an extension of their work Apostolova-Mihaylova (2014) shows that this effect is not robust in a human-capital augmented growth regression, but that there is a possible nonlinear effect. She finds that economic growth rates of countries with low levels of income inequality are favorably affected by increases in differential fertility while growth rates of more equal countries are negatively correlated with higher differential fertility.

While the cross-country growth literature has examined differential fertility as a determinant of growth rates, to my knowledge there are no attempts to test the relationship

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[16] Henceforth DD.

[17] Total fertility rate is the total number of children that would be born to each woman if she were to live to the end of her child-bearing years and give birth to children in agreement with the prevailing age-specific fertility rates. See http://www.oecd-ilibrary.org/sites/factbook-2013-en/01/01/02/index.html?itemId=/content/chapter/factbook-2013-2-en (accessed on 04/23/2014).

within a country. I examine this relationship among U.S. states and contribute to the existing literature in two ways. First, I construct a state-level measure of differential fertility using individual-level data from the Decennial Census and the CPS. Second, using the variation in income inequality and differential fertility across U.S. states, I explore whether the nonlinear relationship between these variables and economic growth observed at the cross-country level also holds at the state level.

There are many advantages to using U.S. state-level data as opposed to cross-country data. Cross-country data for most variables typically used in a neoclassical growth framework are available at either annual or quinquennial form but data on differential fertility are limited to a relatively small group of countries at irregular and inconsistent time intervals. Due to the great variation across countries, cross-country data are richer but also prone to measurement error. In contrast, data for the United States are much more frequent and more reliable. The high frequency of state-level data broadens the set of possible estimation techniques that can be used to account for temporal dynamics and state-specific unobserved factors affecting economic development. A disadvantage of state-level data is that there is less variation in income inequality across states than across countries. However, the same is true for observable and unobservable variables, allowing for better identification of the primary drivers of economic growth in a cross-state analysis.

I hypothesize that the cross-country nonlinearity does not hold in the U.S. case. Intuitively, combining the results of Apostolova-Mihaylova (2014) and the theoretical model of Galor and Mountford (2008) the positive effect of increases in differential fertility on growth rates of highly unequal countries could be explained by the fact that since highly unequal countries typically rely more on unskilled labor, higher differential fertility leads to an increase in the relative proportion of unskilled labor, which is the main production factor in those countries. In contrast, for countries with a more equal income distribution, the increase in differential fertility will lead to a reduction of the relative share of the more productive skilled labor, which will negatively affect the rates of future economic growth in those countries.[18] Thus, it is reasonable to believe that for the U.S., where income inequality is lower[19] and the dependence on skilled labor is significantly higher compared to other countries (Appendix 2.D, Figure 2), the relationship between increases in differential fertility and economic growth is linear and negative because an increase in differential fertility would lower the proportion of skilled labor in the population which will then lower subsequent growth. In section 2, I survey the literature on the effect of inequality and demographics on economic growth at the cross-country and at the cross-state level. Section 3 discusses the construction of the differential fertility variable for the United States as well as other data used in this analysis. I present the empirical estimation and results in section 4 and conduct robustness checks in section 5. Section 6 concludes.

3.2 Review of the Literature

3.2.1 Income Inequality and Economic Growth at the Cross-Country Level

Although there is a large literature examining the effect of income inequality on economic growth, there is hardly a consensus about the direction of this effect at either the cross-country level or at the state level. Early cross-country studies by Persson and Tabellini

[18] Using educational attainment as a proxy for skill level, Figure 1 in Appendix 2.D presents the percentage of the population 15 years and over with completed tertiary education for a sample of countries by level of income inequality. Countries that are more unequal like Botswana, Brazil, and Kenya, have a smaller relative share of highly-skilled workers compared to countries with lower levels of income inequality, like Norway, Finland, and Spain.

[19] While wealth inequality in the U.S. has increased dramatically over time, income inequality in the U.S. is much lower than in other countries. See http://gabriel-zucman.eu/files/SaezZucman2014Slides.pdf (accessed on 05/07/2014) and http://www.gfmag.com/tools/global-database/economic-data/11944-wealth-distribution-income-inequality.html#axzz312wdXvRJ (accessed on 05/07/2014).

(1994) and Deininger and Squire (1996) find evidence for a negative relationship. Barro (2000) hypothesizes that income inequality affects growth rates of poor and rich countries in different ways and finds empirical evidence for a nonlinear effect - a more unequal income distribution slows down growth rates of poor countries and speeds up growth rates of richer economies. Easterly (2007) recognizes the potential endogeneity of income inequality and uses instrumental variable estimation where the abundance of land suitable for growing wheat relative to that suitable for growing sugarcane is a novel instrument. He also finds that inequality and economic development are negatively correlated.

Other cross-country studies that use panel data and account for country fixed effects, like Li et al. (1998) and Forbes (2000), find that income inequality has a positive effect on growth rates.

Several cross-country studies have suggested that income inequality might have an indirect, rather than a direct, effect on economic growth. More specifically, there is a literature that examines the interaction between differential fertility and economic growth by emphasizing the role of income inequality in that relationship. An early study by Kremer and Chen (2002) provides empirical support relating income inequality to future demographic dynamics. They find that in countries with a more unequal income distribution, the proportion of poor and low educated women grows over time. The basic assumption is that given some degree of intergenerational persistence of human capital, the children born to less-educated women will also be relatively less educated, so the fraction of the population with less education will increase over time. DD use this idea to link income inequality and economic growth through the differential fertility channel. They show theoretically that an increase in differential fertility leads to a reduction of the future aggregate level of human capital in a given country, which will, in turn, lower the rate of economic growth. They also demonstrate empirically that income inequality does not matter for growth once differential fertility is accounted for. Apostolova-Mihaylova (2014) augments the DD growth regression with a measure of contemporaneous human capital, which is a well-established determinant of economic growth. Her findings suggest that the linear relationship between differential fertility and economic growth is not robust to the inclusion of various measures of human capital and that these variables could be related in a nonlinear way where highly unequal countries benefit from increases in differential fertility while growth rates of less unequal countries are affected negatively.

3.2.2 Income Inequality and Economic Growth at the State Level

The research on inequality and economic growth at the state level was spurred by the seminal cross-country study of Persson and Tabellini (1994). The studies that I survey below illustrate the lack of conclusive results and the apparent dependence of the results on the methodological approach taken. Persson and Tabellini (1994) use two cross-country datasets from different periods and find evidence in support of their theoretical prediction that with higher income inequality, the political process does not favor long-run economic growth because of a distorted redistribution mechanism. Partridge (1997) responds to this study by analyzing the effect of income inequality (measured by the Gini coefficient and middle quintile income share derived from survey data) on U.S. state-level economic growth between 1960 and 1990. He uses several different models to test Persson and Tabellini's theory of a negative relationship between income inequality and economic growth and the dependence of future growth on the median voter income share. Results from pooled OLS and instrumental variable estimation show that higher initial income inequality (measured by the Gini coefficient) has a positive and statistically significant effect on subsequent economic growth, even accounting for the correlation between past and future economic activity, government policies, and state-specific industrial composition. He finds the opposite result when using the median quintile share of income as an alternative measure of income inequality - increasing the income share of the middle class (lower income inequality) has a favorable effect on growth rates. By using earlier data and different sources and methodologies, Panizza (2002) overturns Partridge's conclusion to some degree. His analysis focuses on U.S. state-level growth rates between 1940 and 1980. He relies on measures of income inequality (Gini coefficient and income share of the third quintile) that are based on income data from the Internal Revenue Service (IRS), which are more accurate than survey data. Using the fixed-effects estimator he finds evidence of a negative relationship between income inequality and growth. Panizza's main result is that the Gini coefficient appears to be the more robust measure of income inequality that remains negatively and statistically significantly related to growth rates regardless of the type of estimation procedure. In an effort to reconcile the conflicting findings in the state-level literature, Partridge (2005) separates the short-term from the long-term effects of income inequality on economic growth. He analyzes the 1960 – 2000 period using Decennial Census data as the source of income inequality measures. He argues that the relationship between the income distribution and economic growth is complex and cannot be captured by a single variable. Since the Gini coefficient and the third quintile income share reflect different aspects of that relationship he includes both in the same specification. To test the long-run relationship between income inequality and growth, he uses pooled OLS with regional dummy variables and finds evidence for a positive relationship. For assessing the short-run effects, Partridge suggests using the fixed effects estimator because it relies on within-state variation to explain changes in the dependent variable over time. Similar to Panizza, he observes that with a fixed effects model, the sign and statistical significance are highly sensitive to whether initial income per capita is represented in its log or level form. Frank (2009) constructs a new set of income inequality measures for 1945-2004 that are based on IRS data. These measures include the top 1% income share, the top decile income share, the Atkinson Index, and the Theil Entropy Index.[20] Another notable feature of this dataset is its time dimension – earlier studies typically measure income inequality at 10 year-intervals based on the Decennial Census, but Frank (2009) calculates them annually. Due to the low-income reporting cutoff for filing tax returns those measures are truncated so the author uses the top decile income share to analyze the effect of income inequality on economic growth. Using several different estimators, he finds that higher income inequality increases growth rates. Spurred by these conflicting and often inconclusive results, several recent studies test for a nonlinear relationship between inequality and growth at the U.S state level. For example, Hasanov and Izraeli (2011) test for three types of nonlinearities. They introduce Gini squared as an explanatory variable and find that the relationship between the Gini coefficient and income growth has an inverted U shape, such that extreme income inequality affects state growth rates negatively, while the opposite is true for moderate levels of income inequality. The authors also test for an interaction effect with income levels and find, similar to Barro (2000), that higher income inequality supports growth in states with higher income. When the change in income inequality is introduced in the regression, it appears that economic growth slows down when inequality decreases and when it increases beyond a certain level.

3.2.3 Income Inequality, Demographic Dynamics, and Economic Growth

To date, the state-level growth literature has not factored in the correlation between income inequality and differential fertility proposed by Kremer and Chen (2002) like DD did

[20] I return to these measures in section 6. See Appendix A for a complete description of the Atkinson index and the Theil Entropy Index.

at the cross-country level. However, several studies have included demographic dynamics as a determinant of sub-national and regional growth rates. For example, Glaeser et al. (1995) explore the role of initial urban characteristics in 1960 in the evolution of growth rates of population and income for U.S. cities. They analyze the effects of population levels and growth rates on income growth over a 30-year period. They find that city income growth depends on initial values of manufacturing share, unemployment rate, per capita income, and the region where the city is located, but not on the initial population size or its subsequent growth. In order to analyze the effect of human capital on national and regional rates of economic growth, Gennaioli et al. (2013) construct a dataset of 1,569 regions from 110 countries. They test for scale effects in regional externalities by including the log of population as an explanatory variable in the growth regression. They find that a larger population has a beneficial effect on regional economic growth.

While the cross-state literature focuses on how overall population growth matters for growth, I am interested in examining how fertility differences between certain groups might affect income inequality and growth. Fertility differences by mother's education level could matter in at least two ways for state-level growth. First, if the proportion of low-income people is significantly larger than the proportion of high-income people (as a result of high inequality), children of low-educated parents are also relatively low-educated and outnumber the children born to more highly educated parents.[21] As a result, the future aggregate level of human capital will decrease because it is a weighted average of the human capital of low-educated and high-educated people. Given that poor people, who are typically less educated, tend to migrate less (Basker, 2003; Ott et al., 2011), one might expect that in a state where

[21] This is due to the quantity-quality tradeoff introduced by Becker and Lewis (1974), which is the idea that if people have few children, those children are likely to be more educated while if people have more children, they are likely to be less educated.

the education-based fertility gap increases, the resulting lower aggregate level of human capital will reduce future growth rates. Second, it is also possible that there exists a nonlinear effect related to the level of income inequality where increases in differential fertility in less unequal states have a smaller effect on future growth rates, because educational opportunities are similar for all children, while in more unequal states growth rates could decrease.

In this paper, I examine the relationship between income inequality and economic growth among U.S. states, particularly focusing on the potential role of differential fertility. Using the Decennial Census and the CPS June supplement survey data I construct a panel dataset of state-level differential fertility rates reflecting differences in total fertility rate by educational attainment of the mother for 1960-2009. A detailed explanation of the construction of this variable is included in the following section.

3.3 Data

3.3.1 Variables

The data are cross-state covering 40 years from 1970 until 2009. I use the data as a cross section and as a panel (four 10-year periods and two 20-year periods). I drop Alaska, Hawaii, and the District of Columbia from the analysis resulting in 48 observations per time period but do include a robustness check with Alaska and Hawaii. For the set of control variables I follow Panizza (2002). Summary statistics for selected variables over the entire period and for each 10-year and 20-year period are included in Appendix B. All variables except growth rates are measured at the beginning of each period. The growth rate of personal income (gr) is measured as the average annual growth rate during a 10-year period or a 20-year period, depending on the specification. Data on nominal personal income per capita come from the Bureau of Economic Analysis. I use the Bureau of Labor Statistics Consumer Price Index for 2009 (CPI) to adjust nominal variables for inflation and obtain real per capita personal income (y). In the spirit of the human capital-augmented neoclassical growth model I include the percent of the population with completed college or higher ($college$) or the percent of the population with completed high school (hs) to account for the effect of human capital on economic growth. The Population Census is the source for data on educational attainment. A measure of the percentage of the population aged 65 and over ($over65$) is used to control for the state-specific age composition. I also include the fraction of the population living in urban areas ($urban$) to account for the urban/rural makeup. I include several measures of income inequality constructed by Frank (2009).[22] For my main analysis I use the Gini coefficient ($gini$)[23] but as a robustness check I consider alternative measures of income inequality in section 5.[24] I also include a measure of the birth rate, which comes from the Natality Volume of the Vital Statistics of the United States for 1970 and 1980 and the National Vital Statistics Reports for 1990 and 2000. In all fixed effects specifications I use decade dummy variables to capture the time-varying characteristics of the growth process. The specification does not include a measure of interstate migration. I exclude this variable because interstate migration is likely to be endogenous in a state-level growth regression under the assumption that migration is economically induced. An alternative would be to use instrumental variables to overcome the endogeneity problem. However, Barro and Sala-i-Martin (2004) show that with this approach the effect of migration on state-level growth is statistically insignificant. Moreover,

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[22] Frank (2009) created a high frequency income inequality dataset for the U.S. states. His main contribution is the use of annual IRS income data while the typical source for the calculation of income inequality measures that is used by the literature is survey data.

[23] Frank's calculation of the Gini coefficient uses individual adjusted pre-tax income as the income measure. Adjusted gross income includes wages, interest, dividends, business income and rental income.

[24] For a detailed description of inequality measures, see Appendix A.

the interstate migration rate[25] ranges between 1.6 and 3 percent for most of the period under study (Molloy et al., 2011) so I argue that its effect on growth is likely to be minimal.

Although state-level data have many advantages over cross-country data, one potentially problematic aspect is their limited variation. Table 3.1 presents a comparison between the variation of the cross-state sample and the DD cross-country sample for the Gini coefficient and differential fertility. As expected, the cross-state sample shows less variability. The coefficient of variation (C.V.) of the Gini coefficient ranges between 0.04 and 0.11 for the cross-state sample compared to 0.23 for the cross-country sample. Differential fertility exhibits more variation at the cross-state level with a C.V. of 0.09 to 0.39. This is more than half the C.V. for differential fertility in DD's cross-country sample.

Table 3.1 Variation of Gini and Differential Fertility
U.S. States vs. DD Cross-country sample

$gini$	U.S. States					Cross-country DD
	1970	1980	1990	2000	1970-2000	1960-1992
Min.	0.42	0.45	0.53	0.53	0.42	0.23
Max.	0.51	0.55	0.62	0.66	0.66	0.69
Mean	0.46	0.49	0.56	0.58	0.52	0.45
St. Dev.	0.019	0.019	0.020	0.031	0.057	0.103
Coefficient of Variation	0.04	0.04	0.04	0.05	0.11	0.23

$differential\ fertility$	U.S. States					Cross-country DD
	1970	1980	1990	2000	1970-2000	1960-1992
Min.	0.11	1.05	0.51	0.26	0.26	0.10
Max.	2.19	1.7	1.41	1.82	2.19	5.30
Mean	1.75	1.47	1.07	1.02	1.33	2.32
St. Dev.	0.255	0.139	0.191	0.399	0.399	1.287
Coefficient of Variation	0.15	0.09	0.18	0.39	0.30	0.55

[25] Interstate migration is defined as the percentage of people who lived in a different state one year ago.

3.3.2 Construction of the Differential Fertility Variable

A novel feature of this paper is the construction of a state-level differential fertility variable similar to the cross-country differential fertility variable used by DD. Differential fertility is defined as the difference between fertility rates of women with low levels of education and fertility rates of women with high levels of education. Unlike the DD cross-country study where the definitions of high and low level of education vary by country based on the particulars of the surveys used, here these definitions are consistent for all states. I define "less educated" women as having completed high school or less, while "more educated" refers to women with at least a college degree. In order to calculate differential fertility by state I combine micro-level data on educational attainment with data on total fertility rate. For the years 1970, 1980, and 1990 I use data from the Decennial Census because it contains questions about educational attainment and children ever born (total fertility rate). I am unable to use the 2000 Decennial Census because the 1990 Census was the last one to include a question about the number of children ever born to a woman. For the year 2000 this information can be found in the June 2000 supplement of the CPS which contains data on fertility. I use sampling weights to obtain population-weighted total fertility rates by education level for each state. For the start year of each period I begin by restricting the sample to women with completed high school or less (less-educated women), who are 15 to 44 years old. I then weigh the $children\ ever\ born$ variable for each observation by the observation's sampling weight in order to account for the probability of selection. Thus, I obtain a state-level aggregated total fertility rate for less-educated women of child-bearing age. I then restrict the sample to women of child-bearing age with completed college or more (more educated women). Using the procedure described above I obtain a state-level aggregated total fertility rate for more educated women of child-bearing age. The final step is to subtract the total fertility rate of more educated women from the total fertility rate of less-educated women for each state to obtain a state-level aggregate measure of differential fertility for the first year in each period. Appendix C shows the trends in differential fertility over 1970-2000 by state.

3.4 Empirical Methodology

The focus of this paper is to empirically investigate the relationship between differential fertility and the rate of economic growth at the U.S. state level. Since Apostolova-Mihaylova (2014) demonstrated that this relationship could exhibit nonlinearities at the cross-country level, I also explore the possibility for a heterogeneous effect in the U.S. based on the level of income inequality. I use two main empirical specifications, which allow for both a linear and a non-linear effect. I estimate a state-level human-capital augmented growth model following Panizza (2002) to which I add differential fertility.

I estimate the following two models:

$$\left(\frac{1}{\mathrm{t}}\right)\left(\ln\left(y_{i,t+n}\right)-\ln\left(y_{i,t}\right)\right)=\beta_1\ln\left(y_{i,t}\right)+\ \beta_2 gini_{i,t}+\beta_3 dtfr_{i,t}+\beta_4 X_{i,t}+\alpha_i+\gamma_t+\varepsilon_{i,t} \tag{1}$$

$$\left(\frac{1}{\mathrm{t}}\right)\left(\ln\left(y_{i,t+n}\right)-\ln\left(y_{i,t}\right)\right)=\beta_1\ln\left(y_{i,t}\right)+\ \beta_2 gini_{i,t}+\beta_3 dtfr_{i,t}+\beta_4 dtfrXgini_{i,t}+\beta_5 X_{i,t}+\alpha_i+\gamma_t+\varepsilon_{i,t} \tag{2}$$

The dependent variable is the average annual growth rate of real personal income per capita in state i in period $t+n$ (n=10 or 20). For n=10, the periods are 1970-1979, 1980-1989, 1990-1999, and 2000-2009. For n=20, the periods are 1970-1989 and 1990-2009. The availability of high-frequency data at the U.S. state level is a major advantage of cross-state studies compared to cross-country analyses where many variables of interest rarely reflect initial conditions. To minimize endogeneity here all control variables are measured at the beginning of each period. I control for the initial real per capita personal income ($\ln(y_{i,t})$), which is expected to have a negative sign indicating the existence of convergence effects. The primary measure of income inequality in the main specifications is the Gini coefficient ($gini$). I conduct robustness checks in section 6 where I replace the Gini coefficient with several alternative measures of income inequality constructed by Frank (2009). In the cross-state analysis of Panizza (2002), income inequality has a negative effect on economic growth so I expect this effect to be negative here too. The matrix X_i includes variables that are correlated with both income inequality and growth. The percentage of the population with a college degree or more (college) is included to reflect the effect of human capital accumulation on economic growth[26]. I also control for the percentage of the population that lives in urban areas ($urban$) as well as the fraction of the population over 65 years old ($over65$). In addition, for specifications including differential fertility, I add the birth rate ($birth\,rate$. I do this because it is important to separate the effect of general population trends from the effect of group-specific fertility. If population trends are not accounted for, the coefficient on differential fertility might also capture the overall effect of fertility on growth rather than just the effect of differential fertility. In other words, in order to understand if who has children (rather than the overall number of children) matters for growth, the regression should explicitly control for the general population trends. Following Apostolova-Mihaylova (2014) who finds that the effect of differential fertility on growth depends on the level of income inequality, in model (2) I introduce an interaction term

[26] As a robustness check I replace the percentage of the population with a college degree or more with the percentage of the population with a high school degree or more.

between $differential\, fertility$ and $gini$. In this non-linear model, the effect of differential fertility is represented by $\beta_3 + \beta_4 * gini$.

3.5 Results

3.5.1 Linear Model

Table 3.2 presents results from the fixed effects estimation corresponding to model (1). In the discussion that follows I refer to the results in the preferred specification 1.2. The coefficient on initial personal income is negative and statistically significant. This result supports the idea that poorer states grow faster than rich ones, after controlling for factors contributing to long-run growth, so that all states eventually reach the same steady state (conditional convergence). Similar to Panizza (2002), the coefficient on income inequality is negative and highly statistically significant indicating that if income inequality increases by 0.10, on average growth rates will be reduced by 0.63 percentage points on an annual basis. As expected, human capital accumulation represented by the percentage of the population with a college degree or higher, has a favorable effect on growth. Economic growth is negatively affected by higher birth rates but differential fertility does not seem to have any effect when growth is measured over a 10-year period. In DD, differential fertility affects the level of human capital by changing the relative proportions of high-educated and low-educated people. To the extent that the same mechanism works at the state level, the lack of statistical significance of initial differential fertility on average 10-year growth could be explained by the fact that a longer term effect of differential fertility on human capital will need more time to materialize because in the U.S., human capital accumulation is typically not complete until approximately two decades after birth (late teens for completed high school and early twenties for completed college). In contrast, human capital accumulation and entry into the labor market vary substantially across countries and in the case of developing countries, are typically finalized much earlier.

To test if the effect of differential fertility on economic growth depends on the length of the growth episode, I next estimate model (1) but I replace the dependent variable with the average annual growth rate of personal income per capita over a 20-year period instead of a 10-year period (Table 3.3).

Table 3.2 Linear Model; 10-year growth periods: 1970 – 2009

	Fixed Effects	
Dep. var.: Avg. annual growth 1970-2009	1.1	1.2
ln(y)	-0.62*	-0.83**
	(0.33)	(0.33)
gini	-8.09***	-6.25**
	(2.76)	(2.77)
urban	-0.06**	-0.04*
	(0.02)	(0.02)
over65	0.34**	0.11
	(0.13)	(0.09)
college	0.01*	0.01**
	(0.00)	(0.01)
birth rate		-0.32***
		(0.04)
dtfr		0.09
		(0.25)
Observations	192	192
R-squared	0.58	0.69
Number of groups	48	48

Notes: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Constant term and time indicator variables omitted from table.

The results from Table 3.2 hold only partially in this case. Initial income per capita is still a very strong predictor of future growth rates and supports the convergence hypothesis. However, the initial percentage of the population with completed college or higher is not correlated with growth. The effect of the initial level of income inequality disappears over such a long period of time compared to the 10-year growth episodes where its effect was very pronounced.[27] It is interesting to note that the coefficient on differential fertility is only marginally insignificant (it is statistically significant at 10.2%).

Table 3.3 Linear Model; 20-year growth periods: 1970 – 2009

Fixed Effects		
Dependent variable: Average annual growth rate of personal income 1960 – 2009	1.3	1.4
ln(y)	-6.63***	-7.16***
	(0.35)	(0.37)
gini	-4.48	-1.29
	(4.59)	(4.27)
urban	0.03	0.02
	(0.03)	(0.03)
over65	-0.22**	-0.13
	(0.09)	(0.10)
college	-0.01	0.02
	(0.05)	(0.06)
birth rate		-0.11
		(0.09)
dtfr		-0.59
		(0.36)
Observations	96	96
R-squared	0.63	0.68
Number of groups	48	48

Notes: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Constant term and time indicator variables omitted from table.

To explore the possibility that the relationship between differential fertility and growth could change over time, I do a cross sectional analysis of 10-year and 20-year periods. The coefficients on income inequality and differential fertility are presented in Table 3.4.

Differential fertility and income inequality are not statistically significant for any of the 10-year growth periods but do become significant in the last 20-year period between 1990 and 2009. This suggests that if the fertility rate by educational attainment increases by

[27] This result is similar to Panizza (2002) who also finds that income inequality matters more for U.S. state-level economic growth over ten years while its effect on average 20-year growth rates disappears.

1, average annual growth will be reduced by 0.62 on an annual basis. As a result of the modest decrease in differential fertility by 0.04 between 1990 and 2000, annual growth rates increase by 0.02 percentage points on average. We can conclude that there is weak evidence for a linear relationship between differential fertility and growth in the long term (20 years) but that result is limited to the later part of the period under study and might be influenced by time invariant unobserved state-specific characteristics that are not accounted for.

Table 3.4 Cross sectional regressions
10-year and 20-year growth periods

Dependent variable: Average annual growth rate of personal income	gini	differential fertility
10-year periods		
1970-1979	2.91	0.11
	(4.58)	(0.89)
1980-1989	-2.32	-0.57
	(8.25)	(0.81)
1990-1999	1.84	-0.14
	(3.69)	(0.28)
2000-2009	2.89	-0.26
	(4.78)	(0.21)
20-year periods		
1970-1989	7.43	-0.58
	(9.50)	(0.89)
1980-1999	-6.95	-1.33
	(8.56)	(1.18)
1990-2009	8.45***	-0.62*
	(2.96)	(0.36)

Notes: Standard errors in parentheses.

It is important to point out that even though differential fertility appears to be correlated with growth in the last 20 years, there is no empirical evidence that it serves as a channel for the effect of income inequality as in DD. In their cross-country empirical analysis, income inequality is a determinant of growth but not when differential fertility is controlled for. Here this is not the case because income inequality and differential fertility each have a separate effect on 1990-2009 growth.

3.5.2 Nonlinear Model

Apostolova-Mihaylova (2014) shows that in the cross-country context, the effect of differential fertility on growth depends on the level of income inequality. Her results suggest that this effect is positive for highly unequal countries and negative for countries with a more equal income distribution. Intuitively, this finding could be related to the fact that higher differential fertility in developing countries increases the proportion of unskilled labor which is relatively more abundant and is the main growth driver in those countries.[28] If this is the case, for more equal countries that rely primarily on skilled labor, the larger share of unskilled labor (and smaller share of skilled labor) slows down growth. To the extent that the role of skilled and unskilled labor in the production function varies across states, a similar mechanism could be at play on a subnational level too. Alternatively, it could be the case that in states with high levels of income inequality, an increase in differential fertility and a subsequent increase in the share of low-educated people will exacerbate income inequality further and create an inequality trap which will in turn reduce growth rates. Finally, it is also possible that such a nonlinear effect does not exist because of the relative homogeneity of states in terms of observable and unobservable factors affecting growth. Table 3.5 presents the empirical results from estimating model (2) which takes into consideration the possibility for a nonlinear relationship.

As expected, there is no effect of differential fertility on average annual growth over 10 years. However, there is strong evidence of a nonlinear effect when analyzing growth over 20 years. The coefficients on both differential fertility and the interaction term between differential fertility and income inequality are statistically significant and their linear combination is also highly statistically significant at the 1% significance level in regression

[28] Since those countries have specialized in unskilled labor intensive processes due to the abundance of unskilled labor (Galor and Mountford, 2008).

2.2. For states with a Gini coefficient above 0.43 (relatively high inequality), an increase in differential fertility will lower growth, but if the income distribution in a state is more equal (below 0.43), higher differential fertility will have a favorable effect on growth. It should be noted that in this sample the only period when income inequality is below 0.43 is 1970 and that was the case for only five states - Maine, Nevada, New Hampshire, Ohio, and Pennsylvania. This means that the relationship between differential fertility and economic growth is generally negative for most U.S. states. The point estimates indicate that for levels of the Gini coefficient above 0.43, differential fertility is negatively correlated with growth rates. At the mean level of income inequality (gini=0.51), the effect of increasing the education-based fertility gap by 1 would lead to a decrease in average annual rates of economic growth by approximately 0.75 percentage points.

At the country level this finding is consistent with the previous literature showing a positive relationship for highly unequal countries and a negative relationship for countries with more equal income distributions like the U.S. However, the results also imply that states with more (less) unequal income distributions experience lower (higher) growth when the education-based fertility differential increases, which is the opposite to the cross-country results of Apostolova-Mihaylova (2014). This suggests that if differential fertility is a determinant of growth rates, the transmission mechanism and effects might be different for states and for countries. One possible explanation for the effect on state-level growth is related to the role of differential fertility as a potential determinant of future human capital as in DD. Higher differential fertility in a more unequal state will increase the share of low-educated people since in the U.S. there is a certain degree of intergenerational persistence of economic status[29]. In turn, this will lower the future level of human capital which will reduce growth rates.

Table 3.5 Nonlinear Model 1970 – 2009

Dependent variable: Average annual growth rate of personal income 1960 – 2009	2.1 10-year growth periods	2.2 20-year growth periods
ln(y)	-0.79**	-6.92***
	(0.33)	(0.33)
gini	-2.47	12.09**
	(4.79)	(4.88)
urban	-0.05*	-0.01
	(0.02)	(0.02)
over65	0.14	-0.08
	(0.12)	(0.08)
college	0.01	0.06
	(0.04)	(0.05)
birth rate	-0.31***	-0.08
	(0.05)	(0.06)
dtfr	2.34	4.06***
	(2.14)	(1.39)
dtfr * gini	-4.12	-9.44***
	(3.69)	(2.56)
Observations	192	96
Prob>F $dtfr + dtfr * gini = 0$	0.27	0.01
R-squared	0.69	0.72
Number of groups	48	48

Notes: Robust standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. Constant term omitted from table.

3.6 Sensitivity Analysis

3.6.1 Measures of Income Inequality

From a theoretical cross-country perspective there is reason to believe that differential fertility channels the effect of income inequality on growth as in DD. In section 5, I find that differential fertility is correlated with economic growth in the long run but the results in Tables 3.4 and 3.5 support the idea that income inequality has an independent

[29] Stokey (1998) and Solon (1999) discuss the literature on intergenerational persistence of economic status.

effect on growth rates that is separate from the effect of differential fertility. The preferred measure of income inequality used in the cross-country literature is the Gini coefficient, which I also use in the previous section. However, the cross-state literature focusing on the effect of income inequality on economic growth has shown that the magnitude and statistical strength of the coefficient on income inequality depends significantly on the type of income inequality measure. I begin this section by using the income inequality measures constructed by Frank (2009) to check the sensitivity of my results. In Table 3.6 I replace the Gini coefficient from regression 1.8 and 2.2 with the top decile income share, the income share of the top 1%, the Theil entropy index, and the Atkinson index. The top decile and top 1% income share are typical measures used in the cross-country literature and reflect the share of income earned by the wealthiest 10% and 1% of the population respectively. The Theil entropy index belongs to the entropy class of inequality indices that measure deviations from perfect equality. Its distinguishing feature is that it is a decomposable inequality measure which is sensitive to changes in the upper tail of the income distribution.[30] It is the sum of within-group inequality and between-group inequality (Schorrock, 1980) and its advantage over the Gini coefficient is that, since it is a decomposable measure, it is informative of the importance of between group inequality for the overall observed inequality.[31] The Atkinson index belongs to the class of welfare-based measures of income inequality. It takes into account the sensitivity of observed inequality to income changes in the ends of the income distribution by using an inequality aversion parameter (Allison, 1978). The higher the inequality aversion parameter, the more sensitive the index is to changes in the lower end of the income distribution. The Atkinson index used here was calculated with an inequality

[30] See http://www.fao.org/docs/up/easypol/445/theil_index_051en.pdf (accessed 5/15/2014).
[31] See Appendix A for the calculation of the Theil entropy index.

aversion parameter of 0.5 which makes it sensitive to changes in the upper end of the income distribution.

The results from the sensitivity check generally agree with the main results although they exhibit a certain degree of sensitivity. In the linear 20-year growth model the coefficient on differential fertility is never statistically significant. In fact, it is strongest (but still not statistically significant) in the baseline specification using the Gini coefficient. The results from the nonlinear model are also in line with my previous findings confirming the existence of a nonlinear effect. The positive main effect of differential fertility implies that for countries with a perfectly equal income distribution (gini=0), higher differential fertility is positively correlated with growth but the negative coefficient on the interaction term suggests that this positive effect decreases with higher levels of inequality. The correlation between differential fertility and income growth is positive at very low levels of inequality and is negative for the levels of inequality observed in this sample.

Table 3.6 Sensitivity Check with Different Measures of Income Inequality
Fixed Effects Model, 20-year growth periods

Dependent variable: Average annual growth rate of personal income 1960 – 2009	Gini	Top 10% income share	Top 1% Income share	Theil Entropy index	Atkinson index
Linear model					
dtfr	-0.59	-0.49	-0.52	-0.37	-0.30
	(0.36)	(0.39)	(0.39)	(0.41)	(0.42)
Nonlinear model					
dtfr	4.06***	4.15**	1.06	1.27*	1.85
	(1.39)	(1.57)	(0.85)	(0.64)	(1.21)
dtfr * inequality	-9.44***	-14.78***	-19.75**	-3.99***	-12.17*
	(2.56)	(4.62)	(8.98)	(1.30)	(6.57)
Prob>F $dtfr + dtfr * inequality = 0$	0.01	0.01	0.03	0.02	0.06

3.6.2 Expanded Sample

Often, the cross-state literature excludes Alaska, Hawaii, and the District of Columbia but when assessing the impact of the education-based fertility differential on economic growth there is no compelling reason to restrict the sample to the contiguous states only. Table 3.7 presents results from the 20-year linear and nonlinear models from the sample of 48 states (regressions 1.4 and 2.2) along with the results using the expanded sample. The main results remain largely unchanged with no effect on differential fertility in the linear model and a large and statistically significant effect in the nonlinear model.

Table 3.7 Sensitivity Check with Expanded Sample;
20-year growth periods Fixed Effects

Dependent variable: Average annual growth rate of personal income 1960 – 2009	48 state sample	50 state sample
Linear model		
dtfr	-0.59	-0.31
	(0.36)	(0.40)
Nonlinear model		
dtfr	4.06***	5.02***
	(1.39)	(1.55)
dtfr * gini	-9.44***	-10.88***
	(2.56)	(2.96)
Prob>F $dtfr + dtfr * gini = 0$	0.01	0.01

3.7 Conclusion

Past studies on the relationship between population dynamics and economic growth have focused extensively on the effects of overall fertility rates without taking into account the possibility that the fertility dynamics within different parts of the population might play a vital role for the development path. Moreover, such studies often ignore subnational variation in demographic trends by focusing exclusively on cross-country analyses. In this paper, I construct a dataset measuring differences in fertility rates of women with different levels of educational attainment using the Decennial Census and the CPS to evaluate the role of differential fertility on long-run growth at the U.S. state-level.

Although the existing cross-country literature has suggested that differential fertility could channel the effect of income inequality on growth I do not find evidence that this is the case. Using a fixed effects model that accounts for unobserved state-specific characteristics I find evidence suggesting that differential fertility is a stand-alone determinant of long-run growth rates in the U.S. A larger gap in fertility rates between highly-educated and less-educated women is strongly associated with a decrease in the rate of long-run economic growth across U.S. states, even after accounting for the levels of inequality and fertility. This effect could possibly be related to the role of differential fertility in altering the future educational composition of the population. However, additional investigation is necessary to test this hypothesis and pinpoint the exact causes of this effect.

4. Health Insurance, Fertility, and the Wantedness of Pregnancies: Evidence from Massachusetts

4.1 Introduction

The Patient Protection and Affordable Care Act (PPACA) is the first successful attempt in the U.S. to provide near-universal health insurance coverage at the national level but in recent years similar policies have been implemented at the state and local levels.[32] Among these reforms, the Massachusetts health care law is the most prominent example of increasing health insurance coverage. The Massachusetts experience has been used to study questions of critical importance like changes in health outcomes and costs following the expansion of health insurance but given that the Massachusetts legislation served as a model for the design of the PPACA, the answers to these questions have broader implications about the future consequences of the national reform.

It is well established that coverage rates increased as a result of the reform in Massachusetts, although there is disagreement about the exact magnitude of the effect.[33] One of the intended consequences was that the out-of-pocket cost of expensive medical events, which include pregnancy-related expenses, was reduced due to increased insurance coverage.[34] Thus, women of child-bearing age who wanted to have children could have been incentivized by the reform to plan and carry out a pregnancy if they were previously

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[32] In 2003 Maine enacted the "Dirigo Health Reform", in 2006 Vermont adopted "Catamount Health", in 2007 the city of San Francisco launched the program "Healthy San Francisco", and in 2006 Massachusetts enacted the "Act Providing Access to Affordable, Quality, Accountable Health Care". The first three reforms rely primarily on subsidies for purchasing health insurance, while the Massachusetts law also includes an individual mandate, an employer mandate, and an expansion in Medicaid.

[33] Official estimates for the uninsured rate in 2008 were 2.6 percent, but Yelowitz and Cannon (2010) find that uninsured rates are underreported because the reform incentivizes people to hide their true insurance status if they are uninsured. According to their estimates, which exclude imputed values for health insurance questions, the uninsured rate is 3.8 percent.

[34] Birth-related expenses in the U.S. range from $10,657 to $23,927 for 2011 depending on the site and method of birth U.S. Agency for Healthcare Research and Quality, *HCUPnet, Healthcare Cost and Utilization Project*. Rockville, MD: AHRQ. See http://transform.childbirthconnection.org/resources/datacenter/chargeschart/ (accessed 11/16/2013).

uninsured. In addition to moral hazard from expanding health insurance coverage, adverse selection may still be important in the design of the Massachusetts legislation and the PPACA. Even with an individual mandate, individuals are given the option to remain uninsured by paying a penalty (which starts off relatively small, and increases over time) or purchase less comprehensive coverage.[35] With guaranteed issue and modified community rating, women of childbearing age might then purchase more comprehensive coverage when anticipating pregnancy and childbirth and avoid such coverage if they do not anticipate pregnancy.[36] The ease of movement in and out of generous plans due to adverse selection further subsidizes high-cost, anticipated medical events like pregnancy.

In addition to lowering the costs of having a baby, the Massachusetts law also lowered the costs of preventing a pregnancy because the use of family planning services and access to reliable contraception became easier.[37] As a result, women of child-bearing age who did not want to get pregnant might have increased their use of reliable birth control and decreased their fertility. In terms of the PPACA, funding for birth control, family planning, and abortion has become a very controversial topic with several attempts to alter the relevant provisions of the law. At present, the use of federal funding for abortion, except in

[35] For example, catastrophic health insurance plans offered under the PPACA are available to those under age 30. It covers essential health benefits (including maternity and newborn care) but the high deductibles (approximately $6300 for an individual) would likely deter many women who anticipate pregnancy from purchasing such a policy. See https://www.healthcare.gov/can-i-buy-a-catastrophic-plan/ for eligibility requirements (accessed 11/19/2013), and https://www.nebraskablue.com/~/media/Broker%20Communications/2014_Individual_Renewal/92139.pdf for an example of specific provisions related to deductibles and pregnancy expenses.

[36] Feldstein (2013) argues such a design will encourage those who are healthy to strategically remain uninsured until they have a potentially costly medical diagnosis. See http://www.project-syndicate.org/commentary/martin-feldstein-on-how-america-s-health-care-reform-could-unravel (accessed 11/19/2013).

[37] The most reliable, non-permanent, forms of contraception include IUDs and implants (with less than 1 pregnancy per 100 women each year), and shots, pills, rings and patches (with 2-9 pregnancies per 100 women each year). Each of these requires either a doctor's prescription or contact with a health care provider and can involve significant out-of-pocket costs if uninsured. Less reliable forms of contraception (with between 15-25 pregnancies per 100 women) include diaphragms, male condoms, female condoms, withdrawal, sponges, cervical caps, and spermicide. These typically do not require contact with physicians or health care providers, and often entail lower out-of-pockets costs for the uninsured. See http://www.plannedparenthood.org/health-topics/birth-control/birth-control-effectiveness-chart-22710.htm, (accessed 11/19/2013).

rare cases, is prohibited by an executive order of the President. The national legislation also includes a mandate for contraception coverage applicable to all health insurance. In addition, all new health plans must cover certain women's preventive services with no co-payments, including the full range of FDA-approved contraception methods and contraceptive counseling.[38] To the extent that this mandate remains unchanged, studying the response of birth rates in Massachusetts can provide useful insights into the broader demographic effects of the PPACA.[39]

In this paper we use the exogenous nature of the Massachusetts healthcare reform to identify the effect of changes in insurance coverage on fertility behavior. Previous studies exploring the fertility effects of Medicaid expansions for the poor have found limited evidence of moral hazard effects. To our knowledge, our study is the first to examine fertility responses in the context of the Massachusetts healthcare reform. We rely on the American Community Survey (ACS), which is uniquely positioned to study this issue because of its explicit questions on fertility and sizable samples. When we use a straightforward difference-in-differences strategy, we do not find any change in fertility rates for the full sample of women of childbearing age (15-44 years old), a result which is consistent with some earlier work. Since insurance coverage rates also vary based on socioeconomic characteristics (rather than just by state and year), we further parameterize the changes in coverage. Our preferred specification replaces the standard difference-in-differences estimator with this more parameterized version of insurance coverage. Even with this parameterized

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[38] See http://www.hrsa.gov/womensguidelines/ and http://www.nwlc.org/sites/default/files/pdfs/us_healthstateprofiles.pdf (accessed 11/19/2013). The guidelines concerning contraceptive methods and counseling do not apply to women who are participants or beneficiaries in group health plans sponsored by religious employers. See http://www.gpo.gov/fdsys/pkg/FR-2013-07-02/pdf/2013-15866.pdf (accessed 11/19/2013).

[39] There is ongoing litigation on the birth control mandate, mostly centered on the argument that it violates the religious beliefs of various religious groups and employers. See Greene, "ACA Contraception Mandate Spurs Litigation Onslaught", National Law Journal, November 4, 2013, accessed from http://www.law.com/jsp/nlj/PubArticleNLJ.jsp?id=1202626192894 on 11/19/2013.

specification, we do not find an effect on fertility when we examine all women or stratify the sample based on age. Our key finding emerges when we analyze the fertility effect by age and marital status – the Massachusetts law increased fertility rates for married women aged 20-34 by 1 percent and decreased fertility rates for unmarried women in the same age group by 9 percent. These opposite-signed results potentially reflect the differential degree of wantedness of pregnancies that varies by marital status. These effects cancel each other out which is why we do not observe a fertility effect in the aggregate. Fertility rates for women aged 15-19 and 35-44 did not change as a result of the Massachusetts reform. The lack of effect is not surprising given that younger women did not experience large gains in insurance coverage (hence, identification is more difficult) and fertility rates for older women are generally very low (hence, there is a heterogeneous behavioral response). These results are robust to the inclusion of different sets of control variables and a variety of specification checks.

The remainder of the paper is arranged as follows. In Section II we survey the existing literature on the Massachusetts health insurance reform and the fertility responses to expanding public health insurance coverage. Section III provides a description and timeline for health insurance reform in Massachusetts. In Section IV we discuss the predicted effects of expanding health insurance coverage on fertility, and show how the response should vary by observable characteristics. Section V describes our data. Section VI presents the empirical framework and the findings are shown in section VII. Finally, Section VIII concludes.

4.2 Literature Review

Our paper adds to an emerging literature evaluating the causal effect of the Massachusetts health care reform on various outcomes of significant policy relevance. This is an important topic because of the unique opportunity to draw conclusions and make predictions about the possible effects of the Affordable Care Act, the main provisions of which are closely aligned with those of the Massachusetts health care reform. Insurance coverage and health care utilization are among the main outcomes that have been examined to date by the literature.[40] Our paper adds to the broader understanding of the effects of this policy by evaluating the extent to which an important and permanent outcome – individual fertility behavior – changes in response to increased health insurance coverage.

Several studies examine the effect of this reform on changes in insurance status since a key goal of the Massachusetts health insurance law was to achieve nearly-universal coverage. There is a general consensus that uninsured rates decreased although there is some disagreement on the exact magnitude. Early studies by Long (2008) and Long, Stockley, and Yemane (2009) find reductions in the uninsured rate of approximately 50 percent among all adults aged 18-64, while Kolstad and Kowalski (2012a) attribute only a 36 percent decrease in the uninsured rates to the new law.[41],[42] Yelowitz and Cannon (2010) show that Massachusetts residents with incomes between 150-300 percent of the Federal Poverty Level (FPL), who are most likely to be affected by the reform, tend to underreport their insurance

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[40] Other outcomes of interest are health outcomes, crowd-out of private health insurance, labor market effects, and adverse selection. Courtemanche and Zapata (2012) find that the reform lead to improved self-reported health for minority, low-income, and near-elderly individuals. Miller (2012b) finds evidence that the probability for a child to be in excellent health increased by 6 percentage points after implementation. Yelowitz and Cannon (2010) show reductions in self-reported excellent health but also show gains in good self-reported health. Long (2008) finds that the share of people who had employer-provided health insurance remained the same in the early stages of the Massachusetts reform and Miller (2012b) demonstrates that among children private insurance coverage increased by 8-10 percentage points. Kolstad and Kowalski (2012a) find limited evidence that private health insurance was replaced by Medicaid among hospitalized patients only, while Yelowitz and Cannon (2010) report that private coverage decreased among children and low-income adults. Kolstad and Kowalski (2012b) examine the efficiency and welfare impact of the reform in the labor market. Hackman, Kolstrad, and Kowalski (2012) find that increased coverage resulted in lower costs per enrollee which is evidence for the existence of adverse selection in the pre-reform Massachusetts health insurance market.

[41] Long (2008) uses data collected from two a telephone surveys – one conducted in the fall of 2006 and one conducted in the fall of 2007. Long, Stockley and Yemane (2009) use CPS data from 2004-2007.

[42] Long (2008) finds that the uninsured rate decreased from 13.0 percent from fall 2006 to 7.1 percent in fall 2007 among adults. Long, Stockley, and Yemane (2009) find that the uninsured rate decreased from 12 percent to 5.4 percent in the first year after the reform.

status in the CPS, which likely results in an underestimation of the officially reported uninsured rate.

The reform-induced gains in health insurance coverage were different based on socioeconomic characteristics because the law did not impact all state residents in the same way. Several studies find that the drop in uninsured rates was more substantial among low-income adults and young adults while it was very modest for older and wealthier individuals.[43] For example, Niedzwiecki (2013) shows that insurance coverage increased mostly for poor adults and individuals aged 19-30 years. On the other hand, the reform did not significantly affect children's health insurance status. Long, Stockley, and Yemane (2009) find that uninsured rates among children did not change immediately after the reform while Miller (2012b) shows that children and young teens (less than 18 years old) saw an economically insignificant increase in insurance coverage in the order of 2 percentage points.[44] These findings are not surprising given that coverage rates of children and teenagers are typically quite high because they are often eligible under a parent's health insurance policy or through the Medicaid.

In addition to lowering uninsured rates, the Massachusetts reform also changed healthcare utilization; the results suggest greater efficiency afterwards. The use of preventive healthcare services increased following the implementation of the law. Miller (2012a) examines how increased health insurance coverage affected emergency room (ER) use and finds that the reform resulted in reductions between 5-8.4 percent in ER visits mainly for nonemergency medical events and during normal business hours. Kolstad and Kowalski

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[43] Long (2008) shows that the overall reduction in uninsured rates was driven by a 46 percent drop for adults with incomes up to 300 percent of the FPL. She also finds a statistically significant decrease in uninsured rates for adults with incomes over 300 percent of the FPL but Long, Stockley, and Yemane (2009) do not find such an effect using CPS data.

[44] Even though the overall effect on insured rate among children is small, Miller (2012b) does find that the reform altered substantially the type of insurance coverage children were getting.

(2012a) observe a similar effect on emergency room hospitalizations which decreased by 5.2 percentage points following the reform and were largely driven by reductions for patients from poor areas. They also examine preventable admissions and find reductions for severe patients of about 2.7 percent. Niedzwiecki (2013) shows that the use of preventive healthcare services increased through a reduction in avoidable hospitalizations, although he also finds an overall increase in emergency department visits.

To our knowledge, there are no studies that examine moral hazard in the context of the Massachusetts reform as it relates to individual fertility behavior. Most work focusing on fertility-related moral hazard effects uses the exogenous variation in state Medicaid expansions that occurred in the 1980s and 1990s. A notable exception is Leibowitz (1990) who uses data from the RAND health insurance experiment to show that pregnancy rates and births increased temporarily by 29 percent in response to random assignment of free health insurance coverage.[45]

Work using the Medicaid expansions mostly shows a heterogeneous response of birth rates based on socio-demographic characteristics with little evidence for an overall effect.[46] Joyce, Kaestner, and Kwan (1998) examine birth rates of unmarried young women (19-27 years old) with less than 12 years of education and find that Medicaid expansions increased birth rates of white women by 5 percent. They further demonstrate that the fertility response varies by income because birth rates increased more during the first wave of the Medicaid expansions when coverage was extended to individuals with incomes up to 100 percent of the FPL.[47] Zavodny and Bitler (2010) analyze the fertility effects of Medicaid

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[45] Insurance coverage was randomly assigned and varied based on the level of co-insurance rate and the maximum out-of-pocket expenditure.

[46] An exception is Yelowitz (1994) who does find an overall increase in birth rates of 5 percent for women aged 15-44. He also finds a differential effect by race and marital status.

[47] The second wave of Medicaid expansions in the late 1980s and early 1990s qualified pregnant women for Medicaid if family income was less than 185 percent FPL.

expansions for all women of childbearing age (15 to 44 years old). They measure the fertility effect of Medicaid expansions by using the fraction of women eligible or the statutory Medicaid income eligibility threshold. They find no evidence for an overall effect, but do find that a 100 percentage point increase in the income eligibility threshold for Medicaid would increase birth rates by 7.7 percent among low-educated white women. This is consistent with the idea that there are heterogeneous effects for different subgroups in the population. DeLeire, Lopoo, and Simon (2011) construct birth rates by state, year, quarter, and demographic cell based on age, marital status, and education for women aged 15-44. Recognizing that Medicaid expansions affected women differently, they construct a policy variable as the fraction of the population eligible for Medicaid which varies by quarter, state, year, and demographic cell. They find weak evidence that expansions of public health insurance coverage had an effect on birth rates. In models that only include state, year, and quarter fixed effects, and state-year fixed effects, but do not control for demographic characteristics, increasing Medicaid eligibility has a positive and statistically significant effect on birth rates of approximately 1.2 percentage points for whites and 2.4 percentage points for African-Americans. However, this result is quite sensitive to changes in the specification. A limitation of this study is that it ignores the potentially differential effect of insurance on birth rates for groups with different demographic characteristics, which is a key contribution of our study.

The increased availability of health insurance not only lowers the cost of having a baby but also lowers the cost of not having a baby, because almost all health plans cover contraception (and some cover abortion).[48] Importantly, in Massachusetts after the reform,

[48] The PPACA contraception mandate requiring all health insurance plans to offer contraceptive coverage at no cost exempts churches and non-profit religious groups from this provision while their female employees can still have contraceptive coverage paid directly by the insurance company. This mandate also spurred litigation

the publicly subsidized "Commonwealth Care" plan covered a full range of family planning services including abortion care. Using non-representative data collected through surveys and interviews Dennis et al. (2012) conclude that access to affordable contraception improved for low-income women post-reform even though they faced several challenges.[49] Family planning community centers have provided critical support for overcoming these obstacles (Dennis et al, 2009) and might play an important role of entry to the health care system for particular groups of women in the context of the national health care law (Gold, 2009). An important distinction between the Massachusetts experience and the PPACA is that national health care reform mandates contraception coverage at no cost while in Massachusetts there was still an element of cost-sharing.[50] Since both the cost of having a baby and the cost of not having a baby are typically reduced by increased availability of health insurance, the net effect on birth rates is ambiguous.

The literature examining the effect of Medicaid expansions on fertility behavior focuses primarily on net birth rates with few studies analyzing the impact on abortion rates.[51,52] Zavodny and Bitler (2010) do not find an overall effect on abortion rates but due to

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on the basis of employers' religious beliefs where for-profit business owners also fight for an exemption. This issue is pending review by the Supreme Court in November 2013. Source: http://www.nytimes.com/2013/11/02/us/court-rules-contraception-mandate-infringes-on-religious-freedom.html?ref=contraception accessed on 11/17/2013.

[49] Particular problems identified in this study for low-income women include understanding and maintaining health insurance coverage, filling out prescriptions, and obtaining appointments with a healthcare provider mostly stemming from the fact that before the reform these women's contraceptive needs were met almost exclusively by family planning community centers but after the reform these women had to, independently, understand their coverage, select a doctor, make an appointment, and fill a prescription.

[50] The national reform allows a co-pay can be charged for use of brand name contraceptives if a generic contraceptive exists National Women's Law Center, ("Contraceptive Coverage in the Health Care Law: Frequently Asked Questions", February 2013 from: http://www.nwlc.org/sites/default/files/pdfs/us_healthstateprofiles.pdf., accessed on 11/19/2013; Dennis et al. (2012).

[51] Since 1972 Medicaid has covered the use of contraception (Kearney and Levine, 2009).

[52] The Hyde Amendment, passed in 1976, prohibits the use of federal funds for abortions except in cases of rape and incest or when the life of the mother is endangered. As a federally-funded program, Medicaid does not cover abortions under both fee-for-service and managed care frameworks (National Committee for a Human Life Amendment, "The Hyde Amendment", April 2008 from: http://nchla.org/issues.asp?ID=1, from: accessed on 11/16/2013).

data limitations they are unable to stratify the sample by demographic characteristics. Joyce, Kaestner, and Kwan (1998) examine birth rates and abortion rates separately in order to split the confounding effects of subsidized health insurance. They also do not find an overall effect but show that restricted Medicaid funding for abortions led to a decrease in abortion rates of approximately 10 percent among white women, which is consistent with increased use of family planning services for this group. Joyce and Kaestner (1996) also show a reduced likelihood of abortion for young, low-educated nonblack women. Kearney and Levine (2009) specifically examine the impact of income-based expanded Medicaid eligibility for family planning services on teen and adult birth rates and contraceptive use.[53] They find that fertility of women in different age groups responds differently to the income-based expansions with the largest effect among 18-24 year-olds where birth rates declined by 5.1-6.8 percentage points. They are able to show that this result is mainly driven by an increased probability of contraceptive use. These findings provide strong motivation for analyzing the fertility responses separately for different demographic groups because of the variation in their underlying fertility rates and possibly wantedness of the pregnancy. We expand on this hypothesis in the next section.

Our survey of the relevant literature indicates that the Massachusetts reform achieved its goal of expanding insurance coverage although some groups saw larger gains in insurance coverage than others. It also led to increased health care services utilization. Studies focusing on the Medicaid expansions generally find that the fertility behavior of different demographic groups is affected differently with little evidence for an overall effect. Policies expanding subsidized family planning services have been found to be effective in reducing unintended births through an increased use of contraception.

[53] Kearney and Levine (2009) also analyze the effect on abortions and sexual activity.

4.3 The Massachusetts Health Care Reform Timeline[54]

The sweeping healthcare law dramatically changed the landscape of the Massachusetts health insurance market. The implementation of the reform began in October 2006 and continued through July 2007 (see Table 4.1 for a timeline of its major stages).

Table 4.1 Timeline of Health Care Reform Implementation

April 2006	Health Care Reform legislation passed
July 2006	Federal Government approves Medicaid waiver for health care reform
October 2006	Plan Type I for Commonwealth Care open for enrollment (for residents at 100% of FPL)
January 2007	Plan Types II, III and IV for Commonwealth Care open for enrollment (for residents between 100% and 300% of FPL)
March 2007	Deadline for Connector Board to set minimum "creditable" coverage standards
May 2007	Commonwealth Choice plans available – individuals and small businesses can buy insurance
July 1, 2007	Individual mandate to purchase health insurance Deadline for employers to provide health insurance to full-time employees Deadline for merging the individual and small-group insurance markets
January 2008	Individual mandate penalty: 50% of premium per month if uninsured

Based on: The Henry J. Kaiser Family Foundation, "Focus on Health Reform", June 2007, accessed on 11/16/2013 at http://kaiserfamilyfoundation.files.wordpress.com/2013/01/7494-02.pdf; State of Massachusetts, "Massachusetts Health Care Reform Fact Sheet", accessed on 11/16/2013 at www.mass.gov/eohhs/docs/mrc/health-care-reform-fact-sheet.rtf

During that transition period, the state expanded coverage under Medicaid and the Children's Health Insurance Program (CHIP) for children with family incomes up to 300 percent FPL and raised enrollment caps for adults. The law also allowed adults younger than 26 years to remain on their parents' health insurance plans. In addition, the state provided subsidized coverage to individuals with family incomes up to 300 percent FPL on a sliding-scale basis with full subsidies for those with incomes up to 150 percent FPL (Commonwealth Care).

The individual mandate – effective July 2007 – required individuals to purchase health insurance or pay a fine equal to their personal state income tax exemption (in the first

[54] This section is based on The Henry J. Kaiser Family Foundation, "Focus on Health Reform", May 2012, accessed on 11/16/2013 at http://kaiserfamilyfoundation.files.wordpress.com/2013/01/8311.pdf.

year) or a penalty of up to 50 percent of the lowest health insurance premium they would be eligible for (after the first year).

Standards of coverage and costs were established for insurance companies who had to offer health insurance at (modified) community-rated premiums, mandated minimum coverage, and maximum premiums irrespective of preexisting health conditions and claims made. The employer mandate required employers with 11 or more full-time employees to offer employer-provided health insurance or face modest penalties.

As demonstrated by the existing literature, the reform resulted in expanding health insurance to the vast majority of Massachusetts residents. However, the gains in insurance were not evenly distributed among the whole population with some demographic groups gaining more from than others. For example, low-income individuals with family income close to the FPL were more likely to be covered by Medicaid so the reform did little to improve coverage rates for them. Likewise, wealthier individuals who tend to get insurance from employers did not gain much. We use these uneven gains to predict fertility responses in the next section.

4.4 Predicted Effects of Expanding Health Insurance on Fertility

Predicting the effects of health insurance reform on fertility in the aggregate is not a straightforward exercise because in addition to the availability of health insurance, several other elements, like latent fertility (proxied by age) and wantedness of children (proxied by marital status) factor into the decision to have a baby. Younger women have higher fertility rates than older women, because older women are both more likely to have reached their desired fertility and more likely to suffer from infertility.[55] All else equal, married women are more likely to become pregnant and carry a baby to term than unmarried women, because pregnancies are more likely to be planned and wanted.[56]

These considerations suggest that if expansion of health insurance coverage has effects on fertility, the effect would vary by age and marital status. All else equal, expanding insurance coverage will increase fertility of married women (wanted pregnancies) due to lowering the out-of-pocket cost of pregnancy, while reducing fertility for single women (unwanted pregnancies) due to better access to reliable contraception. As health insurance becomes more widely available, births for younger women should increase more than for older women due to the higher latent fertility rates of the former group.

In addition to the considerations related to latent fertility and wantedness of pregnancies, the insurance coverage gains varied widely within age/marital status group. There were clearly gains in Massachusetts (relative to the rest of New England) from 2008 onward (relative to 2003-2006). Moreover, those gains in Massachusetts after the reform varied by family income. Some groups experienced minimal gains in insurance (such relatively affluent women who were often covered by private insurance), while others experienced much larger gains (such as near-poor women). Larger gains in coverage should lead to larger fertility responses within each age-marital status cell. Figure 4.1 summarizes the expected fertility effects by age, marital status, and income which reflect variations in latent fertility, child wantedness, and insurance gains. A woman who was young, married, and near-poor experienced larger relative gains in insurance coverage and would have been relatively

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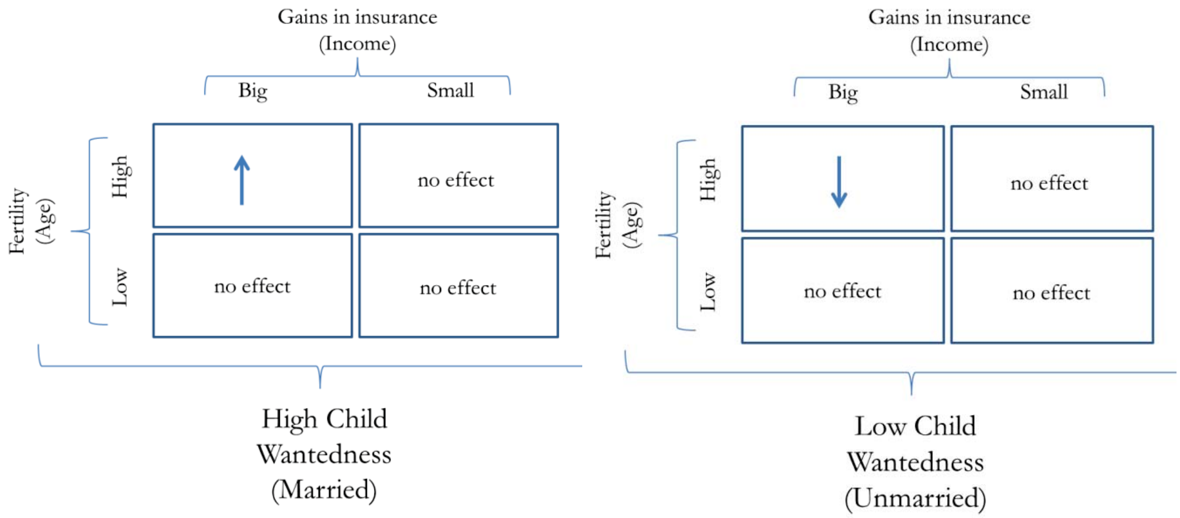
[55] Around one-third of couples in which the woman is over 35 have fertility problems. See http://www.womenshealth.gov/publications/our-publications/fact-sheet/infertility.html, accessed 11/20/2013.

[56] The majority of children born as the result of an unplanned pregnancy are born to women who are either single or cohabiting. See http://www.thenationalcampaign.org/resources/pdf/FactSheet-Consequences.pdf, accessed 11/20/2013.

more likely to have a baby than a similar woman who was richer. A woman who was young, unmarried, and near-poor experienced larger relative gains in insurance coverage and would have seen larger relative reductions in fertility compared to a similar woman who was richer.

Figure 4.1 Expected Fertility Effects by Age, Marital Status and Gains In Insurance Coverage



It is also important to note the importance of the interaction of age and marital status. One would expect that the fertility responses for older women – regardless of whether pregnancies were wanted or insurance gains were large – would be much smaller due to lower latent fertility. For very young women (teenagers), one might expect smaller fertility responses as well if for no other reason than the insurance gains were typically much smaller.

4.5 Data Description: ACS, CPS and Vital Statistics

Our primary data source is the Census Bureau's American Community Survey (ACS) Public Use Microdata Sample (PUMS). We use the one-year sample of the ACS PUMS for the years 2003-2011 (excluding the transition year of 2007 when the reform was being phased in). Starting with the 2005 PUMS, approximately one percent of all households in the

U.S. were surveyed (in 2003 and 2004, the samples are approximately 40 percent the size of subsequent years). As a consequence, we are able to examine the fertility responses in Massachusetts relative to other New England states, while retaining sizable samples. Moreover, we are able to examine responses for narrow demographic groups, such as married women aged 20-34, where we can more accurately characterize the wantedness of pregnancies and latent fertility. The ACS often asks similar questions to the now phased-out decennial Census long forms. Unlike most other household surveys that the Census Bureau conducts, respondents are required by law to participate in the ACS.[57]

Important for our purposes, the ACS directly asks fertility questions pertaining to each woman aged 15-50 in a surveyed household. Specifically, the survey asks "Has this person given birth to any children in the past 12 months?" Other datasets, such as the March Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) do not directly ask about fertility; instead, one might impute fertility from the presence of infants in a household (i.e. 0-year-olds on the household roster). It is clear that such an imputation strategy might have difficulty in assigning an infant to a mother if there is more than one woman of childbearing age in the household. Perhaps more importantly, our investigation of the ACS shows that many infants are potentially not living with their mothers, and this non-presence is related to socioeconomic circumstances. As Table 4.2 shows, across all years, only 80 percent of households where a birth was reported had an infant (0 years) present. Some of this is certainly confusion about the survey question, however, because the fraction of households reporting a birth who also have a zero- or one-year-old present is 88

[57] Source: http://www.census.gov/acs/www/Downloads/language_brochures/ACSQandA_ENG10.pdf. See Title 13, United States Code, Sections 141, 193, and 221. The decennial Census is a notable exception in that it is mandatory.

percent.[58] Nonetheless, there is still an important difference between births and presence of very young children. Roughly 10 percent of infants live in a household where there is not a woman reporting a birth.

Table 4.2 Household ages and the ACS fertility question
"Has this person given birth to any children in the past 12 months?"
Fraction of households with minimum age of zero

	Households where a birth is reported	Households where a birth is not reported	Fraction of zero-year olds in household reporting birth
All Years	79.87%	0.20%	92.52%
2011	76.89%	0.17%	92.56%
2010	78.70%	0.17%	93.24%
2009	79.34%	0.16%	94.03%
2008	79.07%	0.18%	93.58%
2006	81.63%	0.23%	91.84%
2005	81.86%	0.25%	91.51%
2004	82.97%	0.26%	91.16%
2003	81.19%	0.30%	90.00%

Notes: Households with a birth include all households where *any* woman aged 15-50 answered yes to the fertility question. Otherwise, the household is classified as not having a birth. Tabulations include households only if the youngest householder's age is not imputed. All households in US are used in tabulations. Tabulations are unweighted. Source of questions: Q.24 (2011 Survey Instrument) (asked of females aged 15-50); Similar question on other surveys.

In Table 4.3, we show that the modest disconnect between reported births and presence of infants is largely a function of socioeconomic circumstances. We examine 242,006 women aged 15 to 44 in the 2003-2011 ACS across the entire U.S. who reported a birth (and where that woman was the only one in the household reporting a birth). The outcome of interest is whether an infant (defined as age 0) is missing on the household roster. Unmarried, non-white, and less-educated women are far more likely – 8 to 12 percentage points – to not have a baby present in the household; this may be unsurprising if the father lives in a separate household or if members of the extended family, like grandparents, take care of the child. More surprisingly, the likelihood of missing infants increases sharply with age; 35-39 year-olds are 6 percentage points more likely to not have an

[58] If a household misinterpreted "the last 12 months" with "the last year" or "the last calendar year", they might report a one-year-old as a birth.

infant present, while 40-44 year-olds are nearly 24 percentage points more likely to not have an infant present. We interpret these age results somewhat differently than the socioeconomic results, however. Fertility is quite low among these age groups – especially 40-44 year olds – and many of the affirmative responses to the fertility question in the ACS could simply be survey errors for these women. Given this possibility, we also do our empirical analysis separately by age group.

Table 4.3 Baby Not Present In Household (Among Women Indicating Birth In Past Year)

Age 20-24	-0.0074 (0.0068)
Age 25-29	-0.0052 (0.0088)
Age 30-34	0.0119 (0.0089)
Age 35-39	0.0566 (0.0113)
Age 40-44	0.2376 (0.0156)
Married	-0.0886 (0.0027)
Income 150-250% FPL	0.0367 (0.0025)
Income 250-300% FPL	0.0425 (0.0031)
Income 300%+ FPL	0.0565 (0.0031)
White	-0.081 (0.004)
HS Dropout	0.1195 (0.0039)
HS Graduate	0.0718 (0.0026)
Non-mover	0.0018 (0.0024)
Military service	-0.0104 (0.0053)
Non-citizen	0.0056 (0.0039)
R^2	0.0524

Notes: Sample is based on 242,006 women aged 15-44 giving birth in past year in the US, and is limited to households where there is exactly one woman who indicated giving birth in past year. Baby not present is defined as not having a 0-year-old in household. Households excluded if the youngest member's age was imputed. In addition to the variables shown above, specifications include state fixed effects and year fixed effects. Omitted categories include Age 15-19, Unmarried, Income 0-150% FPL, Non-white, College Graduate, Mover, Non-military and Citizen.

There is one unfortunate drawback of the ACS, however. The ACS did not start asking questions on health insurance status until 2008, which is the beginning of our "post" period. As a consequence, we rely on the Current Population Survey (CPS) to derive insurance rates, and append these to each woman in the ACS sample based on various socioeconomic characteristics, state of residence, and time period. We use the 2004-2012 CPS March Supplements, which cover calendar years 2003-2011 (excluding 2007), to compute insured rates for women by demographic category, region and time.[59,60] We do this separately for Massachusetts and the other five New England states combined (Connecticut, Vermont, Maine, Rhode Island, and New Hampshire). The demographic categories are based on age, income, and marital status. There are 6 age groups (15-19, 20-24, 25-29, 30-34, 40-44), 4 income groups (<150% FPL, 150-250% FPL, 250-300% FPL, >300% FPL), 2 marital statuses (married and unmarried). For each demographic group, we create coverage rates for 2 regions (Massachusetts and the rest of New England) and 2 periods ("before" period including calendar years 2003-2006 and "after" period including calendar years 2008-2011).[61] The total number of insurance coverage cells is therefore 192 (6 ages x 4 income x 2 marital x 2 regions x 2 periods). We define a woman as "uninsured" if she is not covered by private health insurance, Medicare, Medicaid, or CHAMPUS. The insurance coverage rate is

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[59] It is thought that CPS answers to health insurance questions are a blend of current coverage and coverage in the previous year. Swartz (1986) argues that CPS respondents ignore the precise wording of the health insurance questions, and instead answer the question as if it referred to coverage as of the survey date.

[60] A similar approach was used by DeLeire, Lopoo, and Simon (2011) where the policy variable is an index of Medicaid eligibility that varies by quarter, state, year, and demographic cell, which is based on age, race, marital status, and education.

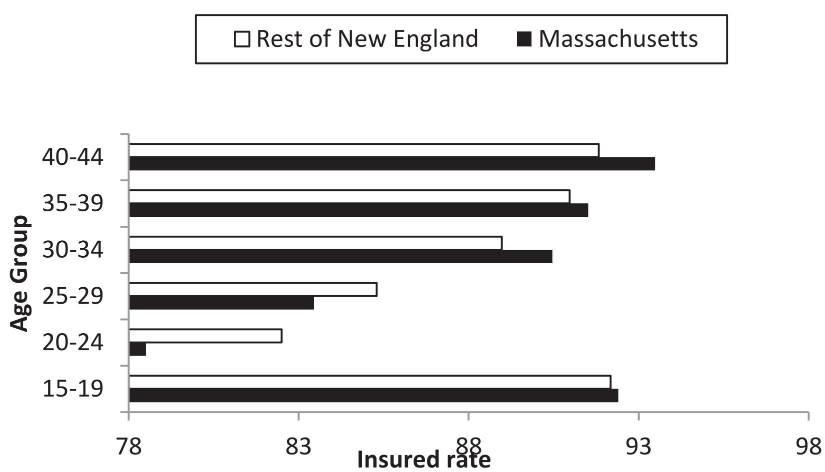
[61] We follow the existing literature in treating 2006 as a "before" year because the earliest provisions went into effect in October 2006. See Hackmann, Kolstad, and Kowalski (2012), Long, Stockley, and Yemane (2009) and Yelowitz and Cannon (2010), all of whom use annual data. Given the time horizon for pregnancy, and the wording of the question in the ACS, the vast majority of pregnancies in this year would have been prior to reform. In addition, the ACS respondents take the survey throughout the year (and it is not possible for us to identify the date when the survey was answered). Virtually all studies classify 2007 – where the individual mandate is implemented in the middle of the year – as a transition year. Our interest lies in the effects of the fully phased-in reform; thus we focus on 2008 onward as the "after" period.

then the weighted ratio of the number of insured women in each cell to the total number of women in the cell.

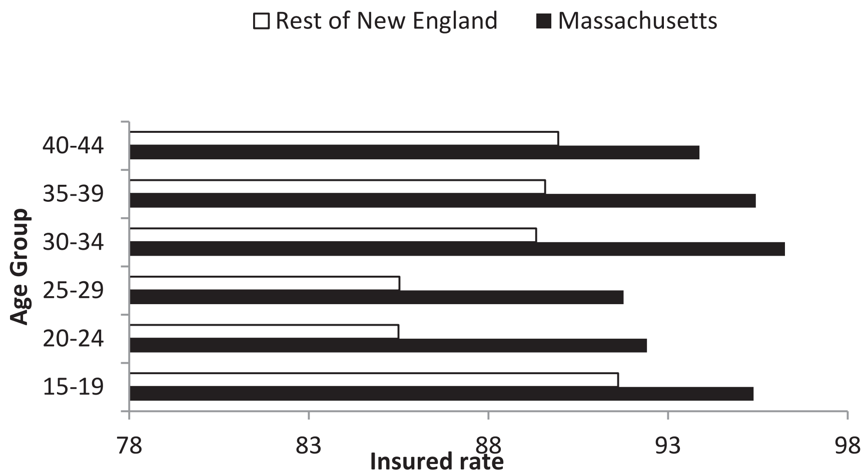
Insurance coverage rates were highest among teenage women (15-19 year-olds) and older women (aged 35-44) both in Massachusetts and the rest of New England in 2003-2006 (Figure 4.2a). This is expected because teenagers are typically covered under their parents' health insurance plan or Medicaid and older adults are more likely to be insured due to improved economic circumstances. The age groups with lowest coverage rates were 20-24 and 25-29 year-olds because young adults leaving college were often no longer covered on a parent's plan and may not have a job with fringe benefits like health insurance. The gains in insurance coverage in Massachusetts following the reform were therefore most pronounced for these age groups (Figures 4.2b and 4.2c); coverage increased by almost 14 percentage points for 20-24 year-olds and 8 percentage points for 25-29 year-olds. The changes among teens and older adults were quite modest in comparison. In contrast to Massachusetts, the rest of New England experienced relatively small gains and even reductions in coverage rates for some age groups.

Figure 4.2 Insurance Coverage Rates By Age Group

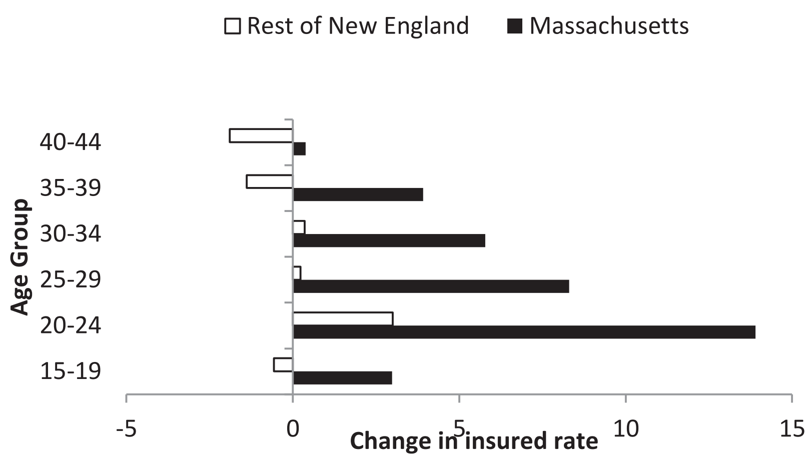
4.2a: Massachusetts vs. rest of New England, 2003-2006



4.2b: Massachusetts vs. rest of New England, 2008-2011



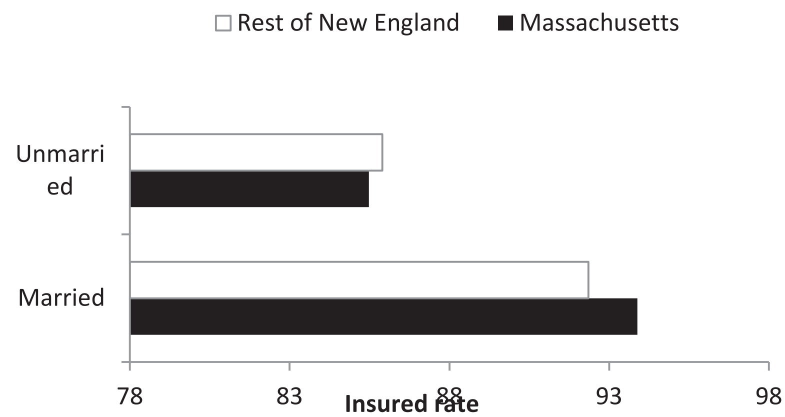
4.2c: Changes in Coverage Rates in Massachusetts vs. rest of New England, Post-Period vs. Pre-Period



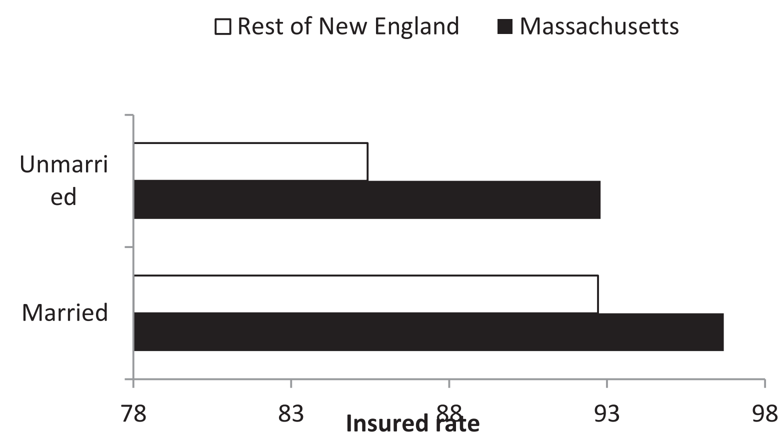
Figures 4.3a, 4.3b, and 4.3c show that coverage rates are higher for married women than unmarried women, because of the availability of spousal health insurance coverage. Massachusetts' reform had an equalizing effect for unmarried women; insurance coverage increased by almost 8 percentage points.

Figure 4.3 Insurance Coverage Rates By Marital Status

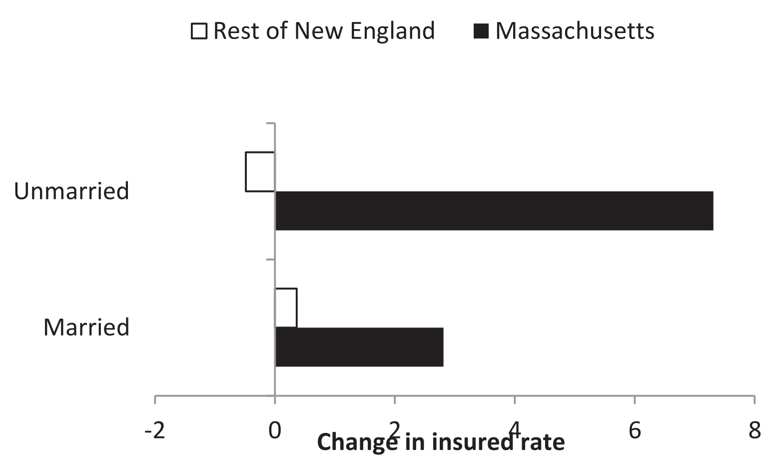
4.3a: Massachusetts vs. rest of New England, 2003-2006



4.3b: Massachusetts vs. rest of New England, 2008-2011



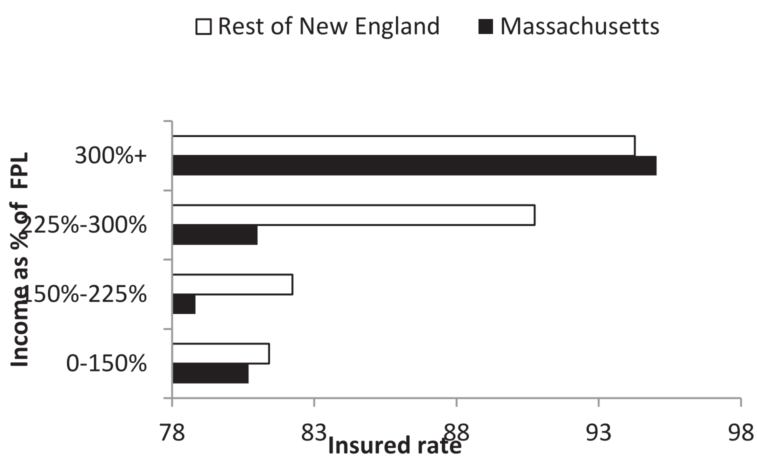
4.3c: Changes in Coverage Rates in Massachusetts vs. rest of New England, Post-Period vs. Pre-Period



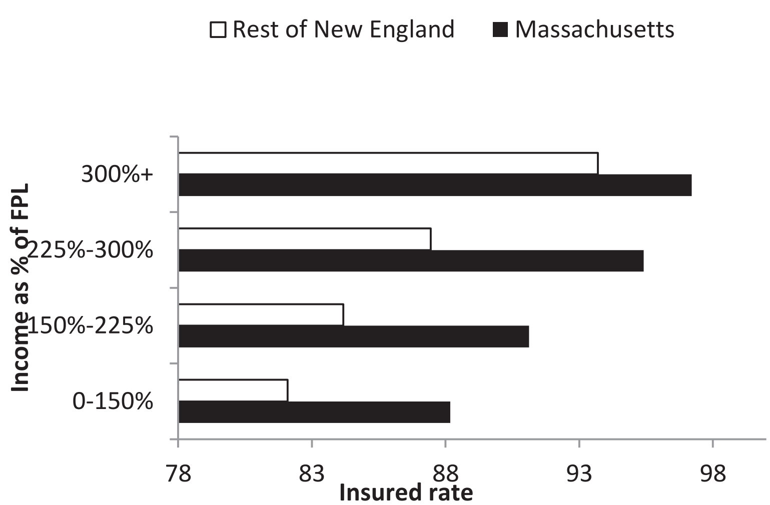
The changes in coverage rates by income are illustrated in Figures 4.4a, 4.4b and 4.4c. Insurance coverage was initially highest for women with incomes over 300 percent of the FPL, and the coverage gains were very small (2 percentage points). The coverage gains were somewhat limited for the poorest women with incomes less than 150 percent of FPL because many had health insurance coverage through Medicaid. In contrast, the middle group with incomes between 150-300 percent FPL saw increases in insurance coverage of 12-14 percentage points.

Figure 4.4 Insurance Coverage Rates By Income Group

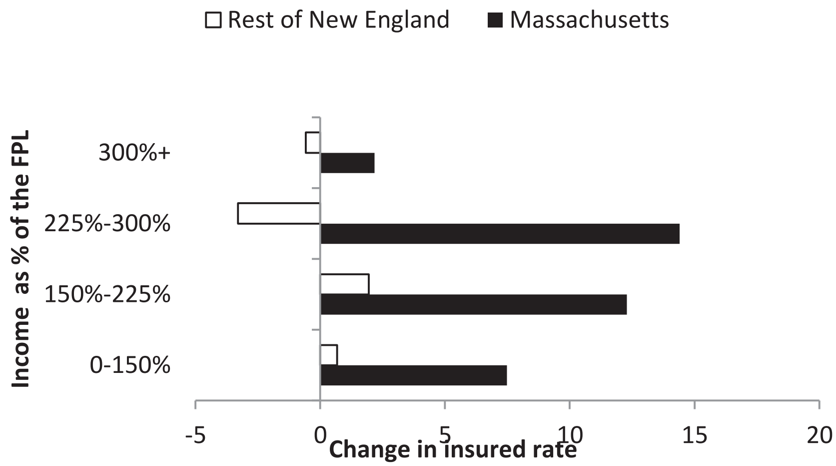
4.4a: Massachusetts vs. rest of New England, 2003-2006



4.4b: Massachusetts vs. rest of New England, 2008-2011



4.4c: Changes in Coverage Rates in Massachusetts vs. rest of New England, Post-Period vs. Pre-Period

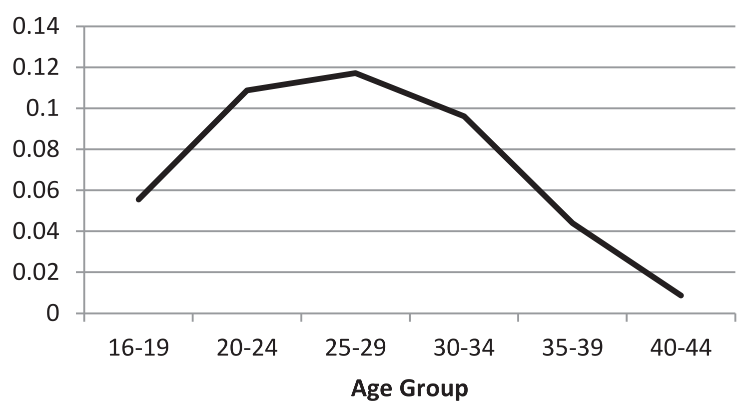


Finally, although women between 15 and 44 are often categorized as being of "child-bearing" age, birth rates vary tremendously by age group. Older women in the sample are more likely to have reached their desired number of children, and as such, one may not expect the same fertility response to insurance coverage that would see with a younger woman. We calculate a latent fertility variable that represents the propensity of a woman to give birth that varies by age, marital status, and race. To construct latent fertility, we use two datasets because the variable is computed as a ratio of the number of births occurring to women within a demographic cell divided by the total number of women in that group and there is no single dataset that provides this information. For the numerator we use the Center for Disease Control and Prevention's Vital Statistics data which records all births in the U.S. for a particular year. We use natality data from 2003, the first year of our analysis, to establish baseline fertility rates. We calculate the number of births for six age groups (16-19, 20-24, 25-29, 30-34, 35-39, and 40-44), two marital statuses (married and unmarried), and two races (white and non-white) for a total of 24 demographic cells. For the denominator we use weighted ACS data from 2003 to obtain the total number of women at risk for birth by demographic cell.

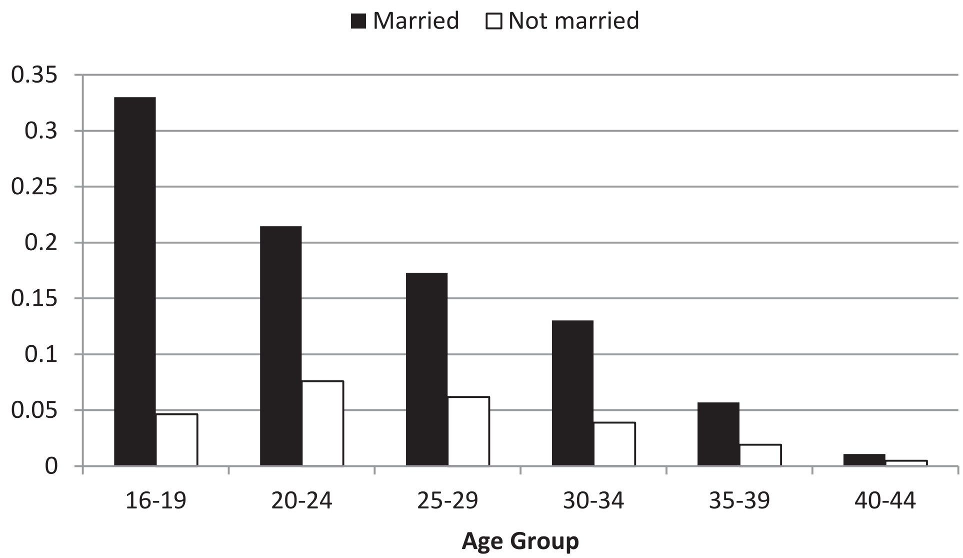
As an example, to compute the latent fertility variable for married non-white women aged 20-24 years, we divide the number of births to women in this demographic cell (59,984) by the total number of women in the U.S. within the same cell (431,350) and obtain a latent fertility rate of 13.9 percent for non-white, married women aged 20-24 years. The inverted-U shape of latent fertility in Figure 4.5a illustrates wide variations of the propensity for having a baby, with young women aged 20-34 being most likely to give birth. Birth rates among married women are significantly higher for each age group than for unmarried women (Figure 4.5b), reflecting a higher degree of child wantedness. Conditional on age and marital status, race is not an important factor affecting latent fertility. We use the constructed fertility rates in two ways. First, the obvious variation of latent fertility provides strong motivation for stratifying the sample, both by age and by age and marital status. Second, as part of the robustness checks, we interact the latent fertility rate with the insured rates to evaluate how the change in insurance coverage rates affect the birth rates for different levels of latent fertility.

Figure 4.5 Fertility Rates

4.5a: Fertility Rates By Age, 2003



4.5b: Fertility Rates by Age/Marital Status, 2003



4.6 Empirical Framework

As is well recognized, the Massachusetts reform creates a quasi-experiment to evaluate the impact of expanding health insurance coverage on various outcomes. The natural starting point for our examination of fertility is a straightforward difference-in-differences (DD) estimator estimated from a linear probability model:

(1) $$BIRTH_{ijt} = \beta_0 + \beta_1 MASS_j * POST_t + \beta_2 MASS_j + \beta_3 POST_t + \beta_4 X_{ijt} + \varepsilon_{ijt}$$

where $BIRTH_{ijt}$ is an dummy variable equal to one if woman *i* in state *j* at time period *t* had a child in the past 12 months, $MASS_j$ is a dummy variable for living in Massachusetts (relative to the other New England states – Connecticut, Maine, New Hampshire, Rhode Island and Vermont), and $POST_t$ is an dummy variable for the years 2008 and beyond (relative to the years 2003-2006).[62],[63] We also include controls for the woman's education (high school dropout, high school graduate with college graduate being omitted), whether the woman has changed residence in the past year, whether she has served in the military and

[62] Results from a probit model are similar.
[63] We omit the transition year of 2007.

whether she is a non-citizen. In later specifications, we also interact age, marital status, and poverty levels. The coefficient estimate on β_1 is then interpreted as the DD estimator.[64]

Although transparent, there are many reasons to go beyond the specification in equation (1). Most importantly, although the near-universal health reform in Massachusetts leveled coverage rates across groups, as discussed in the previous section, there were very different gains based on one's initial socioeconomic circumstances. Thus, we create a parameterized version of equation (1) by attaching to each woman the insurance coverage rate based on her state, time period, and demographic group (48 categories, 6 age x 4 income x 2 marital status).[65] Thus, equation (2), which forms our baseline specification of insurance gains on fertility, is:

$$(2) \qquad BIRTH_{idjt} = \beta_0 + \beta_1 INSURED_{djt} + \beta_2 DEMOG_d + \beta_3 X_{ijt} + \delta_s + \delta_t + \varepsilon_{ijt}$$

where $INSURED_{djt}$ is the fraction of demographic group *d* covered in region *j* in period *t*.[66] It is likely that the key components of $INSURED_{djt}$ – especially demographics like age and marital status – have a direct effect on fertility; thus, we include a full set of dummy variables for demographic group ($DEMOG_d$), as well as state and year fixed effects (δ_s and δ_t). The estimate of the impact of insurance coverage, β_1, is identified from how Massachusetts' changing health insurance landscape over time interacted with different demographic groups. Since the identification of the insurance effect comes from the interaction of state, time and

[64] The large majority of papers studying the effect of the Massachusetts health care law use some form of difference-in-differences identification strategy. See for example, Kolstad and Kowalski (2012a), Courtemanche and Zapata (2012), Yelowitz and Cannon (2010), Long et al. (2009), and Miller (2012a).

[65] Similar methods for constructing a policy variable are consistently used by the literature examining the effect of Medicaid expansions on various outcomes. This measure is typically the fraction of the population eligible for Medicaid (DeLeire et al., 2011; Zavodny and Bitler, 2010; Currie and Gruber, 2001).

[66] Since the variation in INSURED is at a higher level than the individual, all standard errors are clusters at the DEMOG*STATE*YEAR level. The significance of the results is very similar if we simply cluster at the STATE*YEAR level and the significance is much stronger if we cluster at the STATE level alone. Thus, we view our results at the most conservative approach.

demographics, we present further specifications that show the conclusions are relatively robust to including finer controls like state-year interactions.

One key drawback to running equation (2) on the full sample, however, is that such a specification imposes an equal marginal impact on fertility for gains in insurance coverage. There are clearly reasons to think this should not be the case.[67] As discussed in the prior section, older women who are of childbearing age are likely to have reached their desired number of children; as a consequence, one might not expect much impact on fertility for them. Moreover, gains in insurance coverage not only reduce the cost of having a baby, but also reduce the cost of preventing a pregnancy. One would expect that pregnancies are much more likely to be wanted for married women, and unwanted for single women. Thus, the estimate from equation (2) above could combine both positive and negative fertility responses. As a consequence, in addition to examining the full sample, we separately stratify by age group, and also age group and marital status.[68] Further, we provide confirmation that latent fertility matters greatly for the actual fertility response by estimating equation (3):

(3) $$BIRTH_{idjt} = \beta_0 + \beta_1 INSURED_{djt} * FERT_d + \beta_2 INSURED_{djt} + \beta_3 DEMOG_d + \beta_4 X_{ijt} + \delta_s + \delta_t + \varepsilon_{ijt}$$

where $FERT_d$ is the latent fertility rate estimated from the 2003 Vital Statistics and ACS data by age/marital status/race groups, and the other variables are defined as before.[69] Assuming that pregnancies are wanted rather than unwanted, then one would expect β_1 to be positive.

[67] Joyce, Kaestner, and Kwan (1998) only include young, single, and low-educated women in their sample.
[68] Zavodny and Bitler (2010) stratify the sample by race/marital status and race/education to analyze the fertility effects.
[69] The DEMOG variable is then changed to be the interaction of age, marital status, income and race. The FERT variable is not included as a separate regressor because its variation is subsumed by the DEMOG variable.

4.7 Empirical Results

We first summarize fertility rates and insurance rates for our sample. Overall, the sample consists of more than 500,000 women aged 15-44 in Massachusetts and surrounding states. Nearly 8 percent report a birth in the past year, across all years. In addition, our imputed insurance rate is nearly 92 percent – reflecting both the changes in Massachusetts after 2007, and the high overall level of coverage in New England. Consistent with the Vital Statistics data, fertility rates vary dramatically by woman's age. More than 12 percent of women aged 20-34 report having a baby in the previous 12 months, approximately five times the rate of women aged 15-19 or 35-44. The fertility differences are especially pronounced by marital status; nearly 21 percent of married women aged 20-34 reported having a baby, more than three times the rate of unmarried women in the same age group.

Our first attempt at estimating the impact of insurance coverage on fertility is shown in Table 4.4, corresponding to the difference-in-differences specification in equation (1). For both the full sample, as well as each age group, one would conclude the expansions in insurance had little effect on fertility. In all cases, the coefficient estimate is substantively small and insignificant. As noted, however, this specification ignores many important aspects about the fertility decision and the Massachusetts reform, in particular, the uneven gains in insurance coverage, the different latent fertility rates by age group, and the differential wantedness of pregnancies between married and unmarried women.

Table 4.4 Difference-in-differences estimates
Impact of Massachusetts' health reform on fertility

MASS*POST	0.0002 (0.0028)	-0.0004 (0.0036)	0.0020 (0.0052)	0.0004 (0.0045)	0.0008 (0.0091)	0.0031 (0.0035)
MASS	-0.0015 (0.0023)	-0.0015 (0.0031)	-0.0123 (0.0039)	-0.0045 (0.0028)	0.0023 (0.0075)	-0.002 (0.0027)
POST	-0.0014 (0.0021)	0.0000 (0.0026)	-0.0081 (0.0047)	0.0001 (0.0042)	0.0059 (0.0088)	0.0001 (0.003)
N	510,707	79,307	211,135	114,650	96,485	114,533
R^2	0.0087	0.0118	0.0037	0.0263	0.0044	0.0023
Fertility rate (pre-reform)	0.0795	0.0146	0.1305	0.0599	0.2011	0.0239
Sample	All	Ages 15-19	Ages 20-34	Ages 20-34, Unmarried	Ages 20-34, Married	Ages 35-44

Notes: All standard errors are clustered at the STATE*YEAR level. The "pre" period is 2003-2006 and the "post" period is 2008-2011. The treatment state is Massachusetts, and the control states are Maine, New Hampshire, Vermont, Rhode Island and Connecticut. Dependent variable is: "Has this person given birth to any children in the past 12 months?" Individual controls included in regression are: education (dropout, HS graduate, college graduate), non-mover, military service, and non-citizen. Women are included in the analysis if they are aged 15-44, resided in New England, and do not have imputed values for gender, fertility, age, marital status, or race.

Thus, we turn to Table 4.5, which estimates equation (2), by including the parameterized insurance rate. As in the previous table, when one looks at the full sample or particular age groups, insurance gains appear to have no effect on overall fertility. Yet, as shown in columns (3) and (4), there are significant and opposite signed effects for unmarried and married women aged 20-34. Recall this is the group with the highest latent fertility rate. Although not shown, coefficient estimates are insignificant and much smaller for other age/marital status groups. For unmarried women aged 20-34, insurance coverage increased by 11.4 percentage points due to the Massachusetts law.[70] With a coefficient of -0.0459, this would imply that fertility fell by -0.52 percentage points. Since the pre-reform baseline fertility in the ACS was 5.99 percent among this group, then fertility fell by 8.7 percent. For married women, in contrast, gains in insurance coverage led to increased fertility. The overall gain in insurance coverage was much more modest – 2.4 percentage points – which leads to an increase in fertility of 0.23 percentage points from a much higher baseline of 20.11 percent. Thus, among married women, fertility increased by around 1 percent.

[70] We ran difference-in-differences estimates similar to equation (1) to get the change in insurance coverage.

Table 4.5 Impact of insurance gains from Massachusetts' law on fertility

$INSURED_{S,T,DEMOG}$	0.0103 (0.0211)	0.0040 (0.0481)	0.0130 (0.0273)	-0.0459** (0.0216)	0.0982* (0.0504)	-0.0103 (0.0352)
N	510,707	79,307	211,135	114,650	96,485	114,533
R^2	0.0778	0.0394	0.0653	0.0526	0.0155	0.0354
Fertility rate (pre-reform)	0.0795	0.0146	0.1305	0.0599	0.2011	0.0239
Sample	All	Ages 15-19	Ages 20-34	Ages 20-34, Unmarried	Ages 20-34, Married	Ages 35-44

Notes: All standard errors are clustered at the STATE*YEAR*DEMOG level. The "pre" period is 2003-2006 and the "post" period is 2008-2011. The treatment state is Massachusetts, and the control states are Maine, New Hampshire, Vermont, Rhode Island and Connecticut. Dependent variable is: "Has this person given birth to any children in the past 12 months?" Individual controls included in regression are: education (dropout, HS graduate, college graduate), non-mover, military service, and non-citizen. Women are included in the analysis if they are aged 15-44, resided in New England, and do not have imputed values for gender, fertility, age, marital status, or race. All specifications include STATE fixed effects (6 categories), YEAR fixed effects (8 categories) and DEMOG fixed effects (48 categories – 2 groups for marital status x 4 groups for poverty status x 6 groups for age status). ** = significant at 5% level, * = significant at 10% level

Given the striking differences in insurance coverage on married and single women, one may ask whether the marriage decision itself is endogenous to the law. Yelowitz (1998) found that the expansions in Medicaid in the 1980s and 1990s led to higher marriage rates. The key difference between the Medicaid expansions and the more recent Massachusetts context is that Medicaid had been traditionally targeted to poor female headed families on cash welfare (poor married families were largely ineligible); hence the expansions in Medicaid opened up eligibility to married couples and on the margin, created incentives to get married. The expansion in Massachusetts, on the other hand, applied to all groups and was essentially neutral with respect to marriage. In any case, we have run difference-in-differences regressions (parallel to equation 1) where the outcome is whether the woman is married; for both the full sample as well as each age group, the estimate is insignificant and substantively small in all cases.[71]

[71] Chen (2013) examines "marriage lock" and finds reductions in divorce and increases in marriage due to the Massachusetts reform. She uses New Jersey and sometimes Connecticut as control states. Our findings on marriage rates come from examining a younger set of women, and using New England states (which does not include New Jersey) as our control group. Further investigation is certainly needed to reconcile her results on marriage with our non-results.

One concern about Table 4.5 is that the INSURED variable is a complicated function of demographics, state and year. Although we include dummy variables for each of the main effects, a concern may be that there are interactions of DEMOG, STATE and YEAR that are also correlated with fertility decisions independent of the expansions in health insurance coverage. For example, the Great Recession may have affected income or employment in Massachusetts differently than the rest of New England, and those differences, rather than health insurance coverage, may be driving the fertility decisions. In Table 4.6, we test the sensitivity of the coefficient estimates to these kinds of stories for women aged 20-34. For comparison, Columns (1) and (5) replicate the specification and findings for unmarried and married women in the prior table. By including STATE*YEAR effects in columns (2) and (6), we see that such state-specific shocks have little impact on the underlying conclusions (if anything, the negative impact is slightly stronger for unmarried women). The next columns add DEMOG*YEAR interactions (in addition to the STATE*YEAR interactions). Although no longer significant, the coefficient estimate for single women remains quite similar. For married women, the fertility effect is still positive, significant, and much the same magnitude as before. Finally, when one fully saturates the model, by including fixed effects for STATE*YEAR, DEMOG*YEAR and DEMOG*STATE (thus, the identification comes only from the interaction of STATE*YEAR*DEMOG in the INSURED variable), then neither estimate is significant, although it is reassuring that the actual estimate is quite similar to the baseline estimate. Overall, the findings for both unmarried women and married women hold up remarkably well to including additional controls.

Table 4.6 Sensitivity to set of control variables
Impact of insurance gains from Massachusetts' law on fertility, Panel a

$INSURED_{S,T,DEMOG}$	-0.0459** (0.0216)	-0.0637** (0.0266)	-0.0589 (0.0388)	-0.0492 (0.0434)
N	114,650	114,650	114,650	114,650
R^2	0.0526	0.0537	0.0554	0.0580
Fertility rate (pre-reform)	0.0599	0.0599	0.0599	0.0599
Sample	Age 20-34 Unmarried	Age 20-34 Unmarried	Age 20-34 Unmarried	Age 20-34 Unmarried
Interaction Terms	STATE, YEAR, DEMOG (Table 4.4)	STATE*YEAR, DEMOG	STATE*YEAR, DEMOG*YEAR	STATE*YEAR, DEMOG*YEAR, DEMOG*STATE

Notes: All standard errors are clustered at the STATE*YEAR*DEMOG level. The "pre" period is 2003-2006 and the "post" period is 2008-2011. The treatment state is Massachusetts, and the control states are Maine, New Hampshire, Vermont, Rhode Island and Connecticut. Dependent variable is: "Has this person given birth to any children in the past 12 months?" Individual controls included in regression are: education (dropout, HS graduate, college graduate), non-mover, military service, and non-citizen. Women are included in the analysis if they are aged 20-34, resided in New England, and do not have imputed values for gender, fertility, age, marital status, or race. ** = significant at 5% level, ** = significant at 10% level

Table 4.6 Sensitivity to set of control variables
Impact of insurance gains from Massachusetts' law on fertility, Panel b

$INSURED_{S,T,DEMOG}$	0.0982* (0.0504)	0.0998** (0.0501)	0.1144** (0.0544)	0.0988 (0.0664)
N	96485	96485	96485	96485
R^2	0.0155	0.0169	0.0189	0.0222
Fertility rate (pre-reform)	0.2011	0.2011	0.2011	0.2011
Sample	Age 20-34 Married	Age 20-34 Married	Age 20-34 Married	Age 20-34 Married
Interaction Terms	STATE, YEAR, DEMOG (Table 4.4)	STATE*YEAR, DEMOG	STATE*YEAR, DEMOG*YEAR	STATE*YEAR, DEMOG*YEAR, DEMOG*STATE

Notes: All standard errors are clustered at the STATE*YEAR*DEMOG level. The "pre" period is 2003-2006 and the "post" period is 2008-2011. The treatment state is Massachusetts, and the control states are Maine, New Hampshire, Vermont, Rhode Island and Connecticut. Dependent variable is: "Has this person given birth to any children in the past 12 months?" Individual controls included in regression are: education (dropout, HS graduate, college graduate), non-mover, military service, and non-citizen. Women are included in the analysis if they are aged 20-34, resided in New England, and do not have imputed values for gender, fertility, age, marital status, or race. ** = significant at 5% level, ** = significant at 10% level

In addition to exploring the sensitivity of the specification to additional controls, we consider one other important issue. There may be a concern that the generous health insurance benefits in Massachusetts – with community-rated premiums and guaranteed issue – makes the state a more attractive place for individuals with high expected medical costs, such as pregnant women and therefore encourage migration. It is important to note that if this is the case, one might expect to see increases in fertility for all age groups, rather than increases for married women and decreases for unmarried women. Nonetheless, selective migration is clearly a concern.[72] Using the CPS, Yelowitz and Cannon (2010) find that in-migration in Massachusetts fell relative to other New England states as a result of the law, and this effect was particularly pronounced among adults aged 18-29. They interpret the drop in in-migration for the young – who are largely healthy and have low expected medical costs – as arising from the greater implicit tax on them arising from community rating and individual mandates. The same factors that generate implicit taxes for most young adults also create implicit subsidies for pregnant women.

The ACS asks about one-year-migration patterns, and allows us to test this hypothesis. We restrict the sample to women who did not move across state lines in the previous year, and estimate equation (2) on each group. Our results are quite similar to the baseline results in Table 4.5. For the 94 percent of unmarried women aged 20-34 who did not move across state lines, the coefficient estimate (standard error) is now -0.0422 (0.0222) compared with the initial estimate of -0.0459 (0.0216). For the 95 percent of married women aged 20-34 who did not move across state lines, the coefficient estimate (standard error) is now 0.0821 (0.0538) compared with the initial estimate of 0.0982 (0.0504). In both cases, the small fraction of cross-state moves would appear to have greater responses to insurance coverage relative to non-movers, but the basic conclusions remain unchanged by restricting the sample to non-movers.

[72] Gelbach (2004) shows that among women likely to use welfare, movers move to higher-benefit states. Aizer, Currie and Moretti (2007) and Marton, Yelowitz and Talbert (2012) explicitly account for the possibility that relatively attractive Medicaid health insurance packages might induce migration across counties within a state.

Finally, equation (3) interacts latent fertility with gains in insurance coverage and includes the main effect for insurance coverage. In all specifications in Table 4.7, the interaction term is positive, suggesting that gains in insurance coverage have positive effects on fertility for those with higher latent fertility. The main effect of insurance coverage is negative. This would be consistent with the findings in earlier tables, since married women have higher fertility rates (and thus, the interaction term is relatively important), while unmarried women have lower fertility rates (and thus, the main effect is relatively important.

Table 4.7 Interaction of insurance gains with latent fertility - Impact on fertility

$INSURED_{S,T,DEMOG} * FERT_{DEMOG2}$	0.8592** (0.3413)	0.8634*** (0.3419)	0.7980** (0.3838)	0.4198 (0.4638)
$INSURED_{S,T,DEMOG}$	-0.0723*** (0.0272)	-0.0742*** (0.0285)	-0.0564** (0.0334)	-0.0297 (0.0382)
N	510707	510707	510707	510707
R^2				
Mean of dep. variable				
Sample	All	All	All	All
Interaction Terms	STATE, YEAR, DEMOG2	STATE*YEAR, DEMOG2	STATE*YEAR, DEMOG2*YEAR	STATE*YEAR, DEMOG2*YEAR, DEMOG2*STATE

Notes: All standard errors are clustered at the STATE*YEAR*DEMOG2 level. The "pre" period is 2003-2006 and the "post" period is 2008-2011. The treatment state is Massachusetts, and the control states are Maine, New Hampshire, Vermont, Rhode Island and Connecticut. Dependent variable is: "Has this person given birth to any children in the past 12 months?" Individual controls included in regression are: education (dropout, HS graduate, college graduate), non-mover, military service, and non-citizen. Women are included in the analysis if they are aged 15-44, resided in New England, and do not have imputed values for gender, fertility, age, marital status, or race. All specifications include STATE fixed effects (6 categories), YEAR fixed effects (8 categories) and DEMOG fixed effects (96 categories – 2 groups for marital status x 4 groups for poverty status x 6 groups for age status x 2 races) *** = significant at 1% level, ** = significant at 5% level, * = significant at 10% level

Finally, we have examined an alternative definition of fertility. Recall that earlier tables found that some women reported pregnancies but did not have infants living in the household, and on many dimensions the missing infants varied logically with socioeconomic characteristics like marital status, race and education. We have run similar specifications to our baseline result, but where childbirth is now defined as having an infant present on the household roster. Such a measure has difficulty in linking the infant to a mother when there are multiple women of childbearing age in a household, or when the mother is missing from the household. Although we continue to find reductions in fertility for unmarried women aged 20-34 and increases in fertility for married women aged 20-34, the coefficient estimates are roughly one-third as large and not statistically significant. In our view, this provides further evidence of the value of the self-reported pregnancy question over an approach that imputes past pregnancy based on household configurations.

To test if the Massachusetts health care reform affected differentially the fertility rates of women with different levels of educational attainment, model (1) and model (2) were estimated separately for the sample of women with a high school diploma or less and for women with at least a college degree. There is no indication that the reform had an overall effect on the probability of having a child for women with different levels of educational attainment which suggests that the near-universal provision of health insurance in Massachusetts cannot be considered a determinant of differential fertility (difference between the fertility rates of women with low levels of education and women with high levels of education).

In summary, although the expansions in health insurance coverage had close to zero net effect on fertility in Massachusetts, substantial heterogeneity exists for different demographic groups. Our findings suggest that latent fertility and the wantedness of children, along with differential gains in coverage, help explain opposite signed effects for married and unmarried women aged 20-34, and also explain the non-existence of effects for other groups. Married women in this age bracket increase their fertility when experiencing gains in coverage because pregnancies are largely wanted and underlying fertility is high. Single women, on the other hand, decrease their fertility because pregnancies are largely unwanted and better access to contraception helps them prevent pregnancy. For women aged 35 and older, latent fertility is quite low (and insurance coverage was typically high prior to the reform), so the overall fertility responses are small (and insignificant). For teenagers, fertility rates are also quite low, many pregnancies are unwanted, and insurance coverage was fairly high prior to reform. Thus, we find small and insignificant effects for them too.

4.8 Conclusions and Discussion

In this paper we examine the effect of the Massachusetts health care reform on a woman's probability of having a baby. Although we find zero net effect on fertility for women aged 20-34, this masks substantial heterogeneity across married and unmarried women (which proxies for child wantedness). Among young married women, fertility increased by 1 percent while fertility decreased by 9 percent for young unmarried women. We find no effect on birth rates for teens or older women either in total or when we stratify by marital status.

Whether the reform simply shifted the timing of births or changed the total number of children a woman will have in her lifetime remains an open question. Data over a longer period than four years needed to assess the long-term fertility effect of the Massachusetts reform. Regardless of whether the reforms simply reflect a change in timing, the proportion of unintended pregnancies (those that are mistimed, unplanned or unwanted) fell as a result of the law.

Our results are informative about the future consequences of the PPACA which was largely modeled after the Massachusetts law. Expanding insurance would likely wanted pregnancies on a national scale. To the extent that the contraception-related provisions of the legislation remain unchanged, the national reform might also lead to a decrease in unwanted births. Such a reduction in unwanted births could have favorable implications for long-term crime trends in much the same way that legalizing abortion did (Donohue and

Levitt, 2001). Preventing an unwanted birth might lead to increased investment in women's own human capital and the human capital of their children thus increasing the overall level of future human capital and affecting the future rates of economic growth. To the extent that the reduction in unwanted births is due to increased use of contraception (rather than increased abortion rates), potential savings could be realized in terms of resources spent on unintended pregnancies.

Appendices

Appendix 1.A

Variable Definitions and Instruments Used

Explanatory variable	Definition	Instrument
GDP	Level of per capita GDP (initial)	Square of initial per capita GDP
I/GDP	Ratio of investment to GDP (average)	Initial I/GDP
G/GDP	Ratio of government spending to GDP (average)	Initial G/GDP
AFR	Indicator variable for Africa	Own instrument
GINI	Measure of income inequality (0-100) (average)	Indicator variable for sea access and share of land in tropics
TFR	Total fertility rate (initial)	Square of initial total fertility rate
DTFR	Differential fertility[73]	Life expectancy; Square of life expectancy
FRPIMARY	Female primary school completion rate (average)	Initial female primary school completion rate
MFPRIMARY	Male and female primary school completion rate (average)	Initial male and female primary school completion rate
AYSCHOOL (F)	Female average years of schooling (average)	Initial female average years of schooling
AYSCHOOL (MF)	Male and female average years of schooling (average)	Initial male and female average years of schooling
SSCHOOL (F)	Female secondary school completion rates (average)	Initial female secondary school completion rates
SSCHOOL (MF)	Male and female secondary school completion rates (average)	Initial male and female secondary school completion rates

[73] Differential fertility is measured in different years for different countries but generally towards the end of the two periods in question.

Appendix 1.B

Data Availability by Country by Period

Country	1960-1976	1976-1992
Bangladesh	x	x
Benin	x	
Bolivia		x
Botswana		x
Brazil		x
Burundi		x
Cameroon	x	x
Cantral Afr. Rep.		x
Colombia	x	x
Costa Rica	x	
Czechoslovakia	x	
Denmark	x	
Dominican Rep.	x	x
Ecuador	x	x
Egypt		x
El Salvador		x
Finland	x	
France	x	
Ghana	x	x
Guatemala		x
Guyana	x	
Haiti	x	
Indonesia		x
Italy	x	
Ivory Coast	x	
Jamaica	x	
Jordan	x	x
Kenya	x	x
Korea Rep.	x	
Lesotho	x	
Liberia		x
Malawi		x
Malaysia	x	
Mali		x
Mexico	x	x
Morocco	x	x
Namibia		x
Niger		x

Country	1960-1976	1976-1992
Norway	x	
Pakistan	x	x
Panama	x	
Paraguay	x	x
Peru	x	x
Philippines	x	x
Poland	x	
Romania	x	
Rwanda		x
Senegal		x
Spain	x	
Sri Lanka		x
Sudan		x
Syria	x	
Thailand		x
Togo		x
Trinidad & Tobago	x	x
Tunisia		x
Turkey		x
U.K.	x	
U.S.A.	x	
Uganda		x
Venezuela	x	
Yemen	x	
Yugoslavia	x	
Zambia		x
Zimbabwe		x

Appendix 1.C

Selected Summary Statistics

1960-1976

Variable	Obs	Mean	Std. Dev.	Min	Max
GROWTH	40	0.036	0.020	-0.006	0.084
GDPini	40	7.428	0.820	5.746	9.200
I/GDP	40	18.326	9.225	3.340	37.240
G/GDP	40	16.158	5.941	4.750	29.360
AYSCHOOL (MF)	40	4.067	2.391	0.040	10
SSCHOOL(MF)	40	7.238	7.235	0.070	41.970
PRIMARY(MF)	40	21.122	17.978	0.130	76.100
SSCHOOL(F)	40	5.454	6.725	0	41.775
AYSCHOOL(F)	40	3.870	2.543385	0.013	10.364
AFR	40	0.150	0.361	0	1
Gini	40	44.318	11.135	23.3	68.0
DTFR	40	2.231	1.556	0.220	5.300

1976-1992

Variable	Obs	Mean	Std. Dev.	Min	Max
GROWTH	40	0.005	0.019	-0.035	0.050
GDPini	40	7.256	0.688	6.111	9.080
I/GDP	40	12.404	5.754	1.940	23.880
G/GDP	40	20.616	7.052	9.230	36.520
AYSCHOOL (MF)	40	3.907	1.804	0.690	8.010
SSCHOOL(MF)	40	8.070	5.955	0.630	29.800
PRIMARY (MF)	40	14.118	8.252	2.700	35.000
SSCHOOL(F)	40	6.744	5.856	0.433	28.667
AYSCHOOL(F)	40	3.535	2.012	0.376	7.817
AFR	40	0.450	0.504	0	1
Gini	40	46.271	1.702	28.9	69.0
DTFR	40	2.423	1.003	0.100	4.500

Appendix 2.A

Variable Definitions

gr	Average annual growth rate of real personal income per capita
y	Personal income: income received by persons from all sources
coll	Educational attainment (persons 25 and over): percent completing 16 years or more of education
hs	Educational attainment (persons 25 and over): percent completing 12 years or more of education
over65	Percentage of the population aged 65 years and over
dtfr	Differential fertility: difference between completed fertility rates of women with low level of education and fertility rates of women with high level of education
br	Birth rate: live births per 1,000 people in a given year
gini	Gini coefficient: "The average distance between all pairs of proportional income in the population. Scale 0-1 (0 is perfect equality, 1 is perfect inequality). Frank (2009)
atkin	The Atkinson index belongs to the class of welfare-based measures of income inequality. It takes into account the sensitivity of observed inequality to income changes in the ends of the income distribution by using an inequality aversion parameter (Allison, 1978). The higher the inequality aversion parameter, the more sensitive the index is to changes in the lower end of the income distribution. The Atkinson index used here was calculated with an inequality aversion parameter of 0.5 which makes it sensitive to changes in the upper end of the income distribution. Bellu and Liberati (2006) provide the following explanation of the Atkinson index: "The Atkinson index is directly related to the class of additive social welfare functions: $W = \frac{1}{N}\sum_{i=1}^{n} U(y_i)$. [This] [e]xpression say that social welfare is represented by average utility. The form of the function U, according to Atkinson, is the following: $U(y_i) = \frac{1}{1-\varepsilon} y_i^{1-\varepsilon}$ if $\varepsilon \neq 1$ or $U(y_i = \log(y_i)$ if $\varepsilon = 1$."
theil	The Theil entropy index belongs to the entropy class of inequality indices that measure deviations from perfect equality. Its distinguishing feature is that it is a decomposable inequality measure which is sensitive to changes in

the upper tail of the income distribution[74]. It is the sum of within-group inequality and between-group inequality (Schorrock, 1980) and its advantage over the Gini coefficient is that, since it is a decomposable measure, it is informative of the importance of between group inequality for the overall observed inequality. Shorrocks (1980) provides the following explanation of the Theil entropy index: “If $y = (y_1, \ldots\ldots, y_n)$ is the income distribution vector for a population of n individuals, the Theil index can be written as $T(y; n) = \frac{1}{n}\sum_i \frac{y_i}{\mu} \square og \frac{y_i}{\mu}$ where μ is the mean income $\sum_i \frac{y_i}{n}$. Partition the population into G disjoint subgroups where subgroup g consists of n_g (≥ 1) individuals with the distribution vector $y^g = (y_1^g, \ldots, y_{n_g}^g)$ and mean μ_g. Then, using the fact that T is symmetric over y,
$T(y; n) = T(y^1, y^2, \ldots, y^G; n) =$
$\frac{1}{n}\sum_g \sum_{i=1}^{n_g} \frac{y_i^g}{\mu} \log \frac{y_i^g}{\mu} = \sum_g \frac{n_g \mu_g}{n_\mu} T\left(y^g; n_g\right) + \frac{1}{n}\sum_g n_g \frac{\mu_g}{\mu} log \frac{\mu_g}{\mu}$.”

top1 Top 1% share of income

top10 Top decile share of income

[74] See http://www.fao.org/docs/up/easypol/445/theil_index_051en.pdf (accessed 5/15/2014).

Appendix 2.B

Descriptive Statistics Selected Variables, entire period, 1970 - 2009

Variable	N	Mean	St. Dev.	Min	Max
Growth rate of personal income (gr)	192	1.61	1.00	-0.93	4.37
Ln personal income (y)	192	5.60	0.26	4.62	6.22
Differential fertility (dtfr)	192	1.33	0.40	0.26	2.19
Birth rate (br)	192	16.32	2.61	10.70	28.6
Income inequality (gini)	192	0.52	0.06	0.42	0.66
Top 10 share (top10)	192	0.36	0.06	0.28	0.53
Top 1 share (top1)	192	0.11	0.05	0.06	0.28
Theil entropy index (theil)	192	0.57	0.22	0.33	1.33
Atkinson (atkinson)	192	0.23	0.05	0.16	0.38
% completed college (coll)	192	16.86	6.63	4.78	33.19
% urban population (urban)	192	67.92	14.64	32.20	94.40
% population over 65 (over65)	192	11.60	2.08	6.30	18.23

Descriptive Statistics for Selected Variables, by Time Period
10-year Growth Episodes 1970-1979

Variable	N	Mean	St. Dev.	Min	Max
Growth rate of personal income (gr)	48	2.26	0.71	0.78	4.37
Ln personal income (y)	48	5.34	0.16	4.98	5.64
Differential fertility (dtfr)	48	1.75	0.26	1.09	2.19
Birth rate (br)	48	18.63	1.76	16.30	25.50
Income inequality (gini)	48	0.46	0.02	0.42	0.51
Top 10 share (top10)	48	0.30	0.01	0.28	0.36
Top 1 share (top1)	48	0.08	0.01	0.07	0.10
Theil entropy index (theil)	48	0.38	0.03	0.33	0.44
Atkinson (atkinson)	48	0.18	0.01	0.16	0.21
% completed college (coll)	48	8.22	2.11	4.78	12.88
% urban population (urban)	48	65.90	14.39	32.20	90.90
% population over 65 (over65)	48	9.87	1.68	6.30	14.51

1980 - 1989

Growth rate of personal income (gr)	48	2.04	1.00	-0.67	3.89
Ln personal income (y)	48	5.51	0.20	4.62	5.97
Differential fertility (dtfr)	48	1.47	0.14	1.05	1.70
Birth rate (br)	48	16.61	2.80	12.50	28.60
Income inequality (gini)	48	0.49	0.02	0.45	0.55
Top 10 share (top10)	48	0.31	0.01	0.29	0.35
Top 1 share (top1)	48	0.08	0.01	0.06	0.10
Theil entropy index (theil)	48	0.41	0.03	0.36	0.49
Atkinson (atkinson)	48	0.19	0.01	0.17	0.22
% completed college (coll)	48	15.90	2.87	10.40	23.00
% urban population (urban)	48	66.59	14.42	33.80	91.30
% population over 65 (over65)	48	11.23	1.81	7.49	17.32

1990 - 1999

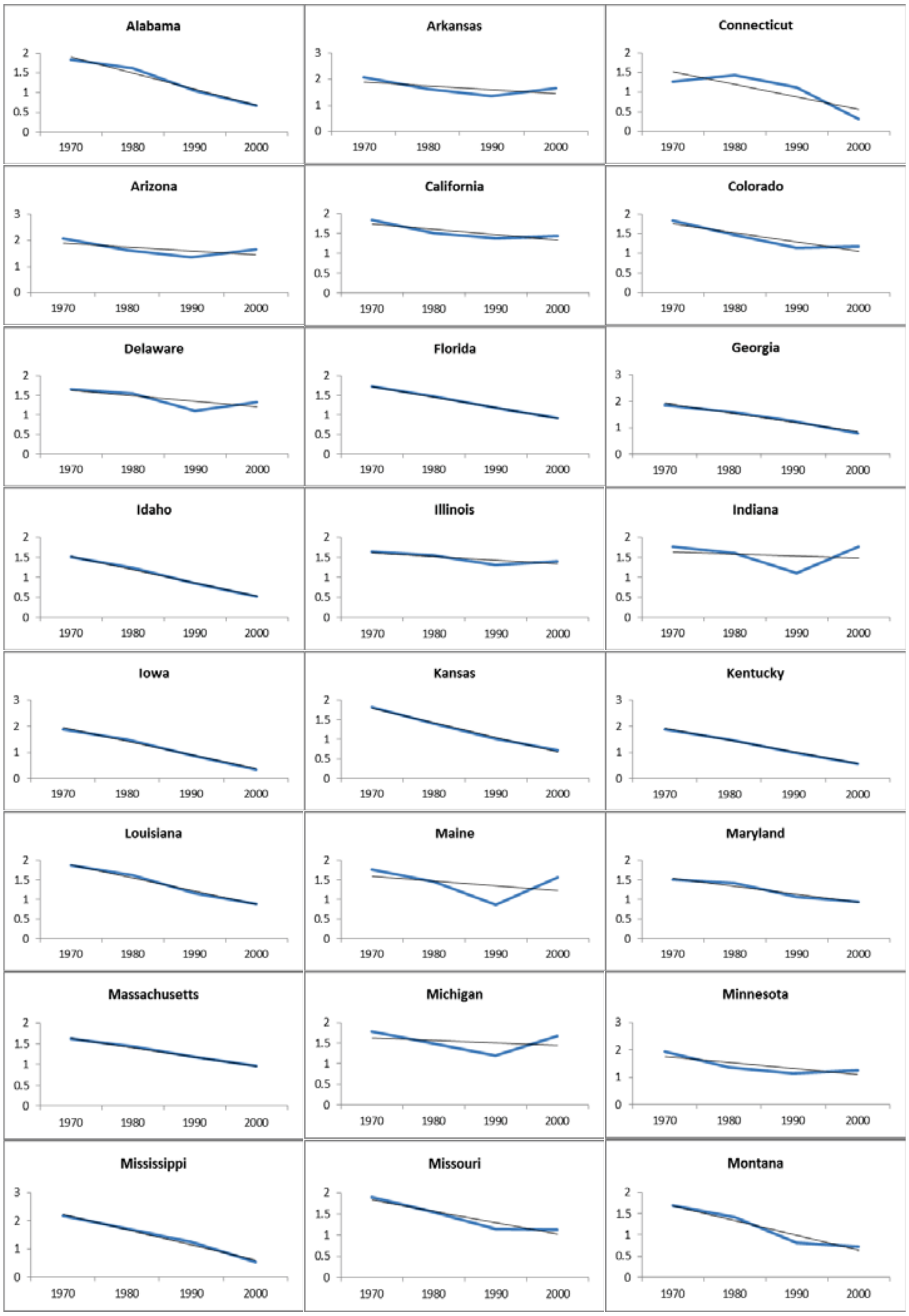
Growth rate of personal income (gr)	48	1.65	0.38	0.75	2.52
Ln personal income (y)	48	5.70	0.17	5.25	6.06
Differential fertility (dtfr)	48	1.07	0.19	0.51	1.41
Birth rate (br)	48	16.05	1.56	12.60	21.10
Income inequality (gini)	48	0.56	0.02	0.53	0.62
Top 10 share (top10)	48	0.37	0.02	0.34	0.43
Top 1 share (top1)	48	0.12	0.02	0.10	0.19
Theil entropy index (theil)	48	0.65	0.10	0.51	0.96
Atkinson (atkinson)	48	0.23	0.02	0.20	0.28
% completed college (coll)	48	19.62	3.76	12.33	27.23
% urban population (urban)	48	67.76	14.66	32.20	92.60
% population over 65 (over65)	48	12.65	1.78	8.72	18.23

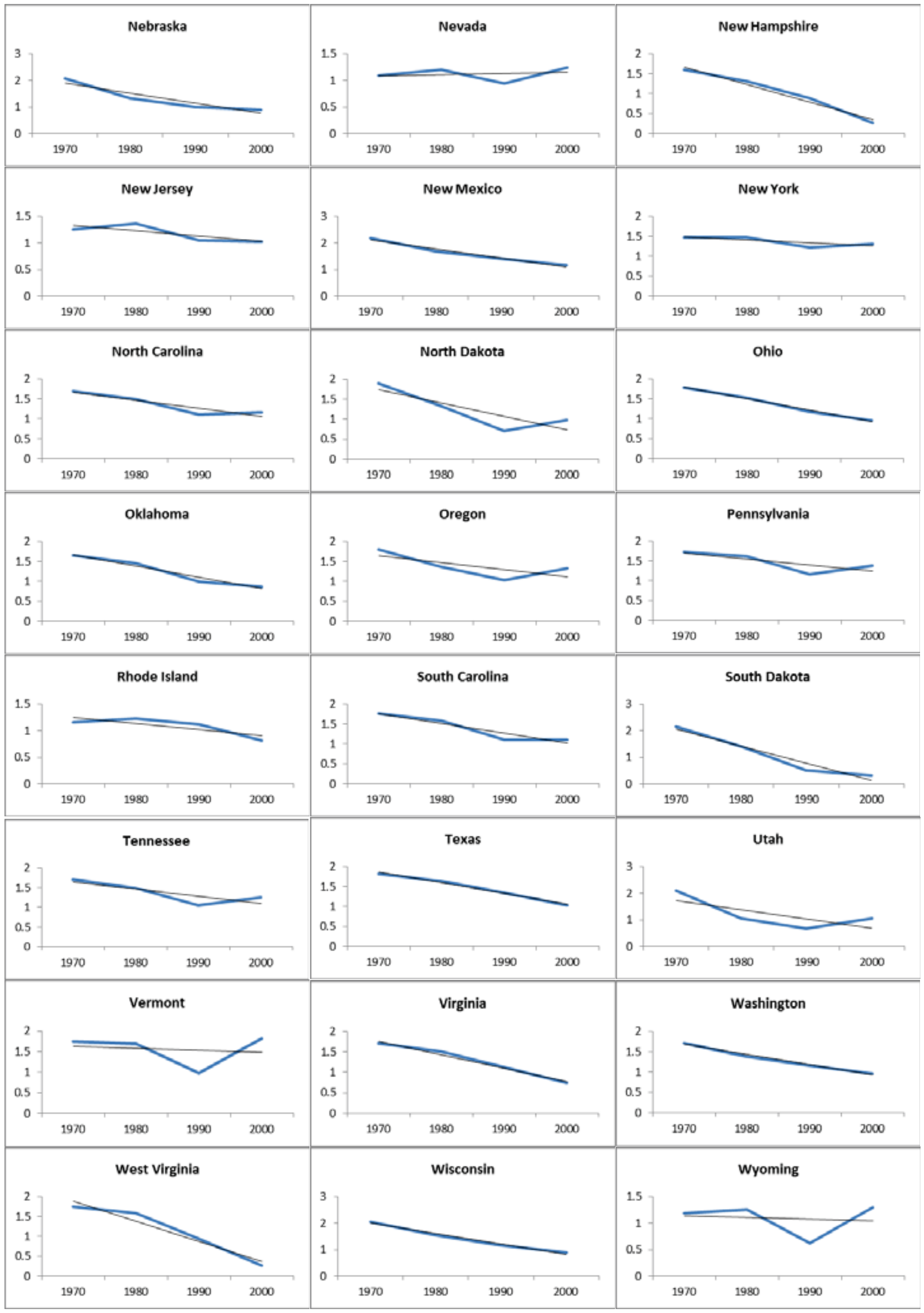
2000 - 2009

Growth rate of personal income (gr)	48	0.51	0.72	-0.93	2.35
Ln personal income (y)	48	5.86	0.16	5.41	6.22
Differential fertility (dtfr)	48	1.02	0.40	0.26	1.82
Birth rate (br)	48	13.99	1.79	10.70	21.20
Income inequality (gini)	48	0.58	0.03	0.52	0.66
Top 10 share (top10)	48	0.43	0.04	0.37	0.53
Top 1 share (top1)	48	0.17	0.04	0.11	0.28
Theil entropy index (theil)	48	0.84	0.20	0.55	1.33
Atkinson (atkinson)	48	0.28	0.04	0.23	0.40
% completed college (coll)	48	23.71	4.35	14.83	33.19
% urban population (urban)	48	71.41	14.91	38.20	94.40
% population over 65 (over65)	48	12.66	1.66	8.52	17.57

Appendix 2.C

Trends in Differential Fertility by State, 1970-2000



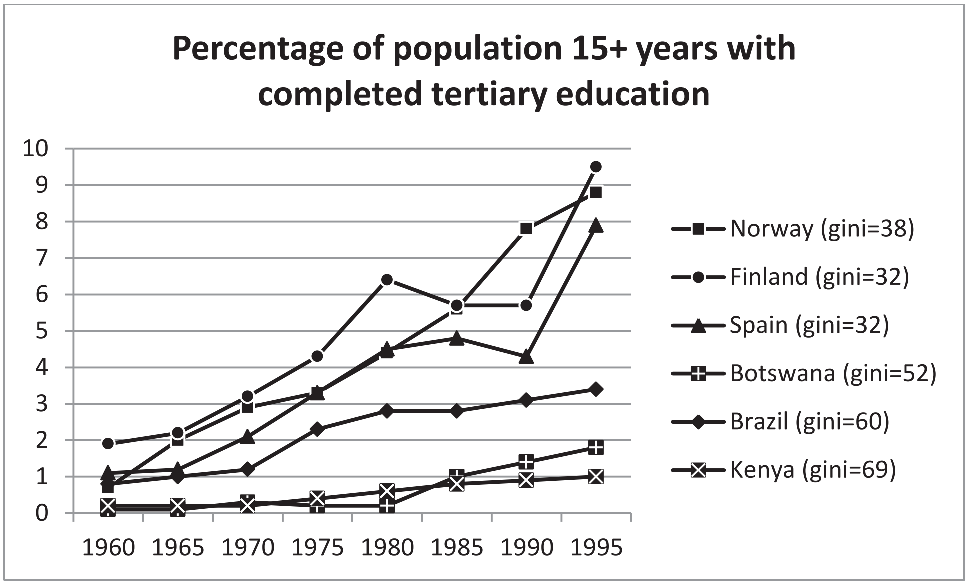


Nebraska
Nevada
New Hampshire
New Jersey
New Mexico
New York
North Carolina
North Dakota
Ohio
Oklahoma
Oregon
Pennsylvania
Rhode Island
South Carolina
South Dakota
Tennessee
Texas
Utah
Vermont
Virginia
Washington
West Virginia
Wisconsin
Wyoming
1970
1980
1990
2000

Appendix 2.D

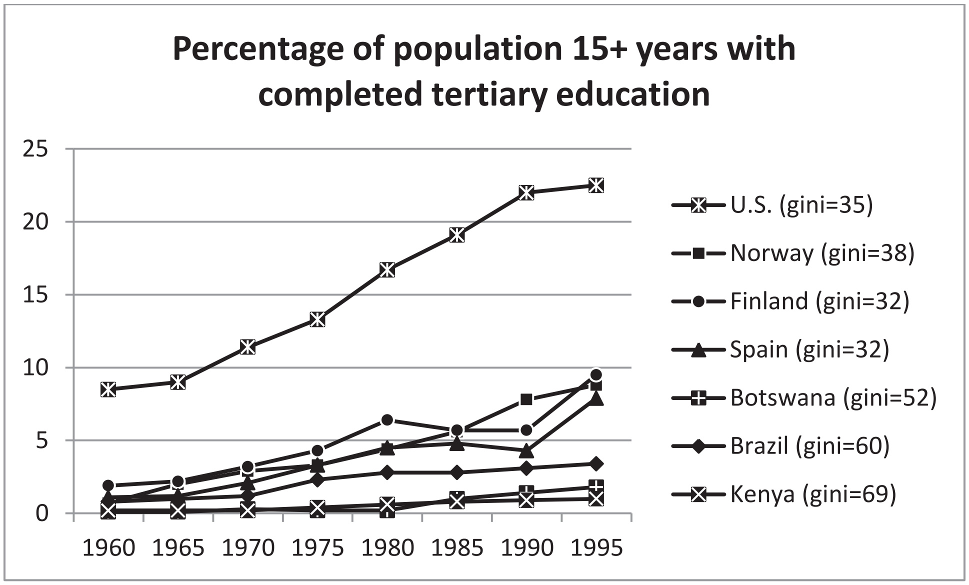
Tertiary Education Completion Rate for Selected Countries

Figure 1
Percentage of population 15 years and over with completed tertiary education for selected countries by income inequality, 1960-1995



Source: Barro, Robert J., and Jong Wha Lee. "A new data set of educational attainment in the world, 1950–2010." Journal of development economics 104 (2013): 184-198.

Figure 2
Percentage of population 15 years and over with completed tertiary education for selected countries by income inequality, 1960-1995



Source: Barro, Robert J., and Jong Wha Lee. "A new data set of educational attainment in the world, 1950–2010." Journal of development economics 104 (2013): 184-198.

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